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3rd Edition

Artificial Intelligence

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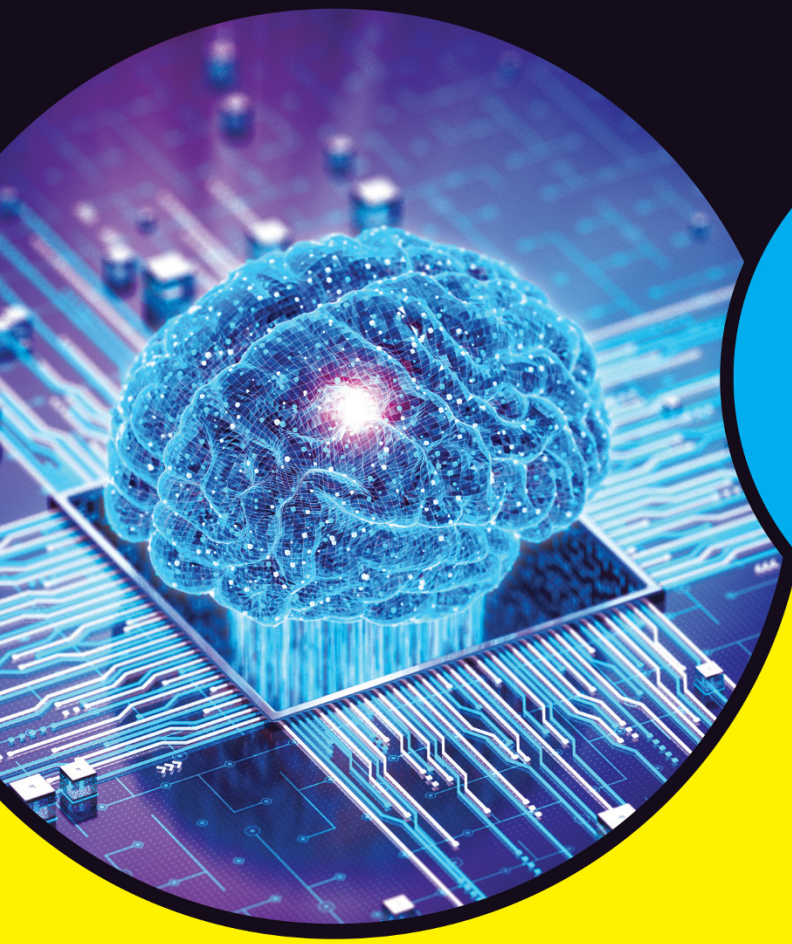

Look under the hood of AI platforms

Connect the dots between data and AI output

Grasp how AI influences our daily lives

John Paul Mueller

Luca Massaron

Stephanie Diamond

Artificial Intelligence

3rd Edition

by John Paul Mueller, Luca Massaron, and Stephanie Diamond

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Contents at a Glance

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Introduction

You can hardly avoid hearing about AI these days. You see AI in the movies, in books, in the news, and online. AI is part of robots, self-driving (SD) cars, drones, medical systems, online shopping sites, and all sorts of other technologies that affect your daily life in innumerable ways.

Many pundits are burying you in information (and disinformation) about AI, too. Much of the hype about AI originates from the excessive and unrealistic expectations of scientists, entrepreneurs, and businesspersons. *Artificial Intelligence For Dummies,* 3rd Edition, is the book you need if you feel as though you truly don't know anything about a technology that purports to be an essential element of your life.

Using various media as a starting point, you might notice that most of the useful technologies are almost boring. Certainly, no one gushes over them. AI is like that: so ubiquitous as to be humdrum. You're using AI in some way today; in fact, you probably rely on AI in many different ways — you just don't notice it because it's so mundane. This book makes you aware of these very real and essential uses of AI. A smart thermostat for your home may not sound exciting, but it's an incredibly practical use for a technology that has some people running for the hills in terror.

This book also covers various cool uses of AI. For example, you may not realize that a medical monitoring device can now predict when you might have a heart problem — but such a device exists. AI powers drones, drives cars, and makes all sorts of robots possible. You see AI used now in all sorts of space applications, and AI figures prominently in all the space adventures humans will have tomorrow.

In contrast to many books on the topic, *Artificial Intelligence For Dummies,* 3rd Edition, also tells you the truth about where and how AI *can't* work. In fact, AI will never be able to engage in certain essential activities and tasks, and it will be unable to engage in other ones until far into the future. One takeaway from this book is that humans will always be important. In fact, if anything, AI makes humans even more important because AI helps humans excel in ways that you frankly might not be able to imagine.

About This Book

Artificial Intelligence For Dummies, 3rd Edition starts by helping you understand AI, especially what AI needs to work and why it has failed in the past. You also discover the basis for some of the issues with AI today and how those issues might prove to be nearly impossible to solve in certain cases. Of course, along with the issues, you discover the fixes for various problems and consider where scientists are taking AI in search of answers. Most important, you discover where AI is falling short and where it excels. You likely won't have a self-driving car anytime soon, and that vacation in space will have to wait. On the other hand, you find that telepresence can help people stay in their homes when they might otherwise need to go to a hospital or nursing home.

This book also contains links to external information because AI has become a huge and complex topic. Follow these links to gain additional information that just won't fit in this book — and to gain a full appreciation of just how astounding the impact of AI is on your daily life. If you're reading the print version of this book, you can type the URL provided into your browser; e-book readers can simply click the links. Many other links use what's called a TinyURL (`tinyurl.com`), in case the original link is too long and confusing to type accurately into a search engine. To check whether a TinyURL is real, you can use the preview feature by adding the word *preview* as part of the link, like this: `preview.tinyurl.com/pd88943u`.

AI has a truly bright future because it has become an essential technology. This book also shows you the paths that AI is likely to follow in the future. The various trends discussed in this book are based on what people are actually trying to do now. The new technology hasn't succeeded yet, but because people are working on it, it does have a good chance of success at some point.

To make absorbing the concepts even easier, this book uses the following conventions:

- Web addresses appear in `monofont`. If you're reading a digital version of this book on a device connected to the Internet, note that you can click the web address to visit that website, like this: `www.dummies.com`. Many article titles of additional resources also appear as clickable links.
- Words in *italics* are defined inline as special terms you should remember. You see these words used (and sometimes misused) in many different ways in the press and other media, such as movies. Knowing the meaning of these terms can help you clear away some of the hype surrounding AI.

Icons Used in This Book

As you read this book, you see icons in the margins that indicate material of interest (or not, as the case may be). This section briefly describes each icon in this book.

Tips are gratifying because they help you save time or perform a task without creating a lot of extra work. The tips in this book are time-saving techniques or pointers to resources that you should try in order to gain the maximum benefit from learning about AI. Just think of them as extras that we're paying to reward you for reading our book.

If you get nothing else out of a particular chapter or section, remember the material marked by this icon. This text usually contains an essential process or a bit of information that you must know to interact with AI successfully.

We don't want to sound like angry parents or some kind of maniacs, but you should avoid doing anything marked with a Warning icon. Otherwise, you might find that you engage in the sort of disinformation that now has people terrified of AI.

Whenever you see this icon, think "advanced tip or technique." You can fall asleep from reading this material, and we don't want to be responsible for that. However, you might find that these tidbits of useful information contain the solution you need in order to create or use an AI solution. Skip these bits of information whenever you like.

Beyond the Book

Every book in the For Dummies series comes supplied with an online Cheat Sheet. You remember using crib notes in school to make a better mark on a test, don't you? You do? Well, a cheat sheet is sort of like that. It provides you with some special notes about tasks that you can do with AI that not everyone else knows about. You can find the cheat sheet for this book by going to `www.dummies.com` and typing **Artificial Intelligence For Dummies Cheat Sheet** in the search box. The cheat sheet contains neat-o information, such as the meaning of all those strange acronyms and abbreviations associated with AI, machine learning, and deep learning.

Where to Go from Here

It's time to start discovering AI and see what it can do for you. If you know nothing about AI, start with Chapter 1. You may not want to read every chapter in the book, but starting with Chapter 1 helps you understand the AI basics that you need when working through other places in the book.

If your main goal in reading this book is to build knowledge of where AI is used today, start with Chapter 5. The materials in Part 2 can help you see where AI is used today.

If you have a bit more advanced knowledge of AI, you can start with Chapter 9. Part 3 of this book contains the most advanced material that you'll encounter. If you don't want to know how AI works at a low level (not as a developer but simply as someone interested in AI), you might decide to skip this part of the book.

Okay, so you want to know the super fantastic ways in which people are either using AI today or will use AI in the future. If that's the case, start with Chapter 12. All of Parts 4 and 5 show you the incredible ways in which AI is used without forcing you to deal with piles of hype as a result. The information in Part 4 focuses on hardware that relies on AI, and the material in Part 5 focuses more on futuristic uses of AI.

1 Introducing AI

IN THIS PART . . .

Discover what AI can actually do for you.

Consider how data affects the use of AI.

Understand how AI relies on algorithms to perform useful work.

See how using specialized hardware makes AI perform better.

IN THIS CHAPTER

- Defining AI and its history
- Using AI for practical tasks
- Seeing through AI hype
- Connecting AI with computer technology

Chapter 1
Delving into What AI Means

Common apps, such as Google Assistant Alexa, and Siri, have all of us who are online every day, using artificial intelligence (AI) without even thinking about it. Productivity and creative apps such as ChatGPT, Synesthesia, and Gemini help us focus on the content rather than on how to get there. The media floods our entire social environment with so much information and disinformation that many people see AI as a kind of magic (which it most certainly isn't). So the best way to start this book is to define what AI is, what it isn't, and how it connects to computers today.

REMEMBER

Of course, the basis for what you expect from AI is a combination of how you define AI, the technology you have for implementing AI, and the goals you have for AI. Consequently, everyone sees AI differently. This book takes a middle-of-the-road approach by viewing AI from as many different perspectives as possible. We don't buy into the hype offered by proponents, nor do we indulge in the negativity espoused by detractors. Instead, we strive to give you the best possible view of AI as a technology. As a result, you may find that you have expectations somewhat different from those you encounter in this book, which is fine, but it's essential to consider what the technology can actually do for you — rather than expect something it can't.

Defining the Term AI

Before you can use a term in any meaningful and useful way, you must have a definition for it. After all, if nobody agrees on a meaning, the term has none; it's just a collection of characters. Defining the idiom (a term whose meaning isn't clear from the meanings of its constituent elements) is especially important with technical terms that have received more than a little press coverage at various times and in various ways.


REMEMBER

Saying that AI is an artificial intelligence doesn't tell you anything meaningful, which is why people have so many discussions and disagreements over this term. Yes, you can argue that what occurs is artificial, not having come from a natural source. However, the intelligence part is, at best, ambiguous. Even if you don't necessarily agree with the definition of AI as it appears in the sections that follow, this book uses AI according to that definition, and knowing it will help you follow the text more easily.

Discerning intelligence

People define intelligence in many different ways. However, you can say that intelligence involves certain mental activities composed of the following activities:

- **Learning:** Having the ability to obtain and process new information
- **Reasoning:** Being able to manipulate information in various ways
- **Understanding:** Considering the result of information manipulation
- **Grasping truths:** Determining the validity of the manipulated information
- **Seeing relationships:** Divining how validated data interacts with other data
- **Considering meanings:** Applying truths to particular situations in a manner consistent with their relationship
- **Separating fact from belief:** Determining whether the data is adequately supported by provable sources that can be demonstrated to be consistently valid

The list could easily grow quite long, but even this list is relatively prone to interpretation by anyone who accepts it as viable. As you can see from the list, however, intelligence often follows a process that a computer system can mimic as part of a simulation:

1. Set a goal (the information to process and the desired output) based on needs or wants.
2. Assess the value of any known information in support of the goal.
3. Gather additional information that could support the goal. The emphasis here is on information that *could* support the goal rather than on information you know *will* support the goal.
4. Manipulate the data such that it achieves a form consistent with existing information.
5. Define the relationships and truth values between existing and new information.
6. Determine whether the goal is achieved.
7. Modify the goal in light of the new data and its effect on the probability of success.
8. Repeat Steps 2 through 7 as needed until the goal is achieved (found true) or the possibilities for achieving it are exhausted (found false).

REMEMBER

Even though you can create algorithms and provide access to data in support of this process within a computer, a computer's capability to achieve intelligence is severely limited. For example, a computer is incapable of understanding anything because it relies on machine processes to manipulate data using pure math in a strictly mechanical fashion. Likewise, computers can't easily separate truth from mistruth (as described in Chapter 2). In fact, no computer can fully implement any of the mental activities described in the earlier list that describes intelligence.

As part of deciding what intelligence actually involves, categorizing intelligence is also helpful. Humans don't use just one type of intelligence; rather, they rely on multiple intelligences to perform tasks. Howard Gardner a Harvard psychologist has defined a number of these types of intelligence (for details, see the article "Multiple Intelligences" from Project Zero at Harvard University `https://pz.harvard.edu/resources/the-theory-of-multiple-intelligences`) and knowing them helps you relate them to the kinds of tasks a computer can simulate as intelligence. (See Table 1-1 for a modified version of these intelligences with additional description.)

TABLE 1-1 The Kinds of Human Intelligence and How AIs Simulate Them

Type	Simulation Potential	Human Tools	Description
Bodily kinesthetic	Moderate to High	Specialized equipment and real-life objects	Body movements, such as those used by a surgeon or a dancer, require precision and body awareness. Robots commonly use this kind of intelligence to perform repetitive tasks, often with higher precision than humans, but sometimes with less grace. It's essential to differentiate between human augmentation, such as a surgical device that provides a surgeon with enhanced physical ability, and true independent movement. The former is simply a demonstration of mathematical ability in that it depends on the surgeon for input.
Creative	None	Artistic output, new patterns of thought, inventions, new kinds of musical composition	Creativity is the act of developing a new pattern of thought that results in unique output in the form of art, music, or writing. A truly new kind of product is the result of creativity. An AI can simulate existing patterns of thought and even combine them to create what appears to be a unique presentation but is in reality just a mathematically based version of an existing pattern. In order to create, an AI would need to possess self-awareness, which would require intrapersonal intelligence.
Interpersonal	Low to Moderate	Telephone, audioconferencing, videoconferencing, writing, computer conferencing, email	Interacting with others occurs at several levels. The goal of this form of intelligence is to obtain, exchange, give, or manipulate information based on the experiences of others. Computers can answer basic questions because of keyword input, not because they understand the question. The intelligence occurs while obtaining information, locating suitable keywords, and then giving information based on those keywords. Cross-referencing terms in a lookup table and then acting on the instructions provided by the table demonstrates logical intelligence, not interpersonal intelligence.
Intrapersonal	None	Books, creative materials, diaries, privacy, time	Looking inward to understand one's own interests and then setting goals based on those interests is now a human-only kind of intelligence. As machines, computers have no desires, interests, wants, or creative abilities. An AI processes numeric input using a set of algorithms and provides an output; it isn't aware of anything it does, nor does it understand anything it does.

Type	Simulation Potential	Human Tools	Description
Linguistic (often divided into oral, aural, and written)	Low	Games, multimedia, books, voice recorders, spoken words	Working with words is an essential tool for communication because spoken and written information exchange is far faster than any other form. This form of intelligence includes understanding oral, aural, and written input, managing the input to develop an answer, and providing an understandable answer as output. Discerning just how capable computers are in this form of intelligence is difficult in light of AIs such as ChatGPT because it's all too easy to create tests where the AI produces nonsense answers.
Logical mathematical	High (potentially higher than humans)	Logic games, investigations, mysteries, brainteasers	Calculating results, performing comparisons, exploring patterns, and considering relationships are all areas in which computers now excel. When you see a computer defeat a human on a game show, this is the only form of intelligence you're seeing, out of eight kinds of intelligence. Yes, you might see small bits of other kinds of intelligence, but this is the focus. Basing an assessment of human-versus-computer intelligence on just one area isn't a good idea.
Naturalist	None	Identification, exploration, discovery, new tool creation	Humans rely on the ability to identify, classify, and manipulate their environment to interact with plants, animals, and other objects. This type of intelligence informs you that one piece of fruit is safe to eat though another is not. It also gives you a desire to learn how things work or to explore the universe and all that is in it.
Visual spatial	Moderate	Models, graphics, charts, photographs, drawings, 3D modeling, video, television, multimedia	Physical-environment intelligence is used by people like sailors and architects (among many others). To move around, humans need to understand their physical environment — that is, its dimensions and characteristics. Every robot or portable computer intelligence requires this capability, but the capability is often difficult to simulate (as with self-driving cars) or less than accurate (as with vacuums that rely as much on bumping as they do on moving intelligently).

Examining four ways to define AI

As described in the previous section, the first concept that's important to understand is that AI has little to do with human intelligence. Yes, some AI is modeled to simulate human intelligence, but that's what it is: a simulation. When thinking about AI, notice an interplay between goal seeking, data processing used to achieve

that goal, and data acquisition used to better understand the goal. AI relies on algorithms to achieve a result that may or may not have anything to do with human goals or methods of achieving those goals. With this in mind, you can categorize AI in four ways:

- Acting humanly
- Thinking humanly
- Thinking rationally
- Acting rationally

Acting humanly

When a computer acts like a human, it best reflects the *Turing test*, in which the computer succeeds when differentiation between the computer and a human isn't possible. (For details, see "The Turing test" at the Alan Turing Internet Scrapbook `www.turing.org.uk/scrapbook/test.html`). This category also reflects what most media would have you believe AI is all about. You see it employed for technologies such as natural language processing, knowledge representation, automated reasoning, and machine learning (all four of which must be present to pass the test). To pass the Turing test, an AI should have all four previous technologies and, possibly, integrate other solutions (such as expert systems).


TECHNICAL STUFF

The original Turing test didn't include any physical contact. Harnad's Total Turing Test does include physical contact, in the form of perceptual ability interrogation, which means that the computer must also employ both computer vision and robotics to succeed. Here's a quick overview of other Turing test alternatives:

- **Reverse Turing test:** A human tries to prove to a computer that the human is not a computer (for example, the Completely Automated Public Turing Test to Tell Computers and Humans Apart, or CAPTCHA).
- **Minimum intelligent signal test:** Only true/false and yes/no questions are given.
- **Marcus test:** A computer program simulates watching a television show, and the program is tested with meaningful questions about the show's content.
- **Lovelace test 2.0:** A test detects AI by examining its ability to create art.
- **Winograd schema challenge:** This test asks multiple-choice questions in a specific format.

IS THE TURING TEST OUTDATED?

Current discussions about the Turing test have researchers Philip Johnson-Laird, a retired psychology professor from Princeton University, and Marco Ragni, a researcher at the Germany-based Chemnitz University of Technology, asking whether the test is outdated. For example, If AI is making the Turing test obsolete, what might be better? This issue poses several problems with the Turing test and offers a potential solution in the form of a psychological-like evaluation. These tests would use the following three-step process to better test AIs, such as Google's LaMDA and OpenAI's ChatGPT:

- Use tests to check the AI's underlying inferences.
- Verify that the AI understands its own way of reasoning.
- Examine the underlying source code, when possible.

Modern techniques include the idea of achieving the goal rather than mimicking humans completely. For example, the Wright brothers didn't succeed in creating an airplane by precisely copying the flight of birds; rather, the birds provided ideas that led to studying aerodynamics, which eventually led to human flight. The goal is to fly. Both birds and humans achieve this goal, but they use different approaches.

Thinking humanly

A computer that thinks like a human performs tasks that require intelligence (as contrasted with rote procedures) from a human to succeed, such as driving a car. To determine whether a program thinks like a human, you must have some method of determining how humans think, which the cognitive modeling approach defines. This model relies on these three techniques:

- **Introspection:** Detecting and documenting the techniques used to achieve goals by monitoring one's own thought processes.
- **Psychological testing:** Observing a person's behavior and adding it to a database of similar behaviors from other persons given a similar set of circumstances, goals, resources, and environmental conditions (among other factors).
- **Brain imaging:** Monitoring brain activity directly through various mechanical means, such as computerized axial tomography (CAT), positron emission tomography (PET), magnetic resonance imaging (MRI), and magnetoencephalography (MEG).

After creating a model, you can write a program that simulates the model. Given the amount of variability among human thought processes and the difficulty of accurately representing these thought processes as part of a program, the results are experimental at best. This category of thinking humanly is often used in psychology and other fields in which modeling the human thought process to create realistic simulations is essential.

Thinking rationally

Studying how humans think using an established standard enables the creation of guidelines that describe typical human behaviors. A person is considered rational when following these behaviors within certain levels of deviation. A computer that thinks rationally relies on the recorded behaviors to create a guide to how to interact with an environment based on the data at hand.

The goal of this approach is to solve problems logically, when possible. In many cases, this approach would enable the creation of a baseline technique for solving a problem, which would then be modified to actually solve the problem. In other words, the solving of a problem in principle is often different from solving it in practice, but you still need a starting point.

Acting rationally

Studying how humans act in given situations under specific constraints enables you to determine which techniques are both efficient and effective. A computer that acts rationally relies on the recorded actions to interact with an environment based on conditions, environmental factors, and existing data.

As with rational thought, rational acts depend on a solution in principle, which may not prove useful in practice. However, rational acts do provide a baseline on which a computer can begin negotiating the successful completion of a goal.

HUMAN-VERSUS-RATIONAL PROCESSES

Human processes differ from rational processes in their outcome. A process is *rational* if it always does the right thing based on the current information, given an ideal performance measure. In short, rational processes go by the book and assume that the book is correct. Human processes involve instinct, intuition, and other variables that don't necessarily reflect the book and may not even consider the existing data. As an example, the rational way to drive a car is to always follow the law. However, traffic isn't rational. If you follow the law precisely, you end up stuck somewhere because other drivers aren't following the law precisely. To be successful, a self-driving car must therefore act humanly rather than rationally.

Reviewing AI categories

The categories used to define AI offer a way to consider various uses or ways to apply AI. Some of the systems used to classify AI by type are arbitrary and indistinct. For example, some groups view AI as either strong (generalized intelligence that can adapt to a variety of situations) or weak (specific intelligence designed to perform a particular task well).

The problem with strong AI is that it doesn't perform any task well, whereas weak AI is too specific to perform tasks independently. Even so, just two type classifications won't do the job, even in a general sense. The four classification types promoted by Arend Hintze form a better basis for understanding AI:

- **Reactive machines:** The machines you see defeating humans at chess or playing on game shows are examples of reactive machines. A reactive machine has no memory or experience on which to base a decision. Instead, it relies on pure computational power and smart algorithms to re-create every decision every time. This is an example of a weak AI used for a specific purpose.
- **Limited memory:** A self-driving (SD) car or an autonomous robot can't afford the time to make every decision from scratch. These machines rely on a small amount of memory to provide experiential knowledge of various situations. When the machine sees the same situation, it can rely on experience to reduce reaction time and provide more resources for making new decisions that haven't yet been made. This is an example of the current level of strong AI.
- **Theory of mind:** A machine that can assess both its required goals and the potential goals of other entities in the same environment has a kind of understanding that is feasible to some extent today, but not in any commercial form. However, for SD cars to become truly autonomous, this level of AI must be fully developed. An SD car would need to not only know that it must move from one point to another but also intuit the potentially conflicting goals of drivers around it and react accordingly. (Robot soccer, at `www.cs.cmu.edu/~robosoccer/main` and `www.robocup.org`, is another example of this kind of understanding, but at a simple level.)
- **Self-awareness:** This is the sort of AI you see in movies. However, it requires technologies that aren't even remotely possible now because such a machine would have a sense of both self and consciousness. In addition, rather than merely intuit the goals of others based on environment and other entity reactions, this type of machine would be able to infer the intent of others based on experiential knowledge.

For more on these classification types, check out "Understanding the four types of AI, from reactive robots to self-aware beings" at `theconversation.com/understanding-the-four-types-of-ai-from-reactive-robots-to-self-aware-beings-67616`. It's several years old but still pertinent.

Understanding the History of AI

Earlier sections of this chapter help you understand intelligence from the human perspective and see how modern computers are woefully inadequate for simulating such intelligence, much less actually becoming intelligent themselves. However, the desire to create intelligent machines (or, in ancient times, idols) is as old as humans. The desire not to be alone in the universe, to have something with which to communicate without the inconsistencies of other humans, is a strong one. Of course, a single book can't contemplate all of human history, so Figure 1-1 provides a brief, pertinent overview of the history of modern AI attempts.

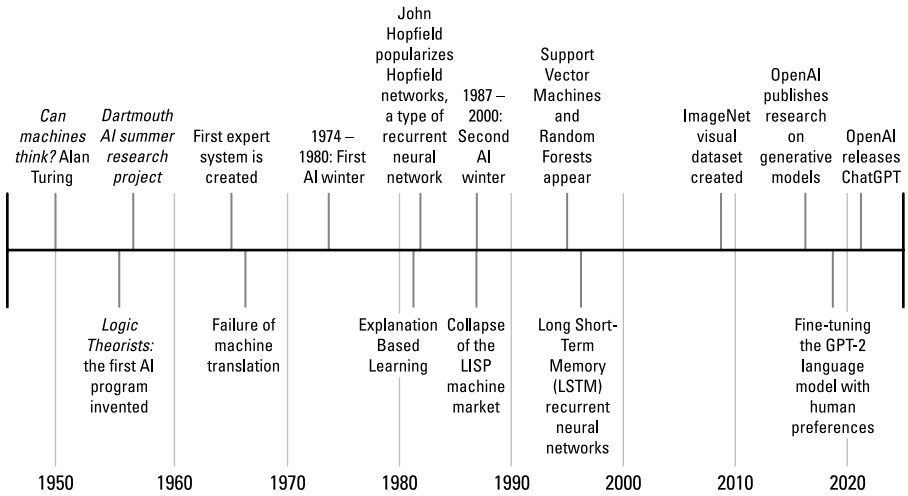

FIGURE 1-1: An overview of the history of AI.

REMEMBER

Figure 1-1 shows you some highlights, nothing like a complete history of AI. One thing you should notice is that the early years were met with a lot of disappointment from overhyping what the technology would do. Yes, people can do amazing things with AI today, but that's because the people creating the underlying technology just kept trying, no matter how often they failed.

Considering AI Uses

You can find AI used in a great many applications today. The only problem is that the technology works so well that you don't know it even exists. In fact, you might be surprised to find that many home devices already make use of AI. For example, some smart thermostats automatically create schedules for you based on how you manually control the temperature. Likewise, voice input that is used to control certain devices learns how you speak so that it can better interact with you. AI definitely appears in your car and most especially in the workplace. In fact, the uses for AI number in the millions — all safely out of sight even when they're quite dramatic in nature. Here are just a few of the ways in which you might see AI used:

- **Fraud detection:** You receive a call from your credit card company asking whether you made a particular purchase. The credit card company isn't being nosy; it's simply alerting you to the fact that someone else might be making a purchase using your card. The AI embedded within the credit card company's code detected an unfamiliar spending pattern and alerted someone to it.
- **Resource scheduling:** Many organizations need to schedule the use of resources efficiently. For example, a hospital may have to determine which room to assign a patient to based on the patient's needs, the availability of skilled experts, and the length of time the doctor expects the patient to be in the hospital.
- **Complex analysis:** Humans often need help with complex analysis because there are literally too many factors to consider. For example, the same set of symptoms might indicate more than one illness. A doctor or another expert might need help making a timely diagnosis to save a patient's life.
- **Automation:** Any form of automation can benefit from the addition of AI to handle unexpected changes or events. A problem with some types of automation is that an unexpected event, such as an object appearing in the wrong place, can cause the automation to stop. Adding AI to the automation can allow the automation to handle unexpected events and continue as if nothing happened.
- **Customer service:** The customer service line you call may not even have a human behind it. The automation is good enough to follow scripts and use various resources to handle the vast majority of your questions. After hearing good voice inflection (provided by AI as well), you may not even be able to tell that you're talking with a computer.
- **Safety systems:** Many of the safety systems now found in machines of various sorts rely on AI to take over operation of the vehicle in a time of crisis. For example, many automatic braking systems (ABSs) rely on AI to stop the

car based on all the inputs a vehicle can provide, such as the direction of a skid. Computerized ABS is, at 40 years, relatively old from a technology perspective.

- **Machine efficiency:** AI can help control a machine to obtain maximum efficiency. The AI controls the use of resources so that the system avoids overshooting speed or other goals. Every ounce of power is used precisely as needed to provide the desired services.
- **Content generation:** When people consider content generation, they often think about ChatGPT because it's in the public eye. However, content generation can exist deep within an application to provide specific functionality. For example, given a photo of the user, how will a new outfit look?

Avoiding AI Hype and Overestimation

You've no doubt seen and heard lots of hype about AI and its potential impact. If you've seen movies such as *Her* and *Ex Machina*, you might be led to believe that AI is further along than it is. The problem is that AI is actually in its infancy, and any sort of application such as those shown in the movies is the creative output of an overactive imagination. The following sections help you understand how hype and overestimation are skewing the goals you can achieve using AI today.

Defining the five tribes and the master algorithm

You may have heard of a concept called the singularity, which is responsible for the potential claims presented in the movies and other media. The *singularity (*when computer intelligence surpasses human intelligence) (when computer intelligence surpasses human intelligence*)* is essentially a master algorithm that encompasses all five "tribes" of learning used within machine learning. To achieve what these sources are telling you, the machine must be able to learn as a human would — as specified by the eight kinds of intelligence discussed in the section "Discerning intelligence," early in this chapter. Here are the five tribes of learning:

- **Symbologists:** The origin of this tribe is in logic and philosophy. It relies on inverse deduction to solve problems.
- **Connectionists:** This tribe's origin is in neuroscience, and the group relies on backpropagation to solve problems.

- **Evolutionaries:** The Evolutionaries' tribe originates in evolutionary biology, relying on genetic programming to solve problems.
- **Bayesians:** This tribe's origin is in statistics and relies on probabilistic inference to solve problems.
- **Analogizers:** The origin of this tribe is in psychology. The group relies on kernel machines to solve problems.


REMEMBER

The ultimate goal of machine learning is to combine the technologies and strategies embraced by the five tribes to create a single algorithm (the *master algorithm*) that can learn anything. Of course, achieving that goal is a long way off. Even so, scientists such as Pedro Domingos at the University of Washington are working toward that goal.

To make things even less clear, the five tribes may not be able to provide enough information to actually solve the problem of human intelligence, so creating master algorithms for all five tribes may still not yield the singularity. At this point, you should be amazed at just how little people know about how they think or why they think in a certain manner.


REMEMBER

Any rumors you hear about AI taking over the world or becoming superior to people are just plain false.

Considering sources of hype

Many sources of AI hype are out there. Quite a bit of the hype comes from the media and is presented by persons who have no idea of what AI is all about, except perhaps from a sci-fi novel they read a few years back. So it's not just movies or television that cause problems with AI hype — it's all sorts of other media sources as well. You can often find news reports presenting AI as being able to do something it can't possibly do because the reporter doesn't understand the technology. Oddly enough, many news articles are now written entirely by AI like ChatGPT, so what you end up with is a recycling of the incorrect information.

Some products should be tested much more before being placed on the market. The article "2020 in Review: 10 AI Failures" at `SyncedReview.com` (`syncedreview.com/2021/01/01/2020-in-review-10-ai-failures/`) discusses ten products, hyped by their developers, that fell flat on their faces. Some of these failures are huge and reflect badly on the ability of AI to perform tasks as a whole. However, something to consider with a few of these failures is that people may have interfered with the device using the AI. Obviously, testing procedures need to start considering the possibility of people purposely tampering with the AI as a potential source of errors. Until that happens, the AI will fail to perform as expected

because people will continue to fiddle with the software in an attempt to cause it to fail in a humorous manner.


WARNING

Another cause of problems stems from asking the wrong person about AI — not every scientist, no matter how smart, knows enough about AI to provide a competent opinion about the technology and the direction it will take in the future. Asking a biologist about the future of AI in general is akin to asking your dentist to perform brain surgery — it simply isn't a good idea. Yet many stories appear with people like these as the information source.


TIP

To discover the future direction of AI, ask a computer scientist or data scientist with a strong background in AI research.

Managing user overestimation

Because of hype (and sometimes laziness or fatigue), users continually overestimate the ability of AI to perform tasks. For example, a Tesla owner was recently found sleeping in his car while the car zoomed along the highway at 90 mph (see "Tesla owner in Canada charged with 'sleeping' while driving over 90 mph"). However, even with the user significantly overestimating the ability of the technology to drive a car, it does apparently work well enough (at least, for this driver) to avoid a complete failure.


WARNING

Be aware that there are also cases where auto drive failed and killed people such. (See the article at `www.washingtonpost.com/technology/interactive/2023/tesla-autopilot-crash-analysis`.)

However, you need not be speeding down a highway at 90 mph to encounter user overestimation. Robot vacuums can also fail to meet expectations, usually because users believe they can just plug in the device and then never think about vacuuming again. After all, movies portray the devices working precisely in this manner, but unfortunately, they still need human intervention. Our point is that most robots eventually need human intervention because they simply lack the knowledge to go it alone.

Connecting AI to the Underlying Computer

To see AI at work, you need to have some sort of computing system, an application that contains the required software, and a knowledge base. The computing system can be anything with a chip inside; in fact, a smartphone does just as well as a desktop computer for certain applications. Of course, if you're Amazon and you

want to provide advice on a particular person's next buying decision, the smartphone won't do — you need a *big* computing system for that application. The size of the computing system is directly proportional to the amount of work you expect the AI to perform.

The application can also vary in size, complexity, and even location. For example, if you're a business owner and you want to analyze client data to determine how best to make a sales pitch, you might rely on a server-based application to perform the task. On the other hand, if you're a customer and you want to find products on Amazon to complement your current purchase items, the application doesn't even reside on your computer; you access it via a web-based application located on Amazon's servers.

The knowledge base (a database that holds information about the facts, assumptions, and rules that the AI can use), varies in location and size as well.) The more complex the data, the more insight you can obtain from it, but the more you need to manipulate the data as well. You get no free lunch when it comes to knowledge management. The interplay between location and time is also important: A network connection affords you access to a large knowledge base online but costs you in time because of the latency of network connections. However, localized databases, though fast, tend to lack details in many cases.

IN THIS CHAPTER

- Seeing data as a universal resource
- Obtaining and manipulating data
- Looking for mistruths in data
- Defining data-acquisitions limits
- Considering data security

Chapter 2
Defining Data's Role In AI

There is nothing new about data. Every interesting application ever written for a computer has data associated with it. Data comes in many forms — some organized, some not. What has changed is the *amount* of data. Some people find it almost terrifying that we now have access to so much data that details nearly every aspect of most people's lives, sometimes to a level that even the person doesn't realize. In addition, the use of advanced hardware and improvements in algorithms make data now *the* universal resource for AI.

To work with data, you must first obtain it. Today, data is collected manually, as done in the past, and also automatically, using new methods. However, it's not a matter of just one or two data collection techniques: Collection methods take place on a continuum from fully manual to fully automatic. You also find a focus today on collecting this data ethically — for example, not collecting data that a person hasn't granted permission for. This chapter explores issues surrounding data collection.

Raw data doesn't usually work well for analysis purposes. This chapter also helps you understand the need for manipulating and shaping the data so that it meets specific requirements. You also discover the need to define the truth value of the data to ensure that analysis outcomes match the goals set for applications in the first place.

REMEMBER

Interestingly, you also have data-acquisition limits to deal with. No technology currently exists for grabbing thoughts from someone's mind by telepathic means. Of course, other limits exist, too — most of which you probably already know about but may not have considered. It also doesn't pay to collect data in a manner that isn't secure. The data must be free of bias, uncorrupted, and from a source you know. You find out more about acquisition limits and data security in this chapter.

Finding Data Ubiquitous in This Age

Big data is more than a just a buzz phrase used by vendors to propose new ways to store data and analyze it. The big data revolution is an everyday reality and a driving force of our times. You may have heard big data mentioned in many specialized scientific and business publications, and you may have even wondered what the term really means. From a technical perspective, *big data* refers to large and complex amounts of computer data, so large and intricate that applications can't deal with the data by simply using additional storage or increasing computer power.

Big data implies a revolution in data storage and manipulation. It affects what you can achieve with data in more qualitative terms (meaning that in addition to doing more, you can perform tasks better). From a human perspective, computers store big data in different data formats (such as database files and `.csv` files), but regardless of storage type, the computer still sees data as a stream of ones and zeros (the core language of computers). You can view data as being one of two types, structured and unstructured, depending on how you produce and consume it. Some data has a clear structure (you know exactly what it contains and where to find every piece of data), whereas other data is unstructured (you have an idea of what it contains, but you don't know exactly how it is arranged).

Typical examples of structured data are database tables, in which information is arranged into columns, and each column contains a specific type of information. Data is often structured by design. You gather it selectively and record it in its correct place. For example, you might want to place a count of the number of people buying a certain product in a specific column, in a specific table, or in a specific database. As with a library, if you know what data you need, you can find it immediately.


TIP

Unstructured data consists of images, videos, and sound recordings. You may use an unstructured form for text so that you can tag it with characteristics, such as size, date, or content type. Usually, you don't know exactly where data appears in an unstructured dataset, because the data appears as sequences of ones and zeros that an application must interpret or visualize.


REMEMBER

Transforming unstructured data into a structured form can cost lots of time and effort and can involve the work of many people. Most of the data of the big data revolution is unstructured and stored as is, unless someone renders it structured.

This copious and sophisticated data store didn't appear suddenly overnight. It took time to develop the technology to store this amount of data. In addition, it took time to spread the technology that generates and delivers data — namely, computers, sensors, smart mobile phones, and the Internet and its World Wide Web services. The following sections help you understand what makes data a universal resource today.

Using data everywhere

Scientists need more powerful computers than the average person because of their scientific experiments. They began dealing with impressive amounts of data years before anyone coined the term *big data.* At that point, the Internet wasn't producing the vast sums of data that it does today.


REMEMBER

That big data isn't a fad created by software and hardware vendors but has a basis in many scientific fields, such as astronomy (space missions), satellite (surveillance and monitoring), meteorology, physics (particle accelerators), and genomics (DNA sequences).

Although an AI application can specialize in a scientific field, such as IBM's Watson, which boasts an impressive medical diagnosis capability because it can learn information from millions of scientific papers on diseases and medicine, the actual AI application driver often has more mundane facets. Actual AI applications are mostly prized for being able to recognize objects, move along paths, or understand what people say and speak to them. Data contribution to the actual AI renaissance that molded it in such a fashion didn't derive from the classical sources of scientific data.


TIP

The Internet now generates and distributes new data in large amounts. Our current daily data production is estimated to amount to about 2.5 quintillion (a number with 18 zeros) bytes, with the lion's share going to unstructured data like video and audio.

All this data is related to common human activities, feelings, experiences, and relations. Roaming through this data, an AI can easily learn how reasoning and acting more human-like works. Here are some examples of the more interesting data you can find:

- **Large repositories of faces and expressions from photos and videos posted on social media websites like Facebook, YouTube, and Google:** They provide information about gender, age, feelings, and possibly sexual orientation, political orientation, or IQ (see "Face-reading AI will be able to detect your politics and IQ, professor says" at The `Guardian.com`).
- **Privately held medical information and biometric data from smartwatches, which measure body data such as temperature and heart rate during both illness and good health:** Interestingly enough, data from smartwatches is seen as a method to detect serious diseases, such as COVID-19, early.
- **Datasets of how people relate to each other and what drives their interest from sources such as social media and search engines:** For instance, a study from Cambridge University's Psychometrics Centre claims that Facebook interactions contain a lot of data about intimate relationships.
- **Information on how we speak, which is recorded by mobile phones.** For example, OK Google, a function found on Android mobile phones, routinely records questions and sometimes even more, as explained in "Google's been quietly recording your voice; here's how to listen to — and delete — the archive" at `qz.com`.

Every day, users connect even more devices to the Internet that start storing new personal data. There are now personal assistants that sit in houses, such as Amazon Echo and other integrated smart home devices that offer ways to regulate and facilitate the domestic environment. These are just the tip of the iceberg because many other common tools of everyday life are becoming interconnected (from the refrigerator to the toothbrush) and able to process, record, and transmit data. The Internet of Things (IoT) is becoming a reality.

Putting algorithms into action

The human race is now at an incredible apex of unprecedented volumes of data, generated by increasingly smaller and powerful hardware. The data is also increasingly processed and analyzed by the same computers that the process helped spread and develop. This statement may seem obvious, but data has become so ubiquitous that its value no longer resides only in the information it contains (such as the case of data stored in a firm's database that allows its daily operations), but rather in its use as a means to create new values. Some people call

such data the "new oil." These new values exist mostly in how applications manicure, store, and retrieve data, and in how you actually use it by means of smart algorithms.

Algorithms and AI changed the data game. As mentioned in Chapter 1, AI algorithms have tried various approaches along the way in the following order:

1. Simple algorithms
2. Symbolic reasoning based on logic
3. Expert systems

In recent years, AI algorithms have moved to neural networks and, in their most mature form, deep learning. As this methodological passage happened, data turned from being the information processed by predetermined algorithms to becoming what molded the algorithm into something useful for the task. Data turned from being just the raw material that fueled the solution to the artisan of the solution itself, as shown in Figure 2-1.

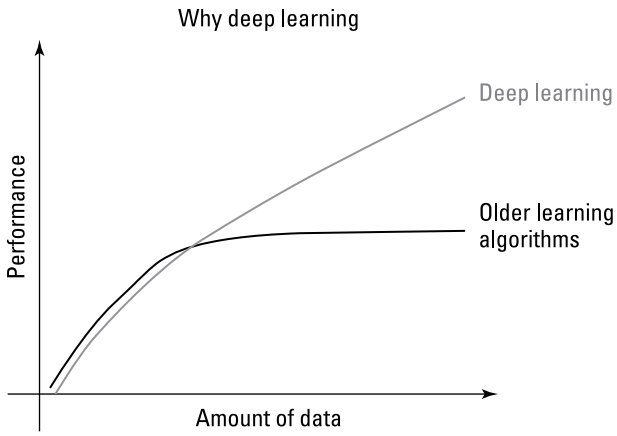

FIGURE 2-1: With the present AI solutions, more data equates to more intelligence.

Thus, a photo of your kittens has become increasingly useful not simply because of its affective value — depicting your cute little cats — but also because it could become part of the learning process of an AI discovering more general concepts, such as which characteristics denote a cat or understanding what defines cute.

On a larger scale, a company like Google feeds its algorithms from freely available data, such as the content of websites or the text found in publicly available texts and books. Google spider software crawls the web, jumping from website to website and retrieving web pages with their content of text and images. Even if Google gives back part of the data to users as search results, it extracts other kinds of

information from the data using its AI algorithms, which learn from it how to achieve other objectives.

Algorithms that process words can help Google AI systems understand and anticipate your needs even when you're expressing them not in a set of keywords but in plain, unclear natural language, the language we speak every day (and yes, everyday language is often unclear). If you currently try to pose questions, not just chains of keywords, to the Google search engine, you'll notice that it tends to answer correctly. Since 2012, with the introduction of the Hummingbird update, Google has steadily become better able to understand synonyms and concepts, a strategy that goes beyond the initial data it acquired, and this is the result of an AI process.

A few years after Hummingbird, Google deployed an even more advanced algorithm named RankBrain, which learns directly from millions of queries every day and can answer ambiguous or unclear search queries, even expressed in slang or colloquial terms or simply riddled with errors. RankBrain doesn't service all the queries, but it learns from data how to better answer queries.

Using Data Successfully

Having plentiful data available isn't enough to create a successful AI. Presently, an AI algorithm can't extract information directly from raw data. Most algorithms rely on external collection and manipulation prior to analysis. When an algorithm collects useful information, it may not represent the right information. The following sections help you understand how to collect, manipulate, and automate data collection from an overview perspective.

Considering the data sources

The data you use comes from a number of sources. The most common data source is from information entered by humans at some point. Even when a system collects shopping-site data automatically, humans initially enter the information. A human clicks various items, adds them to a shopping cart, specifies characteristics (such as size and quantity), and then checks out. Later, after the sale, the human gives the shopping experience, product, and delivery method a rating and makes comments. In short, every shopping experience becomes a data collection exercise as well.

REMEMBER

Many data sources today rely on input gathered from human sources. Humans also provide manual input. You call or go into an office somewhere to make an appointment with a professional. A receptionist then gathers information from you that's needed for the appointment. This manually collected data eventually ends up in a dataset somewhere for analysis purposes.

Data is also collected from sensors, and these sensors can take almost any form. For example, many organizations base physical data collection, such as the number of people viewing an object in a window, on cellphone detection. Facial recognition software could potentially detect repeat customers.

However, sensors can create datasets from almost anything. The weather service relies on datasets created by sensors that monitor environmental conditions such as rain, temperature, humidity, and cloud cover.

TIP

Robotic monitoring systems help correct small flaws in robotic operation by constantly analyzing data collected by monitoring sensors. A sensor, combined with a small AI application, could tell you when your dinner is cooked to perfection tonight. The sensor collects data, but the AI application uses rules to help define when the food is properly cooked.

Obtaining reliable data

The word *reliable* seems so easy to define, yet so hard to implement. Something is reliable when the results it produces are both expected and consistent. A reliable data source produces mundane data that contains no surprises; no one is shocked in the least by the outcome. Depending on your perspective, it could actually be a good thing that most people aren't yawning and then falling asleep when reviewing data. The surprises make the data worth analyzing and reviewing. Consequently, data has an aspect of duality. We want reliable, mundane, fully anticipated data that simply confirms what we already know, but the unexpected is what makes collecting the data useful in the first place.

Still, you don't want data that is so far out of the ordinary that it becomes almost frightening to review. Balance needs to be maintained when obtaining data. The data must fit within certain limits (as described in the "Manicuring the Data" section, later in this chapter). It must also meet the specific criteria of truth value (as described in the "Considering the Five Mistruths in Data" section, later in this chapter). The data must also come at expected intervals, and all the fields of the incoming data record must be complete.

REMEMBER

To some extent, data security also affects data reliability. Data consistency comes in several forms. When the data arrives, you can ensure that it falls within expected ranges and appears in a particular form. However, after you store the data, the reliability can decrease unless you ensure that the data remains in the expected form. An entity fiddling with the data affects reliability, making the data suspect and potentially unusable for analysis later. Ensuring data reliability means that after the data arrives, no one tampers with it to make it fit within an expected domain (making it mundane as a result).

Making human input more reliable

Humans make mistakes — it's part of being human. In fact, expecting that humans won't make mistakes is unreasonable. Yet many application designs assume that humans somehow won't make mistakes of any sort. The design expects that everyone will simply follow the rules. Unfortunately, the vast majority of users are guaranteed to not even read the rules because most humans are also lazy or too pressed for time when it comes to doing things that don't really help them directly.

Consider the entry of a state into a form. If you provide just a text field, some users might input the entire state name, such as Kansas. Of course, some users will make a typo or a capitalization error and come up with Kanzuz, Kansus, or kANSAS. Setting these errors aside, people and organizations also have various approaches to performing tasks. Someone in the publishing industry might use the Associated Press (AP) style guide and input Kan. Someone who is older and used to the Government Printing Office (GPO) guidelines might input Kans. instead. Other abbreviations are used as well. The US Post Office (USPS) uses KS, but the US Coast Guard uses KA. Meanwhile, the International Standards Organization (ISO) form goes with US-KS. Mind you, this is just a state entry, which is reasonably straightforward — or so you thought before reading this section. Clearly, because the state won't change names anytime soon, you could simply provide a drop-down list box on the form for choosing the state in the required format, thereby eliminating differences in abbreviation use, typos, and capitalization errors in one fell swoop.

REMEMBER

Drop-down list boxes work well for an amazing array of data inputs, and using them ensures that human input into those fields becomes extremely reliable because the human has no choice but to use one of the default entries. Of course, the human can always choose the incorrect entry, which is where double-checks come into play. Some newer applications compare the zip code to the city and state entries to see whether they match. When they don't match (sometimes it's just a matter of capitalization), the user is asked again to provide the correct input. This double-check verges on being annoying, but the user is unlikely to see it often, so it shouldn't become too annoying.

Even with cross-checks and static entries, humans still have plenty of room for making mistakes. For example, entering numbers can be problematic. When a user needs to enter 2.00, you might see 2, or 2.0, or 2., or any of a variety of other entries. Fortunately, parsing the entry and reformatting it fixes the problem, and you can perform this task automatically, without the user's aid. (Unfortunately, some online sites want you to enter information like credit cards with dashes, some with spaces, and some with no spacing at all, which makes for a confusing session when the application doesn't fix the entry automatically.)

Unfortunately, reformatting doesn't correct an errant numeric input. You can partially mitigate such errors by including range checks — a customer can't buy –five bars of soap. And, unless the customer is filthy or owns a wombat farm, entering 50,000 bars of soap would likely be a mistake, too. The legitimate way to show that the customer is returning the five bars of soap is to process a return, not a sale. However, the user might have simply made an error, and you can provide a message stating the proper input range for the value.

Using automated data collection

Some people think that automated data collection solves all the human-input issues associated with datasets. In fact, automated data collection does provide a number of benefits:

- Better consistency
- Improved reliability
- Lower probability of missing data
- Enhanced accuracy
- Reduced variance for factors like timed inputs

Unfortunately, to say that automated data collection solves every issue is simply incorrect. Automated data collection still relies on sensors, applications, and computer hardware designed by humans that provide access only to the data that humans decide to allow. Because of the limits that humans place on the characteristics of automated data collection, the outcome often provides less helpful information than hoped for by the designers. Consequently, automated data collection is in a constant state of flux as designers try to solve the input issues.


REMEMBER

Automated data collection also suffers from both software and hardware errors present in any computing system, but with a higher potential for *soft issues* (which arise when the system is apparently working but isn't providing the desired result) than other kinds of computer-based setups. When the system works, the reliability of the input far exceeds human abilities. However, when soft issues occur, the

system often fails to recognize, as a human might, that a problem exists, and therefore the dataset could end up containing more mediocre or even bad data.

Collecting data ethically

For some people, anything that appears on the Internet is automatically considered public domain — including people's faces and all their personal information. The fact is that you should consider everything as being copyrighted and unavailable for use in a public domain manner to use data safely. Even people who realize that material is copyrighted often fall back on fair use principles. Fair use can be quite a tricky subject, as witnessed by the *Author's Guild v. Google* case (see "The Most Important Court Decision for Data Science and Machine Learning" at `towardsdatascience.com`) that was finally decided in favor of Google, but only because Google had met some strict requirements. In addition, this kind of fair use is about books, not people.

The problem with considering fair use alone is that it's also essential to consider a person's right to privacy (you can read about various laws in "Internet privacy laws revealed — how your personal information is protected online" at `legal.thomsonreuters.com`). Consequently, it shouldn't surprise anyone that a major ruckus arose when companies started scraping (screen scraping) images of people wearing masks from the Internet without obtaining any permission whatsoever. In fact, Facebook sued and lost a lwawsuit over its misuse of user data.

The right to privacy has also created a new industry for making a person's face less useful to companies that are determined to get free data without permission by using any means possible (see the *New York Times* article "This Tool Could Protect Your Photos from Facial Recognition"). The fact is, no matter where you stand on the free-use issue, you still need to consider the ethical use of data that you obtain, no matter what the source might be. Here are some considerations to keep in mind as you collect personal data ethically:

- **Obtaining permission:** Some research requires you to be able to identify persons used within a dataset. Going out and grabbing *p*ersonally *i*dentifiable *i*nformation (PII) isn't a good way to gather data. For one thing, you can't be sure that the information is either complete or correct, so any analysis you perform is suspect. For another thing, you could encounter the messy and costly consequences of legal actions. The best way to obtain data with PII is to ask permission.
- **Using sanitization techniques:** *Data sanitization* involves removing personal information — such as name, address, telephone number, and ID — from a dataset so that identifying a particular individual in a dataset becomes impossible. In addition to text and dataset variables, you must consider

every kind of data. For example, if you're working with collections of photos, it is *paramount* that you take steps to blur faces and remove car plates from images.

- **Avoiding data inference:** When collecting data, some users refuse to share personally identifiable information, such as gender and age. Some people recommend you infer this information when a user's picture or other information is available. Unfortunately, names associated with one gender in a particular culture may be assigned to another gender in other cultures. The problem with age inference is even more profound. For example, a machine learning algorithm will likely infer the wrong age for an albino, which can affect as many as 1 in 3,000 individuals, depending on the part of the world the data comes from.
- **Avoiding generalizations:** Many fields of study try to incorrectly apply statistics and machine learning outcomes, with the result that an individual ends up being mistreated in some manner.

REMEMBER

It's essential to remember that statistics apply to groups, not to individuals.

Manicuring the Data

Some people use the term *manipulation* when speaking about data, giving the impression that the data is somehow changed in an unscrupulous or devious manner. Perhaps a better term is *manicuring*, which makes the data well-shaped and lovely. No matter which term you use, however, raw data seldom meets the requirements for processing and analysis. To get something from the data, you must manicure it to meet specific needs. The following sections discuss data manicuring needs.

Dealing with missing data

To answer a given question correctly, you must have all the facts. You can guess the answer to a question without all the facts, but then the answer is just as likely to be wrong as correct. Often, someone who makes a decision, essentially answering a question, without all the facts is said to jump to a conclusion. When analyzing data, you have probably jumped to more conclusions than you think because of missing data. A *data record*, or one entry in a *dataset* (which is all the data), consists of *fields* that contain facts used to answer a question. Each field contains a single kind of data that addresses a single fact. If that field is empty, you don't have the data you need to answer the question using that particular data record.

REMEMBER

As part of the process of dealing with missing data, you must know that the data is missing. Identifying that your dataset is missing information can be quite difficult because it requires you to look at the data at a low level — something that most people are unprepared to do and that is time-consuming even if you do have the required skills. Often, your first clue that data is missing is the preposterous answers that your questions elicit from the algorithm and associated dataset. When the algorithm is the right one to use, the dataset must be at fault. Here are some issues to consider:

- **Essential data missing:** A problem can occur when the data collection process lacks all the data necessary to answer a particular question. Sometimes you're better off to drop a fact than to use a considerably damaged fact.
- **Some data missing:** Less damaged fields can have data missing in one of two ways — randomly or sequentially:
  - **Randomly missing data is often the result of human or sensor error.** Fixing randomly missing data is easiest. You can use a simple median or average value as a replacement. No, the dataset isn't completely accurate, but it will likely work well enough to obtain a reasonable answer.
  - **Sequentially missing data occurs during some type of generalized failure.** Fixing sequentially missing data is significantly harder, if not impossible, because you lack any surrounding data on which to base any sort of guess. If you can find the cause of the missing data, you can sometimes reconstruct it.

Considering data misalignments

Data might exist for each of the data records in a dataset, but it might not align with other data in other datasets you own. For example, the numeric data in a field in one dataset might be a floating-point type (with decimal point), but an integer type in another dataset. Before you can combine the two datasets, the fields must contain the same type of data.

All sorts of other kinds of misalignment can occur. For example, date fields are notorious for being formatted in various ways. To compare dates, the data formats must be the same. However, dates are also insidious in their propensity for looking the same but not being the same. For example, dates in one dataset might use Greenwich Mean Time (GMT) as a basis, whereas the dates in another dataset might use some other time zone. Before you can compare the times, you must

align them to the same time zone. It can become even weirder when dates in one dataset come from a location that uses daylight saving time (DST) but dates from another location don't.

Even when the data types and format are the same, other data misalignments can occur. For example, the fields in one dataset may not match the fields in the other dataset. In some cases, these differences are easy to correct. One dataset may treat first and last names as a single field, while another dataset might use separate fields for first and last names. The answer is to change all datasets to use a single field or to change them all to use separate fields for first and last names. Unfortunately, many misalignments in data content are harder to figure out. In fact, it's entirely possible that you might be unable to figure them out. However, before you give up, consider these potential solutions to the problem:

- Calculate the missing data from other data you can access.
- Locate the missing data in another dataset.
- Combine datasets to create a whole that provides consistent fields.
- Collect additional data from various sources to fill in the missing data.
- Redefine your question so that you no longer need the missing data.

Separating useful data from other data

Some organizations' leaders are of the opinion that they can never have too much data, but an excess of data becomes as much a problem as not enough. To solve problems efficiently, an AI requires just enough data. Defining the question that you want to answer concisely and clearly helps, as does using the correct algorithm (or algorithm ensemble). Of course, the major problems with having too much data are that finding the solution (after wading through all that extra data) takes longer and sometimes you get confusing results because you can't see the forest for the trees.

WARNING

As part of creating the dataset you need for analysis, you make a copy of the original data rather than modify it. Always keep the original, raw data pure so that you can use it for other analysis later. In addition, creating the right data output for analysis can require a number of tries because you may find that the output doesn't meet your needs. The point is to create a dataset that contains only the data needed for analysis, but keep in mind that the data may need specific kinds of pruning to ensure the desired output.

Considering the Five Mistruths in Data

Humans are used to seeing data for what it is in many cases: an opinion. In fact, in some cases, people skew data to the point where it becomes useless, a *mistruth.* A computer can't tell the difference between truthful and untruthful data — all it sees is data. One issue that makes it difficult, if not impossible, to create an AI that actually thinks like a human is that humans can work with mistruths and computers can't. The best you can hope to achieve is to see the errant data as outliers and then filter it out, but that technique doesn't necessarily solve the problem because a human would still use the data and attempt to determine a truth based on the mistruths that are there.

WARNING

A common thought about creating less contaminated datasets is that, instead of allowing humans to enter the data, collecting the data via sensors or other means should be possible. Unfortunately, sensors and other mechanical input methodologies reflect the goals of their human inventors and the limits of what the particular technology is able to detect. Consequently, even machine-derived or sensor-derived data is also subject to generating mistruths that are quite difficult for an AI to detect and overcome.

The following sections use a car accident as the main example to illustrate five types of mistruths that can appear in data. The concepts that the accident is trying to portray may not always appear in data, and they may appear in different ways than discussed. The fact remains that you normally need to deal with these sorts of issues when viewing data.

Commission

Mistruths of *commission* are those that reflect an outright attempt to substitute truthful information for untruthful information. For example, when filling out an accident report, someone could state that the sun momentarily blinded them, making it impossible to see someone they hit. In reality, perhaps the person was distracted by something else or wasn't actually thinking about driving (possibly considering a nice dinner). If no one can disprove this theory, the person might get by with a lesser charge. However, the point is that the data would also be contaminated. The effect is that now an insurance company would base premiums on errant data.

REMEMBER

Although it would seem as though mistruths of commission are completely avoidable, often they aren't. Humans tell "little white lies" to save others from embarrassment or to deal with an issue with the least amount of personal effort. Sometimes a mistruth of commission is based on errant input or hearsay. In fact, the sources of errors of commission are so many that it is truly difficult to

come up with a scenario where someone could avoid them entirely. Regardless, mistruths of commission are one type of mistruth that someone can avoid more often than not.

Omission

Mistruths of *omission* are those where a person tells the truth in every stated fact but leaves out an important fact that would change the perception of an incident as a whole. Thinking again about the accident report, say that your car strikes a deer, causing significant damage to your car. You truthfully say that the road was wet; it was near twilight, so the light wasn't as good as it could be; you were a little late in pressing on the brake; and the deer simply darted out from a thicket at the side of the road. The conclusion would be that the incident is simply an accident.

However, you left out an important fact: You were texting at the time. If law enforcement knew about the texting, it would change the reason for the accident to inattentive driving. You might be fined, and the insurance adjuster would use a different reason when entering the incident into the database. As with the mistruth of commission, the resulting errant data would change how the insurance company adjusts premiums.


REMEMBER

Avoiding mistruths of omission is nearly impossible. Yes, people can purposely leave facts out of a report, but it's just as likely that they'll simply fail to include all the facts. After all, most people are quite rattled after an accident, so they can easily lose focus and report only those truths that leave the most significant impression. Even if a person later remembers additional details and reports them, the database is unlikely to ever contain a full set of truths.

Perspective

Mistruths of *perspective* occur when multiple parties view an incident from multiple vantage points. For example, in considering an accident involving a struck pedestrian, the person driving the car, the person getting hit by the car, and a bystander who witnessed the event would all have different perspectives. An officer taking reports from each person would understandably glean different facts from each one, even assuming that each person tells the truth as each knows it. In fact, experience shows that this is almost always the case, and the info that the officer submits as a report is the middle ground of what each of those involved states, augmented by personal experience. In other words, the report will be close to the truth, but not close enough for an AI.

When dealing with perspective, consider vantage point. The driver of the car can see the dashboard and knows the car's condition at the time of the accident. This is information that the other two parties lack. Likewise, the person getting hit by the car has the best vantage point for seeing the driver's facial expression (intent). The bystander might be in the best position to see whether the driver made an attempt to stop, and assess issues such as whether the driver tried to swerve. Each party will have to make a report based on seen data without the benefit of hidden data.

WARNING

Perspective is perhaps the most dangerous of the mistruths because anyone who tries to derive the truth in this scenario ends up, at best, with an average of the various stories, which will never be fully correct. A human viewing the information can rely on intuition and instinct to potentially obtain a better approximation of the truth, but an AI will always use just the average, which means that the AI is always at a significant disadvantage. Unfortunately, avoiding mistruths of perspective is impossible because no matter how many witnesses you have to the event, the best you can hope to achieve is an approximation of the truth, not the actual truth.

You also have to consider another sort of mistruth, and it's one of perspective. Think about this scenario: You're a deaf person in 1927. Each week, you go to the theater to view a silent film, and for an hour or more, you feel like everyone else. You can experience the movie in the same way everyone else does; there are no differences. In October of that year, you see a sign saying that the theater is upgrading to support a sound system so that it can display *talkies* — films with a soundtrack. The sign says that talkies are the best thing ever, and almost everyone seems to agree, except for you, the deaf person, who is now made to feel like a second-class citizen, different from everyone else and even pretty much excluded from the theater. In the deaf person's eyes, that sign is a mistruth; adding a sound system is the worst possible thing, not the best possible thing. The point is that what seems to be generally true isn't actually true for everyone. The idea of a general truth — one that is true for everyone — is a myth. It doesn't exist.

Bias

Mistruths of *bias* occur when someone is able to see the truth but because of personal concerns or beliefs is unable to actually see it. For example, when thinking about an accident, a driver might focus attention so completely on the middle of the road that the deer at the edge of the road becomes invisible. Consequently, the driver has no time to react when the deer suddenly decides to bolt into the middle of the road in an effort to cross.

REMEMBER

It is known that faster speed blurs peripheral vision so the deer does become harder to see at higher speeds.

A problem with bias is that it can be incredibly hard to categorize. For example, a driver who fails to see the deer can have a genuine accident, meaning that the deer was hidden from view by shrubbery. However, the driver might also be guilty of inattentive driving because of incorrect focus. The driver might also experience a momentary distraction. In short, the fact that the driver didn't see the deer isn't the question; instead, it's a matter of *why* the driver didn't see the deer. In many cases, confirming the source of bias becomes important when creating an algorithm designed to avoid a bias source.


REMEMBER

Theoretically, avoiding mistruths of bias is always possible. In reality, however, all humans have biases of various types, and those biases will always result in mistruths that skew datasets. Just persuading someone to actually look and then see something — to have it register in the person's brain — is a difficult task. Humans rely on filters to avoid information overload, and these filters are also a source of bias because they prevent people from actually seeing things.

Frame of reference

Of the five mistruths, frame of reference need not be the result of any sort of error, but one of understanding. A *frame-of-reference* mistruth occurs when one party describes something, such as an event like an accident, and because a second party lacks experience with the event, the details become muddled or completely misunderstood. Comedy routines abound that rely on frame-of-reference errors. One famous example is from Abbott and Costello, *Who's On First*, which you can find on YouTube.com. Getting one person to understand what a second person is saying can be impossible when the first person lacks experiential knowledge — the frame of reference.

Another frame-of-reference mistruth example occurs when one party can't possibly understand the other. For example, a sailor experiences a storm at sea. Perhaps it's a monsoon, but assume for a moment that the storm is substantial — perhaps life-threatening. Even with the use of videos, interviews, and a simulator, the experience of being at sea in a life-threatening storm would be impossible to convey to someone who hasn't experienced such a storm firsthand; that person has no frame of reference.


REMEMBER

The best way to avoid frame-of-reference mistruths is to ensure that all parties involved can develop similar frames of reference. To accomplish this task, the various parties require similar experiential knowledge to ensure the accurate transfer of data from one person to another. However, when working with a dataset, which is necessarily recorded static data, frame-of-reference errors will still occur when the prospective viewer lacks the required experiential knowledge.

An AI will always experience frame-of-reference issues because it necessarily lacks the ability to create an experience. A data bank of acquired knowledge isn't quite the same thing. The data bank would contain facts, but experience is based on not only facts but also conclusions that current technology is unable to duplicate.

Defining the Limits of Data Acquisition

If you get the feeling that everyone is acquiring your data without thought or reason, you're right. In fact, organizations collect, categorize, and store everyone's data — seemingly without goal or intent.

Data acquisition has become a narcotic for organizations worldwide, and some of their leaders seem to think that the organization that collects the most somehow wins a prize. However, data acquisition, in and of itself, accomplishes nothing. The book *The Hitchhiker's Guide to the Galaxy,* by Douglas Adams, illustrates this problem clearly. In this book, a race of supercreatures builds an immense computer to calculate the meaning of "life, the universe, and everything." The answer of 42 doesn't really solve anything, so some of the creatures complain that the collection, categorization, and analysis of all the data used for the answer hasn't produced a usable result. The computer — a sentient one, no less — tells the people receiving the answer that the answer is indeed correct, but they need to know the question in order for the answer to make sense. Data acquisition can occur in unlimited amounts, but figuring out the right questions to ask can be daunting, if not impossible.


REMEMBER

The main problem that any organization needs to address with regard to data acquisition is which questions to ask and why the questions are important. Tailoring data acquisition to answer the questions you need answered matters. For example, if you're running a shop in town, you might need questions like this answered:

- How many people walk in front of the store each day?
- How many of those people stop to look in the window?
- How long do they look?
- What time of day are they looking?
- Do certain displays tend to produce better results?
- Which of these displays cause people to enter the store and shop?

The list could go on, but the idea is that creating a list of questions that address specific business needs is essential. After you create a list, you must verify that each of the questions is indeed important — that is, addresses a need — and then ascertain what sorts of information you need to answer the question.

WARNING

Of course, trying to collect all this data by hand would be impossible, which is where automation comes into play. Seemingly, automation would produce reliable, repeatable, and consistent data input. However, many factors in automating data acquisition can produce data that isn't particularly useful. For example, consider these issues:

- Sensors can collect only the data they're designed to collect, so you might miss data when the sensors used aren't designed for the purpose.
- People create errant data in various ways (see the "Considering the Five Mistruths in Data" section, earlier in this chapter, for details), which means that data you receive might be false.
- Data can become skewed when the conditions for collecting it are incorrectly defined.
- Interpreting data incorrectly means that the results will also be incorrect.
- Converting a real-world question into an algorithm that the computer can understand is an error-prone process.

Many other issues (enough to fill a book) need to be considered. When you combine poorly collected, ill-formed data with algorithms that don't actually answer your questions, you get output that may actually lead your business in the wrong direction, which is why AI is often blamed for inconsistent or unreliable results. Asking the right question, obtaining the correct data, performing the right processing, and then correctly analyzing the data are all required in order to make data acquisition the kind of tool you can rely on.

Considering Data Security Issues

This section discusses data security from the perspective of protecting data integrity rather than keeping someone from stealing it or guarding privacy. Securing data doesn't mean placing it in a vault — assuming that doing so is even possible with data today. Data is useful only when it's accessible. Of course, the need to make data accessible means taking a risk that someone will do something you don't want done with the data. The following sections discuss a few data security issues you need to consider.

Understanding purposefully biased data

Bias appears in nearly every dataset available today, even custom-created datasets. The dataset is often biased because the collection methods are biased, the analysis methods are biased, and the data itself is biased. You often see articles online with titles like "8 Types of Bias in Data Analysis and How to Avoid Them," which means that people recognize the existence of bias and want to mitigate it as much as possible. However, sometimes you find that the opposite is true: The people using the dataset purposely bias it in some manner. Here are some areas in which data becomes purposely biased:

- **Political:** Political maneuvering can become the source of data bias. Two groups with opposing opinions will use the same dataset and obtain two completely different outcomes that support their particular perspective. At issue are the records selected and the dataset features used to create an outcome. In other cases, a group will resort to techniques like using bogus respondents in polls (see "Assessing the Risks to Online Polls from Bogus Respondents" at `pewresearch.org` for details).
- **Medical:** When medical groups advertise for people to participate in trials of medications, procedures, and other needs, the group they get often doesn't represent the population as a whole, so the data is biased.
- **Legal:** The use of COMPAS software (it's short for Correctional Offender Management Profiling for Alternative Sanctions) to predict the potential for recidivism is another example of data and algorithm bias, as explained in "Injustice Ex Machina: Predictive Algorithms in Criminal Sentencing," at `uclalawreview.org`. The article points out so many flaws with COMPAS that the best idea might be to start from scratch because the software is destroying people's lives at an incredible rate.
- **Hiring:** The use of datasets and well-rounded algorithms supposedly reduces the risk of bias in hiring and promoting individuals within an organization. According to "All the Ways Hiring Algorithms Can Introduce Bias" at `hbr.org`, the opposite is too often true. The datasets become an amplification of biased hiring practices within an organization or within society as a whole.
- **Other:** Anytime a dataset and its associated algorithms become influenced by bias, the outcome is less than ideal. The term *machine learning fairness* presents the idea that the outcome of any analysis should correctly represent the actual conditions within). If the outcome of an analysis doesn't match the result received afterward, the analysis is flawed and the data usually receives a lion's share of the blame.

Dealing with data-source corruption

Even if people don't cherry-pick data or use data sources that fail to reflect the actual conditions in the world, as described in the previous section, data sources can become corrupt. For example, when seeing product reviews on a website, you can't be certain that

- Real people created reviews.
- Some people haven't voted more than once.
- The person wasn't simply having an exceptionally bad (or less likely, good) day.
- The person actually used the product and has no ulterior motive, for example, if they sell the product or are a competitor.
- The reviews reflect a fair segment of society.

In fact, the reviews are likely so biased and corrupt that believing them at all becomes nearly impossible. Unfortunately, data-source corruption comes from many other sources:

- A sensor might be bad, producing erroneous results.
- A virus attack might cause data errors.
- The database or other software contains a flaw.
- Humans enter the data incorrectly into the database.
- Acts of nature, such as lightning, cause momentary glitches in data collection.

You can rely on a number of approaches to deal with all sorts of data corruption. Storing data in the cloud tends to reduce problems associated with hardware, weather, or other issues that cause data loss. Ensuring that you have procedures and training in place, plus constant monitoring, can help reduce human errors. Active administrator participation and the use of firewalls can reduce other sorts of data-source corruption.

REMEMBER

All these measures reflect what you can do locally. When performing screen scraping and other techniques to obtain data from online sources, data scientists must employ other measures to ensure that the data remains pure. Vouching for an online source isn't possible unless the source is vetted every time it's used.

Handling botnets

Botnets are coordinated groups of computers that focus on performing specific tasks, most of them nefarious. This short section focuses on botnets that feed a dataset erroneous data or take over accounts to modify the account information in certain ways. Whatever means is used, whatever the intent, botnets generally corrupt or bias data in ways that cause any kind of analysis to fail.

Botnets represent a significant concern in AI for several reasons, primarily due to their evolving capabilities and the scale and speed of attacks they can launch. Here are three key reasons that botnets are a particular concern:

- **AI-enhanced botnets:** With advances in AI and machine learning, botnets have become more sophisticated, capable of automating and rapidly expanding cyberattacks. AI can enable botnets to analyze network behavior, adapt attack patterns to bypass cyberdefenses, and execute attacks with increased efficiency and stealth. This adaptability makes AI-enhanced botnets formidable adversaries, capable of evading traditional detection mechanisms and launching potent and destructive attacks.
- **Scale and magnitude of attacks:** AI-powered botnets can harness the computational power of numerous compromised devices, including the Internet of Things (IoT), creating massive bot armies. With these vast networks, AI-powered botnets can launch coordinated attacks that overwhelm even the most robust security infrastructures. This scale and magnitude of attacks pose significant challenges to cyberdefenses, requiring advanced detection and mitigation strategies.
- **Rapid attack development:** Unlike traditional botnets that require manual programming for specific targets, AI-powered counterparts leverage algorithms to analyze and exploit vulnerabilities quickly. This enables them to develop new attack techniques at an alarming pace, keeping defenders on their toes and making it difficult to predict and prevent attacks.

WARNING

The continuous mutation of botnets to exploit vulnerabilities and security flaws makes prevention and mitigation challenging. Botnet operators use a variety of IP addresses and devices in their attacks, complicating the task of screening out bad requests and confidently allowing access to valid requests. The proliferation of IP-addressable IoT devices has expanded the potential for botnets to spread and launch attacks.

IN THIS CHAPTER

- Examining the role of algorithms in AI
- Winning games with state-space search and min-max
- Analyzing how expert systems work
- Recognizing that machine learning and deep learning are part of AI

Chapter 3
Considering the Use of Algorithms

Data is a game changer in AI. Advances in AI hint that, for certain problems, choosing the right amount of data is more important than choosing the right algorithm. However, no matter how much data you have, you still need an algorithm to make it useful. In addition, you must perform *data analysis* (a series of definable steps) to make data work correctly with the chosen algorithms — no shortcuts allowed. Even though AI is intelligent automation, sometimes automation must take a back seat to analysis. You won't now find machines that know what's appropriate and can completely cut out any human intervention, but self-learning machines, also known as *self-improving* or *autonomous learning systems,* are already a significant area of research and development in the field of AI.

In this chapter, you explore the relationship between algorithms and the data used to make them perform useful work. You also gain an understanding of the role of expert systems, machine learning, deep learning, and applications such as AlphaGo in bringing future possibilities a little closer to reality.

Understanding the Role of Algorithms

An *algorithm* is a procedure that consists of a sequence of operations. Usually, a computer manages these operations by either finding the correct solution to a problem in a finite time or telling you that no solution exists. Even though people have solved algorithms manually for literally thousands of years, doing so can consume huge amounts of time and require many numeric computations, depending on the complexity of the problem to be solved. Algorithms are all about finding solutions, and the speedier and easier, the better. Algorithms have become hard-coded into the intelligence of humans who devised them, and any machine operating on algorithms cannot but reflect the intelligence embedded into such algorithmic procedures. AI provides the means to simulate the human in processing and solving existing algorithms, but currently, AI can't replace humans or mimic human creativity in devising new algorithms.

People tend to recognize AI when a tool presents a novel approach and interacts with the user in a human-like way. Examples include digital assistants such as Alexa, Cortana, Google Assistant, and Siri. However, certain other common tools, such as GPS routers and specialized planners (like those used to avoid automotive collisions, autopilot airplanes, and arrange production plans) don't even look like AI because they're too common and taken for granted as they act behind the scenes. In addition, it's important to consider alternative forms of AI, such as smart thermostats that control the environment based on past usage and current environmental data, and smart garage door openers that automatically detect when you accidentally leave the door open after you leave for work.

This is clearly the AI effect, as named and described by Pamela McCorduck, who wrote a notable history of AI, *Machines Who Think,* in 1979. (The version at `Amazon.com` is an updated version.) The *AI effect* states that people soon forget about successful, intelligent computer programs, which become silent actors while attention shifts to AI problems that still require resolution. The importance of classic algorithms to AI gets overlooked, and people start fantasizing about AI created from esoteric technology, or they equate it with recent advances, such as machine learning and deep learning.

Examining what an algorithm does

An algorithm always presents a series of steps, but it doesn't necessarily perform all these steps to solve a problem. (Some steps are optional or performed only under specific conditions.) A group of related steps is an *operation*, such as the tea-making operation being composed of these steps:

1. Pour water into the teapot.

2. Turn on the fire to heat the water in the teapot.
3. When water is heated, pour it into the cup.
4. Place a teabag in the cup and steep the tea for the recommended time.
5. Remove the teabag.
6. (Optional) Add sugar to the tea.
7. (Optional) Add milk to the tea.
8. Drink the tea.
9. (Optional) Toss the tea in the sink when it becomes undrinkable.

The scope of algorithms is incredibly large. Operations may involve storing data, exploring it, and ordering or arranging it into data structures. You can find algorithms that solve problems in science, medicine, finance, industrial production and supply, and communication.

All algorithms contain sequences of operations to find the correct solution to a problem in a reasonable time (or report back if no solution is found). A subclass of algorithms, *heuristics*, produce good, but not necessarily perfect, solutions when time is more critical than finding the perfect solution. AI algorithms distinguish themselves from generic algorithms by solving problems whose resolution is considered typically (or even exclusively) the product of human intelligent behavior. AI algorithms tend to deal with complex problems, which are often part of the *NP-complete* class of problems (where NP is *n*ondeterministic *p*olynomial time) that humans routinely deal with by mixing a rational approach with intuition.

Here are just a few examples:

- Scheduling problems and allocating scarce resources
- Searching routes in complex physical or figurative spaces
- Recognizing patterns in image vision (versus something like image restoration or image processing) or sound perception
- Processing language (both text understanding and language translation)
- Playing (and winning) competitive games


TIP

NP-complete problems distinguish themselves from other algorithmic problems because finding a solution for them in a reasonable time frame isn't yet possible. NP-complete isn't the kind of problem you solve by trying all possible combinations or possibilities. Even if you had computers more powerful than those that exist today, a search for the solution would last almost forever. In a similar fashion, in AI, this kind of problem is called *AI-complete*.

Planning and branching: Trees and nodes

Planning helps you determine the sequence of actions to perform to achieve a certain goal. Deciding on the plan is a classic AI problem, and you can find examples of planning in industrial production, resource allocation, and robot motion. Starting from the present state, an AI first determines all possible actions from that state. Technically, it *expands* the current state into a number of future states. Then it expands all future states into their own future states, and so on. When you can no longer expand the states and the AI stops the expansion, the AI has created a *state space,* which is composed of whatever could happen in the future. An AI can take advantage of a state space not just as a prediction (actually, it predicts everything, though some future states are more likely than others) but also because AI can use that state space to explore decisions it can make to reach its goal in the best way. This process is known as the *state-space search.*

Working with a state space requires the use of both particular data structures and algorithms. The core data structures commonly used are trees and graphs. The favored algorithms used to efficiently explore graphs include breadth-first search and depth-first search.

Building a tree works in much the same way that a tree grows in the physical world. Each item you add to the tree is a *node.* Nodes connect to each other using links. The combination of nodes and links forms a structure that looks like a tree, as shown in Figure 3-1.

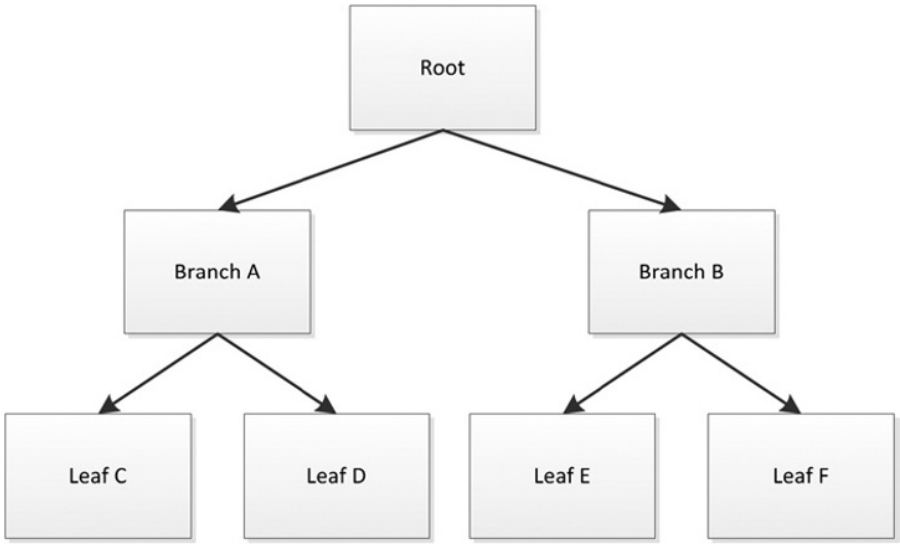

FIGURE 3-1: A tree may look like its physical counterpart or have its roots pointing upward.

REMEMBER

Trees have a single root node, just like a physical tree. The *root node* is the starting point for the processing you perform. Connected to the root are either branches or leaves. A *leaf node* is an ending point for the tree. *Branch nodes* support either other branches or leaves. The type of tree shown in Figure 3-1 is a binary tree because each node has, at most, two connections (but trees representing state spaces can have multiple branches).

In looking at the tree, Branch B is the *child* of the Root node. That's because the Root node appears first in the tree. Leaf E and Leaf F are both children of Branch B, making Branch B the *parent* of Leaf E and Leaf F. The relationship between nodes is important because discussions about trees often consider the child/parent relationship between nodes. Without these terms, discussions of trees could become quite confusing.

Extending the tree using graph nodes

A *graph* is a sort of tree extension. As with trees, you have nodes that connect to each other to create relationships. However, unlike a binary tree, a graph node can have more than one or two connections. In fact, graph nodes often have a multitude of connections, and, most important, nodes can connect in any direction, not just from parent to child. To keep things simple, though, consider the graph shown in Figure 3-2.

Graphs are structures that present a number of nodes (or *vertexes*) connected by a number of edges or arcs (depending on the representation). When you think about a graph, think about a structure like a map, where each location on the map is a node and the streets are the edges. This presentation differs from a tree, where each path ends up in a leaf node. Refer to Figure 3-2 to see a graph represented. Graphs are particularly useful when figuring out states that represent a sort of physical space. For instance, the GPS uses a graph to represent places and streets.

Graphs also add a few new twists that you might not have considered. For example, a graph can include the concept of directionality. Unlike a tree, which has parent/child relationships, a graph node can connect to any other node with a specific direction in mind. Think about streets in a city. Most streets are bidirectional, but some are one-way streets that allow movement in only one direction.

The presentation of a graph connection might not reflect the realities of the physical system it is modeling. A graph can designate a *weight* to a particular connection. The weight can define the distance between two points, define the time required to traverse the route, specify the amount of fuel used to travel the route, or provide other sorts of information.

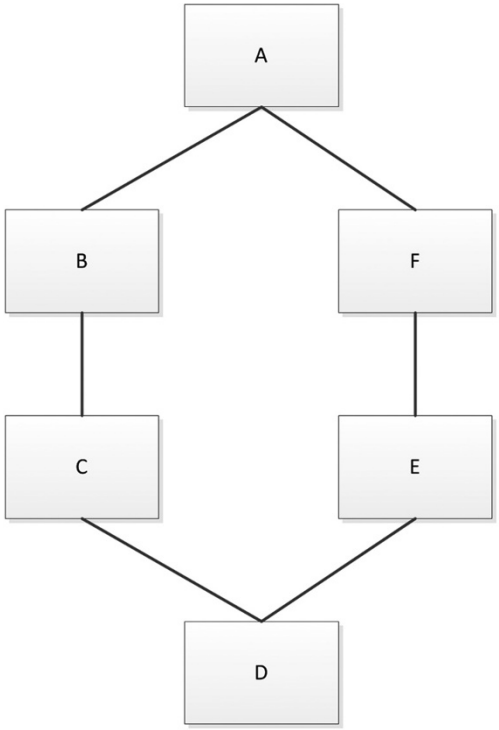

FIGURE 3-2: Graph nodes can connect to each other in myriad ways.

REMEMBER

A tree is nothing more than a graph in which any two vertices are connected by exactly one path, and the tree doesn't allow cycles (to be able to get back to the parent from any child). Many graph algorithms apply only to trees.

Traversing the graph

Traversing a graph means to search (visit) each vertex (node) in a specific order. The process of visiting a vertex can include both reading and updating it. You discover unvisited vertexes as you traverse a graph. The vertex becomes discovered (because you just visited it) or processed (because the algorithm tried all the edges departing from it) after the search. The order of the search determines the kind of search performed:

- **Uninformed (blind search):** The AI explores the state space without additional information except for the graph structure it discovers as it traverses it. Here are two common blind-search algorithms, which are discussed in the sections that follow:
  - *Breadth-first search (BFS):* Begins at the graph root and explores every node that attaches to the root. It then searches the next level, exploring each

level in turn until it reaches the end. Consequently, in the sample graph, the search explores from A to B and F before it moves on to explore C and E. BFS explores the graph in a systematic way, exploring vertexes around the starting vertex in a circular fashion. It begins by visiting all vertexes that are a single step from the starting vertex; it then moves two steps out, and then three steps out, and so on.

- *Depth-first search (DFS):* Begins at the graph root and then explores every node from that root down a single path to the end. It then backtracks and begins exploring the paths not taken in the current search path until it reaches the root again. At that point, if other paths to take from the root are available, the algorithm chooses one and begins the same search again. The idea is to explore each path completely before exploring any other path.


REMEMBER

» **Informed (heuristic):** A heuristic finds or discovers a useful method of traversing the graph based on rules of thumb (such as expert systems) or algorithms that use low-order polynomial time. It's an educated guess about a solution that points to the direction of a desired outcome but can't tell exactly how to reach it. It's like being lost in an unknown city and having people tell you a certain way to reach your hotel (but with no precise instructions). Because this search is informed (even though it isn't precise), it can also estimate the remaining *cost* (time or resources or another value that determines which route is better in a particular instance) to go from a particular state to a solution. Here are three common heuristic search algorithms (see the "Using local search and heuristics" section later in this chapter and Chapter 6 for more details):

- *Best-first search:* An evaluation function assists in the search by determining the desirability of expanding a particular node based on the costs of the nodes that follow. The costs of each node are stored in a queue or another memory structure. Except for the foreknowledge of node cost, this solution works much like a BFS or DFS.
- *Greedy search:* Like a best-first search, the path to follow is informed by node costs. However, the greedy search looks only one node ahead, which saves processing time in the evaluation function, but doesn't always guarantee an optimal solution.
- *A* search:* This is an expansion of the best-first search, which uses two costs: the cost to move from the starting point to another given position in the graph and the cost to move from that given node on the graph to the final destination.

Playing adversarial games

The interesting aspect of state-space search is that it represents both AI's current functionality and future opportunities. This is the case with *adversarial games* (games in which one player wins and the others lose) or with any similar situation in which players pursue an objective that conflicts with the goals of others. A simple game like tic-tac-toe presents a perfect example of a space search game that you may already have seen an AI play. In the 1983 film *WarGames*, the supercomputer WOPR (War Operation Plan Response) plays against itself at a blazing speed, yet it cannot win, because the game is indeed simple, and if you use a state-space search, you won't ever lose.

You have nine cells to fill with *x*'s and *o*'s for each player. The first one to place three marks in a row (horizontal, vertical, or diagonal) wins. When building a state-space tree for the game, each level of the tree represents a game turn. The end nodes represent the final board state and determine a victory, draw, or defeat for the AI. Every terminal node has a higher score for winning, lower for drawing, and even lower or negative for losing. The AI propagates the scores to the upper nodes and branches using summation until reaching the starting node. The starting node represents the actual situation. Using a simple strategy enables you to traverse the tree: When it's AI's turn and you have to propagate the values of many nodes, you sum the maximum value (presumably because AI has to retrieve the maximum result from the game); when it's the adversary's turn, you sum the minimum value instead. In the end, you extract a tree whose branches are qualified by scores. When it's the AI's turn, it chooses its move based on the branch whose value is the highest, because it implies expanding nodes with the highest possibility to win. Figure 3-3 shows a visual example of this strategy.

This approach is called the *min-max approximation.* Ronald Rivest, from the computer science laboratory at MIT, introduced it in 1987. Since then, this algorithm and its variants have powered many competitive games, along with recent game-playing advances, such as AlphaGo from Google DeepMind, which uses an approach that echoes the min-max approximation (which is also found in the *WarGames* film of 1983).

TIP

Sometimes you hear about alpha-beta pruning as connected to min-max approximation. *Alpha-beta pruning* is a smart way to propagate values up the tree hierarchy in complex state spaces limiting computations. Not all games feature compact state-space trees; when branches number in the trillions, you need to prune them and shorten your calculations.

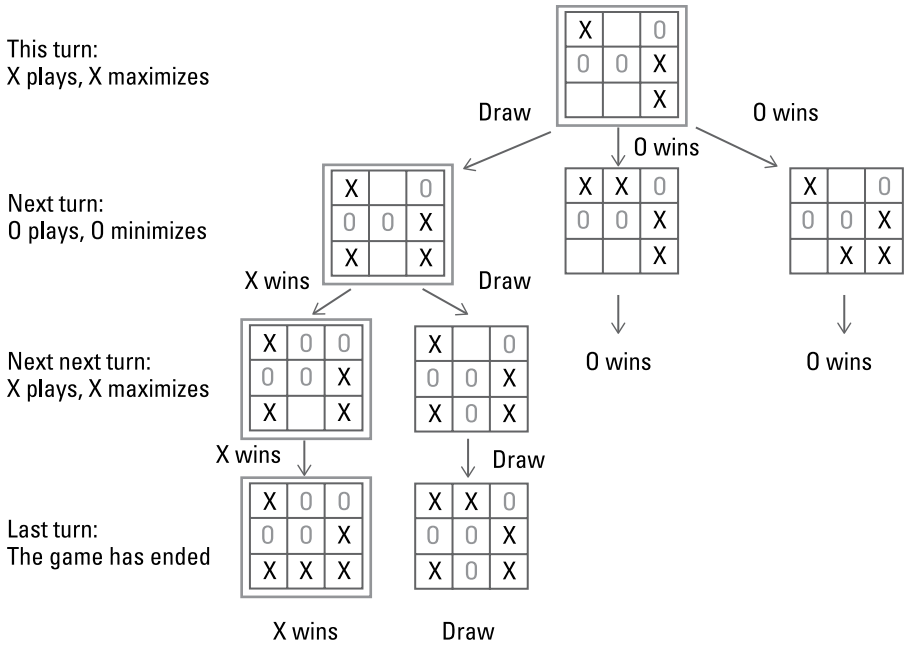

FIGURE 3-3: A glance at min-max approximation in a tic-tac-toe game.

Using local search and heuristics

A lot goes on behind the state-space search approach. In the end, no machine, no matter how powerful, can enumerate all the possibilities that spring from a complex situation. This section continues with games because they are predictable and have fixed rules, whereas many real-world situations are unpredictable and lack clear rules, making games an optimistic and favorable setting.

Checkers, a relatively simple game compared to chess or Go, has 500 billion billion (that's 500,000,000,000,000,000,000) possible board positions, a number that, according to computations by the mathematicians at Hawaii University, equates to all the grains of sand on Earth. It's true that fewer moves are possible as a game of checkers progresses. Yet the number to potentially evaluate at each move is too high. It took 18 years, using powerful computers, to compute all 500 billion billion possible moves — just imagine how long it could take on a consumer's computer to work out even a smaller subset of moves. To be manageable, the result should be a very small subset of all potential moves.

Optimization using local search and heuristics helps by using constraints to limit the beginning number of possible evaluations (as in alpha pruning, where some computations are omitted because they add nothing to the search success). *Local search* is a general problem-solving approach composed of a large range of algorithms that help you escape the exponential complexities of many NP problems.

A local search starts from your present situation or an imperfect problem solution and moves away from it, a step at a time. A local search determines the viability of nearby solutions, potentially leading to a perfect solution, based on random choice or an astute heuristic (which means that no exact method is involved).

Local search algorithms iteratively improve from a starting state, moving one step at a time through neighboring solutions in the state space until they can no longer improve the solution. Because local search algorithms are so simple and intuitive, designing a local search approach for an algorithmic problem isn't difficult; making it effective is usually harder. The key lies in defining the correct procedure:

1. Start with an existing situation (it could be the present situation or a random or known solution).
2. Search for a set of possible new solutions within the current solution's neighborhood, which constitutes the candidates' list.
3. Determine which solution to use in place of the current solution based on the output of a heuristic that accepts the candidates' list as input.
4. Continue performing Steps 2 and 3 until you see no further solution improvement, which means that you have the best solution available.

Although easy to design, local search solutions may not find a solution in a reasonable time (you can stop the process and use the current solution) or produce a minimum-quality solution. You have no guarantee that a local search will arrive at a problem solution, but your chances do improve from the starting point when you provide enough time for the search to run its computations. It stops only after it can't find any further way to improve the solution. The secret is to determine the right "neighborhood" to explore. If you explore everything, you'll fall back to an exhaustive search, which implies an explosion of possibilities to explore and test.

Relying on a heuristic limits where you look based on a rule of thumb. Sometimes, a heuristic is random, and such a solution, despite being a nonintelligent approach, can work well. Few people, for instance, know that Roomba, the autonomous robotic vacuum cleaner created by three MIT graduates (you can see an example, iRobot Roomba, at `Amazon.com`), initially simply roamed around randomly and didn't plan its cleaning path. Yet it was considered a smart device by its owners and did an excellent cleaning job. (Intelligence is actually in the idea of using randomness to solve a problem that is otherwise too complex.)

Random choice isn't the only heuristic available. A local search can rely on more reasoned exploration solutions using well-devised heuristics to find directions:

- **Hill climbing:** Relies on the observation that as a ball rolls down a valley, it takes the steepest descent. When a ball climbs a hill, it tends to take the most

direct upward direction to reach the top, which is the one with the greatest inclination. The AI problem, therefore, is seen as a descent to a valley or an ascent to a mountaintop, and the heuristic is any rule that hints at the best downhill or uphill approach among the possible states of the state space. It's an effective algorithm, though sometimes it gets stuck in situations known as *plateaus* (intermediate valleys) and *peaks* (local maximum points).

- **Twiddle (coordinate descent algorithms):** Similar to hill-climbing algorithms but explores all possible directions. It concentrates the search in the direction of the neighborhood that works best. As it does so, it calibrates its step, slowing down as it finds the discovery of better solutions difficult, until it reaches a stop.
- **Simulated annealing:** Takes its name from a metallurgical technique that heats metal and then slowly cools it to soften it for cold working and to remove crystalline defects. Local search replicates this technique by viewing the solution search as an atomic structure that changes to improve its workability. The temperature is the game changer in the optimization process: Just as high temperatures make the structure of a material relax (solids melt and liquids evaporate at high temperatures), high temperatures in a local search algorithm induce relaxation of the objective function, allowing it to prefer worse solutions over better ones. Simulated annealing modifies the hill-climbing procedure, keeping the objective function for neighbor solution evaluation, but allowing it to determine the search solution choice in a different way.
- **Taboo search:** Uses memorization to remember which parts of the neighborhood to explore. When it seems to have found a solution, it tends to try to retrace to other possible paths that it didn't try in order to ascertain the best solution.

Using measures of direction (upward, downward) or temperature (controlled randomness) or simply restricting or retracing part of the search are all ways to effectively avoid trying everything and concentrating on a good solution. Consider, for instance, a robot walking. Guiding a robot in an unknown environment means avoiding obstacles to reach a specific target. It's both a fundamental and challenging task in artificial intelligence. Robots can rely on a laser rangefinder (lidar) or sonar (which involves devices that use sound to see their environment) to navigate their surroundings. Yet, no matter the level of hardware sophistication, robots still need proper algorithms to

- Find the shortest path to a destination (or at least a reasonably short one)
- Avoid obstacles on the way
- Perform custom behaviors such as minimizing turning or braking

A *pathfinding* algorithm helps a robot start in one location and reach a goal by using the shortest path between the two, anticipating and avoiding obstacles along the way. (Reacting after hitting a wall isn't sufficient.) Pathfinding is also useful when moving any other device to a target in space, even a virtual one, such as in video games or a webpage hosted game. When using pathfinding with a robot, the robot perceives movement as a flow of state spaces to the borders of its sensors. If the goal isn't within range, the robot doesn't know where to go. Heuristics can point it in the right direction (for instance, it can know that the target is in the north direction) and help it avoid obstacles in a timely fashion without having to determine all possible ways for doing so.

Discovering the Learning Machine

All the algorithmic examples given earlier in this chapter are associated with AI because they're smart solutions that solve repetitive and well-delimited yet complex problems requiring intelligence. They require an architect who studies the problem and chooses the right algorithm to solve it. Problem changes, mutations, or unusual characteristic displays can become a real problem for a successful execution of the algorithm. This is because learning the problem and its solution occurs once when you train the algorithm. For instance, you can safely program an AI to solve Sudoku puzzles. You can even provide flexibility that allows the algorithm to accept more rules or larger boards later.

Unfortunately, not all problems can rely on a Sudoku-like solution. Real-life problems are never set in simple worlds of perfect information and well-defined action. Consider the problem of finding a fraudster cheating on insurance claims or the problem of diagnosing a medical disease. You have to contend with these factors:

- **A large set of rules and possibilities:** The number of possible frauds is incredibly high; many diseases have similar symptoms.
- **Missing information:** Fraudsters can conceal information; doctors often rely on incomplete information (examinations may be missing).
- **Problem rules aren't immutable:** Fraudsters discover new ways to arrange swindles or frauds; new diseases arise or are discovered.

To solve such problems, you can't use a predetermined approach; instead, you need a flexible approach and must accumulate useful knowledge to face any new challenge. In other words, you continue learning, as humans do throughout their lives to cope with a changing and challenging environment.

Leveraging expert systems

Expert systems, or systems that use rules to make decisions, were the first attempt to escape the realm of hard-coded algorithms and create more flexible and smart ways to solve real-life problems. The idea at the core of expert systems was simple and well-suited at a time when storing and dealing with lots of data in computer memory was still costly. It may sound strange today, but in the 1970s, AI scientists such as Ross Quillian had to demonstrate how to build working language models based on a vocabulary of only 20 words because computer memory of the time was too limited to handle the data structures needed to process more words. Few options were available if a computer couldn't hold all the data, and a solution was to process key problem information and obtain it from humans who knew it best.


REMEMBER

Expert systems were experts not because they based their knowledge on their own learning process, but rather because they collected it from human experts who provided a predigested system of key information taken from studying books, learning from other experts, or discovering it by themselves. It was basically a smart way to externalize knowledge into a machine.

MYCIN: A beginning expert system

An example of one of the first systems of this kind is MYCIN, a system to diagnose blood-clotting diseases or infections caused by bacteria, such as bacteremia (when bacteria infect the blood) and meningitis (inflammation of the membranes that protect the brain and spinal cord). MYCIN recommended the correct dosage of antibiotics by using well over 500 rules, and it relied, when needed, on the doctor using the system. When there wasn't enough information available — for instance, lab tests were missing — MYCIN then started a consultative dialogue by asking relevant questions to reach a confident diagnosis and therapy.

Written in Lisp as a doctoral dissertation by Edward Shortliffe at Stanford University, MYCIN took more than five years to complete, and it performed better than any junior doctor, reaching the elevated diagnosis accuracy of an experienced doctor. It came from the same laboratory that devised DENDRAL, the first expert system ever created, a few years earlier. DENDRAL, which specializes in organic chemistry, is a challenging application in which brute-force algorithms proved unfeasible when faced with human-based heuristics that rely on field experience.

As for MYCIN's success, some issues arose:

- First, the terms of responsibility were unclear: If the system were to provide an incorrect diagnosis, despite who was responsible?
- Second, MYCIN had a usability issue because the doctor had to connect to MYCIN by using a remote terminal to the mainframe in Stanford, a quite

difficult and slow process at a time when the Internet was still in its infancy. MYCIN still proved its efficacy and usefulness in supporting human decisions, and it paved the way for many other expert systems that proliferated later in the 1970s and 1980s.

The components of expert systems

Generally, expert systems of the time were made of two distinct components: knowledge base and inference engine. The *knowledge base* retains knowledge as a collection of rules in the form of if-then statements (with *if* involving one or multiple conditions and *then* involving conclusion statements). These statements occurred in a symbolic form, differentiating between instances, (single events or facts), classes, and subclasses, which all could be manipulated using Boolean logic or sophisticated first-order logic, which is composed of more possible operations.


TIP

First-order logic is a set of operations that goes beyond simply being bound to combine TRUE and FALSE assertions. For instance, it introduces concepts such as FOR ALL and THERE EXISTS, allowing you to deal with statements that may be true but cannot be proved by the evidence you have at hand at that moment.

The *inference engine* is a set of instructions that tell the system how to manipulate the conditions based on the Boolean logic set of operators such as AND, OR, and NOT. Using this logic set, TRUE or FALSE symbolic conditions can combine into complex reasoning. (When TRUE, a rule is triggered or, technically, "fired"; when FALSE, the rule doesn't apply.)

Because the system was made at the core of a series of ifs (conditions) and thens (conclusions), and was nested and structured in layers, acquiring initial information helped rule out some conclusions while also helping the system interact with the user concerning information that could lead to an answer. When dealing with the inference engine, common operations by the expert systems were as follows:

- **Forward chaining:** Available evidence triggered a series of rules and excluded others at each stage. The system initially concentrated on rules that could trigger an end conclusion by firing. This approach is clearly data-driven.
- **Backward chaining:** The system evaluates every possible conclusion and tries to prove each of them on the basis of the evidence available. This goal-driven approach helps determine which questions to pose and excludes entire sets of goals. MYCIN, described earlier, used backward chaining; progressing from hypothesis backward to evidence is a common strategy in medical diagnosis.

- **Conflict resolution:** If a system reaches more than one conclusion at the same time, the system favors the conclusion that has certain characteristics (in terms of impact, risk, or other factors). Sometimes, the system consults the user and the resolution is realized based on user evaluations. For instance, MYCIN used a certainty factor that estimated the probability of diagnosis exactness.

One great benefit of such systems is to represent knowledge in a human-readable form, rendering the decision-making process transparent. If the system reaches a conclusion, it returns to the rules used to reach that conclusion. The user can systematically review the work of the system and agree or review it for signs of input error. Moreover, expert systems were easy to program using languages such as Lisp, Prolog, or ALGOL. Users improved expert systems over time by adding new rules or updating existing rules. They could even be made to work through uncertain conditions by applying *fuzzy logic*, a kind of multivalued logic in which a value can contain anything between 0, or absolutely false, and 1, or absolutely true. Fuzzy logic avoids the abrupt steps of triggering a rule based on a threshold. For instance, if a rule is set to trigger when the room is hot, the rule is triggered not at an exact temperature but rather when the temperature is around that threshold.

Expert systems witnessed their twilight at the end of the 1980s, and their development stopped, mostly for the following reasons:

- The logic and symbolism of such systems proved limited in expressing the rules behind a decision, leading to the creation of custom systems — that is, falling back again on hard-coding rules with classical algorithms.
- For many challenging problems, expert systems became so complex and intricate that they lost their appeal in terms of feasibility and economic cost.
- Because data was becoming more diffuse and available, it made little sense to struggle to carefully interview, gather, and distill rare expert knowledge when the same (or even better) knowledge could be sifted from data.

Expert systems still exist. You can find them used in credit scoring, fraud detection, and other fields with the imperative to not just provide an answer but also clearly and transparently state the rules behind the decision in a way that the system user deems acceptable (as a subject expert would do). In addition, they're used in situations for which other forms of AI are too slow, such as some self-driving car applications.

Introducing machine learning

Solutions capable of learning directly from data with no preprocessing to render it as symbols arose a few decades before expert systems. Some were statistical in nature; others imitated nature in various ways; and still others tried to generate autonomously symbolic logic in the form of rules from raw information. All these solutions were derived from different schools and appeared under different names that now comprise machine learning. *Machine learning* is part of the world of algorithms, although, contrary to the many algorithms discussed in this book, it's not intended as a series of predefined steps apt to solve a problem. As a rule, machine learning deals with problems that humans don't know how to detail into steps, but that humans naturally solve. An example of such a problem is discerning faces in images or understanding certain words in a spoken discussion.


TIP

Though machine learning is mentioned in almost every chapter of this book, Chapters 6 and 7 are devoted to disclosing how major machine learning algorithms work, especially deep learning in Chapter 7, which is the technology powering the new wave of AI applications that reaches the news headlines almost every day. For a greater understanding of how Generative AI is impacting every aspect of business, see Chapter 8. It looks at such topics as the societal implications of using Generative AI to ways to monetize your own generative AI application.

Achieving new heights

The role of machine learning in the new wave of AI algorithms is to in part replace, and in part supplement, existing algorithms. Machine learning works with activities that require intelligence from a human point of view but that aren't easy to formalize as a precise sequence of steps. A clear example of this role is the mastery displayed by a Go expert that understands, at a glance, the threats and opportunities of a board configuration and intuitively grasps the right moves. (In case you're unfamiliar with Go, it's an abstract strategy board game for two people where the object is to capture more territory than your opponent by fencing off empty space.)

Go is an incredibly complex game for an AI. Chess has an average of 35 possible moves to evaluate on a board, and a game usually spans more than 80 moves, whereas a game of Go has about 140 moves to evaluate, and a game usually spans more than 240 moves. No computational power presently exists in the world to create a complete state space for a game of Go. Google's DeepMind team in London developed AlphaGo, a program that has defeated a number of top-ranked Go players (see `https://deepmind.google/technologies/alphago` and `www.kdnuggets.com/2020/05/deepmind-gaming-ai-dominance.html`). Rather than only rely on an algorithmic approach based on searching an immense state space, the program instead uses the following strategies:

- A smart-search method based on random tests of a possible move. The AI applies a DFS multiple times to determine whether the first outcome found is a positive or negative one (an incomplete and partial state space).
- A deep-learning algorithm processes an image of the board (at a glance) and derives both the best possible move in that situation (the algorithm is called the *policy network*) and an estimate of how likely the AI is to win the game by using that move (the algorithm is called the *value network*).
- A capability to learn by seeing completed games by Go experts and by playing against itself. One version of the program, called AlphaGo Zero, can learn all by itself, with no human examples (see `https://deepmind.google/discover/blog/alphago-zero-starting-from-scratch`). This learning capability is called *reinforcement learning*.

IN THIS CHAPTER

- Using standard hardware
- Using specialized hardware
- Improving your hardware
- Interacting with the environment

Chapter 4
Pioneering Specialized Hardware

Understanding the hardware behind AI is critical for understanding its full potential. As AI advances, the technology supporting it should evolve to meet increasing demands. This chapter explores how AI hardware has evolved, starting with general-purpose components and advancing to specialized processors tailored for complex AI applications. You determine the benefits and limitations of standard hardware, the innovations driving specialized hardware, and the computational advancements boosting AI performance.

Relying on Standard Hardware

Most AI projects you create will at least begin with standard hardware because modern off-the-shelf components provide significant processing power, especially when compared to components from the 1980s, when AI first began to produce usable results. Consequently, even if you can't ultimately perform production-level work by using standard hardware, you can advance far enough along with your experimental and preproduction code to create a working model that will eventually process a full dataset.

Examining the standard hardware

The *architecture* (structure) of the standard PC hasn't changed since John von Neumann first proposed it in 1946. Reviewing the history at `https://lennartb.home.xs4all.nl/coreboot/col2.html` shows you that the processor connects to memory and peripheral devices through a bus in PC products as early as 1981 (and long before). All these systems use the von Neumann architecture because it provides significant benefits in modularity. Reading the history tells you that these devices allow upgrades to every component as individual decisions, allowing increases in *capability.* For example, within limits, you can increase the amount of memory or storage available to any PC. You can also use advanced peripherals. However, all these elements connect through a bus (a link between devices).


REMEMBER

The PC you use today has the same architecture as devices created long ago; they're simply more capable. In addition, almost every device you can conceive of today has a similar architecture, despite having different form factors, bus types, and essential capabilities.

Describing standard hardware deficiencies

- **von Neumann bottleneck:** Of all the deficiencies, the von Neumann bottleneck is the most serious when considering the requirements of disciplines such as AI, machine learning, and even data science. You can find this particular deficiency discussed in more detail in the section "Considering the von Neumann bottleneck," later in this chapter.
- **Single points of failure:** Any loss of connectivity with the bus necessarily means that the computer fails immediately rather than gracefully. Even in systems with multiple processors, the loss of a single processor, which should simply produce a loss of capability, instead inflicts complete system failure. The same problem occurs with the loss of other system components: Rather than reduce functionality, the entire system fails. Given that AI often requires continuous system operation, the potential for serious consequences escalates with the manner in which an application relies on the hardware.
- **Single-mindedness:** The von Neumann bus can either retrieve an instruction or retrieve the data required to execute the instruction, but it can't do both. Consequently, when data retrieval requires several bus cycles, the processor remains idle, further reducing its ability to perform instruction-intensive AI tasks.
- **Tasking:** When the brain performs a task, a number of synapses fire at one time, allowing simultaneous execution of multiple operations. The original von Neumann design allowed just one operation at a time, and only after the system retrieved both the required instruction and data. Computers today

typically have multiple cores, which allow simultaneous execution of operations in each core. However, application code must specifically address this requirement, so the functionality sometimes remains unused.

Relying on new computational techniques

Reading literature about how to perform tasks using AI can feel like you're hearing a marketer on TV proclaiming, "It's new! It's improved! It's downright dazzling!" So it shouldn't surprise you much that people are always coming up with ways to make the AI development experience faster, more precise, and better in other ways. The problem is that many of these new techniques are untested — they might look great, but you have to think about them for a while.

EXAMINING THE HARVARD ARCHITECTURE DIFFERENCE

You may encounter the Harvard architecture during your hardware "travels" because some systems employ a modified form of this architecture to speed processing. Both the von Neumann architecture and Harvard architecture rely on a bus topology. However, when working with a von Neumann architecture system, the hardware relies on a single bus and a single memory area for both instructions and data, whereas the Harvard architecture relies on individual buses for instructions and data, and can use separate physical memory areas. The use of individual buses enables a Harvard architecture system to retrieve the next instruction while waiting for data to arrive from memory for the current instruction, thereby making the Harvard architecture both faster and more efficient. However, reliability suffers because now you have two failure points for each operation: the instruction bus and the data bus.

Microcontrollers, such as those that power your microwave, often use the Harvard architecture. In addition, you might find it in some unusual places for a specific reason. The iPhone and Xbox 360 both use modified versions of the Harvard architecture that rely on a single memory area (rather than two), but still rely on separate buses. The reason for using the architecture in this case is digital rights management (DRM). You can make the code area of memory read-only so that no one can modify it or create new applications without permission. From an AI perspective, this can be problematic because one AI's capability is to write new algorithms (executable code) as needed to deal with unanticipated situations. Because PCs rarely implement a Harvard architecture in its pure form or as the main bus construction, the Harvard architecture doesn't receive much attention in this book.

Using GPUs

After creating a prototypical setup to perform the tasks required to simulate human thought on a given topic, you may need additional hardware to provide sufficient processing power to work with the full dataset required of a production system. Many methods are available to provide such processing power, but a common one is to use graphics processing units (GPUs) in addition to the central processor of a machine. The following sections describe the problem domain that a GPU addresses, what precisely the term GPU means, and why a GPU makes processing faster.

CONSIDERING ALAN TURING'S BOMBE MACHINE

Alan Turing's Bombe machine wasn't any form of AI. In fact, it isn't even a real computer. It broke Enigma cryptographic messages, and that's it. However, it did provide food for thought for Turing, which eventually led to a paper titled "Computing Machinery and Intelligence." Turing published that paper, which describes the imitation game, in the 1950s. (The movie *The Imitation Game* depicts the events surrounding the creation of this game.) However, the Bombe itself was actually based on a Polish machine called the Bomba.

Even though some sources imply that Alan Turing worked alone, the Bombe was produced with the help of many people, most especially Gordon Welchman. Neither did Turing spring from a vacuum, ready-made to break German encryption. His time at Princeton was spent with legendary figures like Albert Einstein and John von Neumann (who would go on to invent the concept of computer software). The papers Turing wrote inspired these other scientists to experiment and see what is possible.

Specialized hardware of all sorts will continue to appear as long as scientists are writing papers, bouncing ideas off each other, creating new ideas of their own, and experimenting. When you see movies or other media, assuming that they're reasonably historically accurate, don't leave with the feeling that these people just woke up one morning and proclaimed, "Today, I will be brilliant!" and then went on to do something marvelous. Everything builds on something else, so history is important because it helps show the path followed and illuminates other promising paths — those not followed.

Considering the von Neumann bottleneck

The von Neumann bottleneck is a natural result of using a bus to transfer data between the processor, memory, long-term storage, and peripheral devices. No matter how fast the bus performs its task, overwhelming it — that is, forming a bottleneck that reduces speed — is always possible. Over time, processor speeds continue to increase while memory and other device improvements focus on *density* — the capability to store more in less space. Consequently, the bottleneck becomes more of an issue with every improvement, causing the processor to spend a lot of time being idle.

Within reason, you can overcome some of the issues that surround the von Neumann bottleneck and produce small, but noticeable, increases in application speed. Here are the most common solutions:

- **Caching:** When problems with obtaining data from memory fast enough with the von Neumann architecture became evident, hardware vendors quickly responded by adding localized memory that didn't require bus access. This memory appears external to the processor but as part of the processor package. High-speed cache is expensive, however, so cache sizes tend to be small.
- **Processor caching:** Unfortunately, external caches still provide insufficient speed. Even using the fastest RAM available and cutting out the bus access completely doesn't meet the processing capacity needs of the processor. Consequently, vendors started adding internal memory — a cache smaller than the external cache, but with even faster access because it's part of the processor.
- **Prefetching:** The problem with caches is that they prove useful only when they contain the correct data. Unfortunately, cache hits prove low in applications that use a lot of data and perform a wide variety of tasks. The next step in making processors work faster is to guess which data the application will require next and load it into a cache before the application requires it.
- **Using specialty RAM:** You can get buried by RAM alphabet soup because more kinds of RAM exist than most people imagine. Each kind of RAM purports to solve at least part of the von Neumann bottleneck problem, and they do work — within limits. In most cases, the improvements revolve around the idea of getting data from memory and onto the bus faster. Two major (and many minor) factors affect speed: *memory speed* (how fast the memory moves data) and *latency* (how long it takes to locate a particular piece of data).

WARNING

As with many other areas of technology, hype can become a problem. For example, *multithreading,* the act of breaking an application or other set of instructions into discrete execution units that the processor can handle one at a time, is often touted as a means to overcome the von Neumann bottleneck, but it doesn't actually help the bottleneck. Multithreading is an answer to another problem: making the application more efficient. When an application adds latency issues to the von Neumann bottleneck, the entire system slows. Multithreading ensures that the processor doesn't waste yet more time waiting for the user or the application, but instead has something to do all the time. Application latency can occur with any processor architecture, not just the von Neumann architecture. Even so, anything that speeds the overall operation of an application is visible to the user and the system as a whole.

Defining the GPU

The original intent of a GPU was to process image data quickly and then display the resulting image onscreen. During the initial phase of PC evolution, the CPU performed all the processing, which meant that graphics could appear slowly while the CPU performed other tasks. During this time, a PC typically came equipped with a *display adapter,* which contains little or no processing power. A display adapter merely converts the computer data into a visual form. In fact, using just one processor proved almost impossible after the PC moved past text-only displays or extremely simple 16-color graphics. However, GPUs didn't make many inroads into computing until people began wanting 3D output. At this point, a combination of a CPU and a display adapter simply couldn't do the job.

A first step in this direction was taken by systems such as the Hauppauge 4860 which included a CPU and a special graphics chip (the 80860, in this case) on the motherboard. The 80860 provides the benefit of performing calculations extremely fast. Unfortunately, these multiprocessor, asynchronous systems didn't quite meet the expectations that people had for them (although they were incredibly fast for systems of the time) and they proved extremely expensive. Plus, there was the whole issue of writing applications that included that second (or subsequent) chip. The two chips also shared memory (which was abundant for these systems).

A GPU moves graphics processing from the motherboard to the graphics peripheral board. The CPU can tell the GPU to perform a task, and then the GPU determines the best method for doing so independently of the CPU. A GPU has a separate memory, and the data path for its bus is immense. In addition, a GPU can access the main memory for obtaining data needed to perform a task and to post results independently of the CPU. Consequently, this setup makes modern graphics displays possible.

However, what truly sets apart a GPU is that a GPU typically contains hundreds or thousands of cores contrasted with just a few cores for a CPU. Eight cores is about the best that you get, even with the newer i9 processor, an A100 GPU can host up to 80 gigabytes (GB) of RAM and has up to 8,192 FP32 (single-precision floating-point format) CUDA (Compute Unified Device Architecture) cores per full GPU. *CUDA* is a parallel computing platform and application programming interface (API) developed by NVIDIA. Even though the CPU provides more general-purpose functionality, the GPU performs calculations incredibly fast and can move data from the GPU to the display even faster. This ability is what makes the special-purpose GPU a critical component in today's systems.

Considering why GPUs work well

As with the 80860 chip, described in the previous section, GPUs now excel at performing the specialized tasks associated with graphics processing, including working with vectors. All those cores performing tasks in parallel truly speed AI calculations.

In 2011, the Google Brain project (`https://research.google/`) trained an AI to recognize the difference between cats and people by watching movies on YouTube. However, to make this task work, Google used 2,000 CPUs in one of its giant data centers. Few people would have the resources required to replicate Google's work.

On the other hand, Bryan Catanzaro (from NVIDIA's research team) and Andrew Ng (from Stanford) were able to replicate Google's work using a set of 12 NVIDIA GPUs. After people understood that GPUs could replace a host of computer systems stocked with CPUs, they could start moving forward with a variety of AI projects. In 2012, Alex Krizhevsky (from Toronto University) won the ImageNet computer image recognition competition using GPUs. In fact, a number of researchers have now used GPUs with amazing success.

Working with Deep Learning Processors (DLPs)

Researchers constantly struggle to discover better ways to train, verify, and test the models used to create AI applications. One of those ways is to use new computing techniques, as described in the section "Relying on new computational techniques," earlier in this chapter. Another way is to throw more processing power at the problem, such as by using a GPU.

However, a GPU is beneficial only because it can perform matrix manipulation quickly, and on a massively parallel level. Otherwise, using a GPU can create problems as well, as discussed earlier, in the "Using GPUs" section of this chapter. So the search for something better is ongoing, and you can find a veritable alphabet soup of processor types described on sites such as Primo.ai — see the page titled "Processing Units — CPU, GPU, APU, TPU, VPU, FPGA, QPU." This resource page will acquaint you with all the current processor types. However, you should start with the overview provided in the following sections because you can easily become mired in the quicksand of facing too many options (and then your head explodes).

Defining the DLP

A *deep learning processor* (DLP) is simply a specialized processor that provides some benefits in training, verifying, testing, and running AI applications. They try to create an environment in which AI applications run quickly even on smaller or less capable devices. Most DLPs follow a similar pattern by providing

- Separate data and code memory areas
- Separate data and code buses
- Specialized instruction sets
- Large on-chip memory
- Large buffers to encourage data reuse patterns

In 2014, Tianshi Chen (and others) proposed the first DLP, called DianNoa (Chinese for *electric brain*). Of course, a first attempt is never good enough, so there's a whole family of DianNoa chips: DaDianNao, ShiDianNao, and PuDianNao (and possibly others).

REMEMBER

Since these first experiments with DLPs, the number and types of DLPs have soared, but most of these endeavors are now part of university research efforts. The exceptions are the neural processing unit (NPU) created by Huawei and Samsung for mobile devices, and the tensor processing unit (TPU) created by Google (`https://cloud.google.com/tpu/docs/intro-to-tpu`) specifically for use with TensorFlow (`www.tensorflow.org`). These two DLP types are described next.

Using the mobile neural processing unit (NPU)

A number of mobile devices — notably, those by Huawei and Samsung — have a neural processing unit (NPU) in addition to a general CPU to perform AI predictive tasks using models such as artificial neural networks (ANNs) and random forests (RFs). You can't use an NPU for general computing needs because it's so specialized. However, an NPU characteristically performs up to ten times faster than a GPU does for the same task. An NPU is specialized in these ways:

- It accelerates the running of predefined models (as contrasted to training, verification, and testing.)
- It's designed for use with small devices.
- It consumes little power when contrasted to other processor types.
- It uses resources, such as memory, efficiently.

Because the precise boundaries between processor types are hard to define, you might see a number of NPU look-alikes or alternatives classified as NPUs. However, here's a list of processors that you can currently classify as true NPUs:

- Ali-NPU, by Alibaba
- Ascend, by Huawei
- Neural Engine, by Apple
- Neural processing unit (NPU), by Samsung
- NNP, Myriad, EyeQ, by Intel
- NVDLA (mostly used for Internet of Things [IoT] devices), by NVIDIA

Accessing the cloud-based tensor processing unit (TPU)

Google specifically designed the tensor processing unit (TPU) in 2015 to more quickly run applications built on the TensorFlow framework. It represents a true chip specialization in that you can't use it effectively without TensorFlow. However, it's different in another way in that it's an application-specific

integrated circuit (ASIC) rather than a full-blown CPU-type chip. The differences are important:

- An ASIC can perform only one task, and you can't change it.
- Because of its specialization, an ASIC is typically much less expensive than a CPU.
- Most ASIC implementations are much smaller than the same implementation created with a CPU.
- Compared to a CPU implementation, an ASIC is more power efficient.
- ASICs are incredibly reliable.

Creating a Specialized Processing Environment

Deep learning and AI are both non-von Neumann processes, according to many experts, including Massimiliano Versace, CEO of Neurala, Inc. (`www.neurala.com`). Because the task the algorithm performs doesn't match the underlying hardware, all sorts of inefficiencies exist, hacks are required, and obtaining a result is much harder than it should be. Therefore, designing hardware that matches the software is quite appealing. The Defense Advanced Research Projects Agency (DARPA) undertook one such project in the form of Systems of Neuromorphic Adaptive Plastic Scalable Electronics (SyNAPSE). The idea behind this approach is to duplicate nature's approach to solving problems by combining memory and processing power rather than keeping the two separate. They actually built the system (it was immense), and you can read more about it at `www.darpa.mil/program/systems-of-neuromorphic-adaptive-plastic-scalable-electronics` and `www.darpa.mil/news-events/2014-08-07`.

The SyNAPSE project did move forward. IBM built a smaller system by using modern technology that was both incredibly fast and power efficient. The only problem is that no one is buying them. The same holds true for IBM's SyNAPSE offering, TrueNorth. It has been hard to find people who are willing to pay the higher price, programmers who can develop software using the new architecture, and products that genuinely benefit from the chip. Consequently, a combination of CPUs and GPUs, even with its inherent weaknesses, continues to win out.

Increasing Hardware Capabilities

The CPU still works well for business systems or in applications in which the need for general flexibility in programming outweighs pure processing power. However, GPUs are now the standard for various kinds of data science, machine learning, AI, and deep learning needs. Of course, developers are constantly looking for the next big thing in the development environment. Both CPUs and GPUs are production-level processors. In the future, you may see one of two kinds of processors used in place of these standards:

- **Application-specific integrated circuits (ASICs):** In contrast to general processors, a vendor creates an ASIC for a specific purpose. An ASIC solution offers extremely fast performance using very little power, but it lacks flexibility. You can find an example of an ASIC in this chapter in the form of a TPU (see the earlier section "Accessing the cloud-based tensor processing unit (TPU)" for details).
- **Field programmable gate arrays (FPGAs):** As with an ASIC, a vendor generally crafts an FPGA for a specific purpose. However, contrary to using an ASIC, you can program an FPGA to change its underlying functionality. An example of an FPGA solution is Microsoft's Brainwave, which is used for deep learning projects.

REMEMBER

The battle between ASICs and FPGAs promises to heat up, with AI developers emerging as the winner. For the time being, Microsoft and FPGAs appear to have taken the lead. The point is that technology is fluid, and you should expect to see new developments

Vendors are also working on entirely new processing types, which may or may not work as expected. For example, Graphcore is working on an intelligence processing unit (IPU). The company has developed the line of processors shown at `www.graphcore.ai/products/ipu`. However, you have to take the news of these new processors with a grain of salt, given the hype that has surrounded the industry in the past. When you see real-life applications from large companies such as Google and Microsoft, you can start to feel a little more certain about the future of the technology involved.

Looking at the future of AI hardware, we authors see two new areas of advancement in hardware capabilities: neuromorphic computing and quantum processors. These cutting-edge technologies can potentially improve processing efficiency and capability, pushing the boundaries of AI. We look at each in turn in the following sections.

Advancing neuromorphic computing

Neuromorphic computing is the field of technology that mimics the neural structure and operation of the brain. It uses specialized hardware to create more efficient and adaptive AI systems. Recent developments in neuromorphic chips, such as Intel's Loihi (`https://open-neuromorphic.org/neuromorphic-computing/hardware/loihi-intel`) and IBM's TrueNorth (`https://open-neuromorphic.org/blog/truenorth-deep-dive-ibm-neuromorphic-chip-design`) have greatly improved power efficiency and processing capabilities for specific AI tasks.


TIP

These chips can handle complex tasks — like pattern recognition, sensory processing, and real-time decision-making — with significantly lower energy consumption than traditional processors.

Neuromorphic systems often utilize *spiking neural networks* (SNNs), which process information like the brain, through the timing of spikes (bursts of activity) rather than continuous signal transmission. This approach allows for more efficient and faster data processing, especially in applications that require real-time analysis and adaptive learning.


TIP

Autonomous drones and robots can benefit from neuromorphic chips by enhancing their ability to navigate and respond to their environments.

Exploring quantum processors

Quantum processors represent a big leap in AI hardware capabilities. Unlike classical processors that use bits to represent data as zeros or ones, *quantum processors* use quantum bits (qubits), which can exist in multiple states at the same time. This unique property allows quantum processors to perform certain calculations much faster than classical computers.

Companies like Google, IBM, and D-Wave are making strides in developing quantum processors. With regard to AI, quantum processors have the potential to revolutionize optimization problems, enhance machine learning algorithms, and accelerate complex simulations.

Quantum computing is still in its infancy but has several potential applications. For instance, it could enable more sophisticated AI models to process and analyze large-scale data more efficiently. This could lead to such events as drug discovery and financial modeling breakthroughs.

Adding Specialized Sensors

An essential component of AI is the capability of the AI to simulate human intelligence using a full set of senses. Input provided by senses helps humans develop the various kinds of intelligence described in Chapter 1. A human's senses provide the right sort of input to create an intelligent human. Even assuming that it becomes possible for an AI to fully implement all eight kinds of intelligence, it still requires the right sort of input to make that intelligence functional.

Humans typically have five senses with which to interact with the environment: sight, sound, touch, taste, and hearing. Oddly enough, humans still don't fully understand their own capabilities, so it's not too surprising that computers lag when it comes to sensing the environment in the same way humans do. For example, until recently, only four elements comprised taste: salt, sweet, bitter, and sour. However, two more tastes now appear on the list: umami and fat. Likewise, some women are tetrachromats, who can see 100 million colors rather than the more usual 1 million. (Only women can be tetrachromats because of the chromosomal requirements.) Knowing how many women have this capability isn't even possible yet, though some sources place the number as high as 20 percent.

The use of filtered static and dynamic data now enables an AI to interact with humans in specific ways. For example, consider Alexa, the Amazon device that seemingly "hears" you and then says something in response. Even though Alexa doesn't actually understand anything you say, the appearance of communication is quite addicting and encourages people to anthropomorphize these devices. To perform any part of its task, Alexa requires access to a special sensor: a microphone that allows it to hear. Actually, Alexa has a number of microphones to help it hear well enough to provide the illusion of understanding. Unfortunately, as advanced as Alexa is, it can't see, feel, touch, or taste anything, which makes it far from human.

TIP

In some cases, humans want their AI to have superior or different senses. An AI that detects motion at night and reacts to it might rely on infrared rather than normal vision. In fact, the use of alternative senses is now one of the valid uses for AI. The capability to work in environments that people can't work in is one reason that some types of robots have become popular, but working in these environments often requires that the robots have, or be connected to, a set of nonhuman sensors. Consequently, the topic of sensors actually falls into two categories (neither of which is fully defined): human-like and alternative environment.

Integrating AI with Advanced Sensor Technology

Integrating advanced sensors with AI is now changing how machines interact with the world and expanding what they can do. Here are some key advancements:

- **Sensor fusion**: Sensor fusion integrates data from multiple sensors to help understand environments. For example, combining inputs from cameras, light detection and ranging (LiDAR), radar, and ultrasonic sensors helps self-driving cars navigate safely.
- **Bio-inspired sensors:** These sensors mimic biological systems. Artificial skin detects pressure, temperature, and texture, allowing robots to handle delicate objects carefully. Other sensors can identify smells like chemical compounds, aiding in early disease detection and pollutant monitoring. (We tell you more about sensing in the next section.)
- **Quantum sensors**: Using principles of quantum mechanics, these sensors achieve high precision. They can detect tiny changes in magnetic fields, gravity, and temperature. This is important for advanced medical imaging and navigation in places where GPS doesn't work well.
- **Environmental sensors:** These sensors detect events like infrared and ultraviolet light and radiation, enabling AI systems to operate in tough conditions. They are crucial for industrial monitoring and military surveillance.

Devising Methods to Interact with the Environment

An AI that is self-contained and never interacts with the environment is useless. Of course, that interaction takes the form of inputs and outputs. The traditional method of providing inputs and outputs is directly through data streams that the computer can understand, such as datasets, text queries, and the like. However, these approaches are hardly human-friendly, and they require special skills to use.


REMEMBER

Interacting with an AI is increasingly occurring in ways that humans understand better than they understand direct computer contact. For example, input occurs via a series of microphones when you ask Alexa a question. The AI turns the keywords in the question into tokens it can understand. These tokens then initiate computations that form an output. The AI tokenizes the output into a

human-understandable form: a spoken sentence. You then hear the sentence as Alexa speaks to you through a speaker. In short, to provide useful functionality, Alexa must interact with the environment in two different ways that appeal to humans but that Alexa doesn't actually understand.

Interactions can take many forms. In fact, the number and forms of interaction are increasing continually. For example, an AI can smell (see "Artificial intelligence grows a nose" at www.science.org/content/article/artificial-intelligence-grows-nose). However, the computer doesn't actually smell anything. Sensors provide a means to turn chemical detection into data that the AI can then use in the same way it uses all other data. The capability to detect chemicals isn't new; the ability to analyze those chemicals isn't new; nor are the algorithms used to interact with the resulting data new. What is new is the datasets used to interpret the incoming data as a smell, and those datasets come from human studies. An AI's "nose" has all sorts of possible uses. For example, think about the AI's capability to use a nose when working in some dangerous environments, such as to smell explosives at an airport before being able to see it by using other sensors.

Physical interactions are also on the rise. Robots that work on assembly lines are old hat, but consider the effects of robots that can drive. These are larger uses of physical interaction. Consider also that an AI can react in smaller ways. Hugh Herr, for example, uses an AI to provide interaction with an intelligent foot, as described in "Is This the Future of Robotic Legs?" at www.smithsonianmag.com/innovation/future-robotic-legs-180953040/ and "New surgery may enable better control of prosthetic limbs" at MITNews.edu. This dynamic foot provides a superior replacement for people who have lost their real foot. Instead of the static sort of feedback that a human receives from a standard prosthetic, this dynamic foot provides the sort of active feedback that humans are used to obtaining from a real foot. For example, the amount of pushback from the foot differs when walking uphill than walking downhill. Likewise, navigating a curb requires a different amount of pushback than navigating a step.

The point is that as AI becomes more able to perform complex calculations in smaller packages with ever-larger datasets, the capability of an AI to perform interesting tasks increases. However, the tasks that the AI performs may not currently have a human equivalent. You may not ever truly interact with an AI that understands your speech, but you may come to rely on an AI that helps you maintain life — or at least make it more livable.

2 Understanding How AI Works

IN THIS PART . . .

Perform data analysis.

Consider the relationship between AI and machine learning.

Consider the relationship between AI and deep learning.

IN THIS CHAPTER

- Understanding how data analysis works
- Using data analysis effectively with machine learning
- Determining what machine learning can achieve
- Examining the various kinds of machine learning algorithms

Chapter 5

Crafting Intelligence for AI Data Analysis

Collecting data isn't a modern phenomenon, although the way we collect it at scale is relatively new. People have recorded data in various forms for centuries. Regardless of whether the information was in text or numeric format, people have always appreciated how data describes the surrounding world, and among other things, they used it to move civilization forward. Data has an inherent value. By using its content, humanity can learn, transmit critical information (avoiding the need to reinvent the wheel), and effectively act in the world.

This chapter discusses how data also contains more than just surface-level information. If data is in a suitable numerical form, you can apply special techniques devised by mathematicians and statisticians (known as *data analysis* techniques) to extract even more insights from it. We also show how, starting from simple data analysis, you can extract meaningful information and subject data to more advanced analytics using *machine learning (ML)* algorithms capable of predicting the future, classifying information, and effectively helping in making optimal decisions.

Data analysis and ML enable people to push data usage beyond its previous limits to develop smarter AI systems. This chapter introduces you to data analysis, which serves not as a lesser solution compared to generative or conversational AI but instead forms its very foundation. You find out how to use data as a learning tool and a starting point for solving complex AI problems, such as suggesting the right product to a customer, understanding spoken language, translating English into German or Japanese, automating car driving, and more.

Defining Data Analysis

The current era is called the information age not simply because we humans have become so data-rich, but also because society has reached a certain maturity in analyzing and extracting information from that data, with artificial intelligence (AI) and ML increasingly playing an important role. Companies such as Alphabet (Google), Amazon, Apple, Facebook, Netflix, and Microsoft, which have built their businesses on data, are ranked among the most valuable companies in the world because they don't simply gather and keep stored data that's provided by their digital processes. All these companies also know how to make data as valuable as oil by employing precise and elaborate data analysis. Google, for instance, records data from the web and from its own search engine, among other sources, and based on that data, it has built a plurality of ML models that are continuously updated to support its business.

You may have encountered the mantra "Data is the new oil" in the news, in magazines, or at conferences. The statement implies that data can make a company rich *and* that it takes skill and hard work to make this happen. Though many have employed the concept and made it incredibly successful, it was Clive Humbly, a British mathematician, who first equated data to oil, given his experience with consumers' data in the retail sector. Humbly is known for being among the founders of Dunnhumby, a UK marketing company, and the mind behind Tesco's fidelity card program. In 2006, Humbly also emphasized that data is not just money that rains from the sky; it requires effort to make it useful. Just as you can't immediately use unrefined oil because it has to be changed into something else by chemical processes that turn it into gas, plastics, or other chemicals, so data must undergo significant transformations to acquire value.

The most basic data transformations are provided by data analysis, and you liken them to the basic chemical transformations that oil undergoes in a refinery before becoming valuable fuel or plastic products. Using just data analysis, you can lay down the foundation for more advanced data analysis processes that you can apply to data. *Data analysis,* depending on the context, refers to a large body of possible data operations, sometimes specific to certain industries or tasks.

You can categorize all these transformations into four large and general families that provide an idea of what happens in data analysis:

- **Transforming:** Changes the data's structure. The term *transforming* refers to different processes, though the most common is putting data into ordered rows and columns in a *matrix format* (also called *flat-file transformation*). For instance, you can't effectively process data of goods bought in a supermarket until you've placed each customer information in a separate row and listed each product they bought in columns within that row. Algorithms analyze each entry individually; therefore, it is important that all relevant information for a single customer is included in one row. You add those products as numeric entries that contain quantities or monetary value. Transforming can also involve numeric operations such as *scaling* and *shifting,* through which you change the *mean* (the average) and the *dispersion* (the way a numeric series is spread around its mean) of the data. These adjustments make the data compatible with ML and deep learning algorithms.
- **Cleansing:** Fixes imperfect data. Depending on the source of the data, you may find various problems because of missing information, extremes in range, or simply wrong values. For instance, data in a supermarket may present errors when goods are labeled with incorrect prices. Some data is *adversarial,* which means that it has been created to spoil your analysis. For instance, a product may have fake reviews on the Internet that change its rank. Cleansing helps to remove adversarial examples from data and to make conclusions reliable.
- **Inspecting:** Validates the data. Data analysis is mainly a human job, though software plays a big role. Humans can easily recognize patterns and spot strange data elements. For this reason, data analysis produces many data statistics and provides useful and insightful visualizations. There are even awards for the most beautiful and meaningful data representation every year at the Information Is Beautiful awards. You can see entries and winners at `https://www.informationisbeautifulawards.com/showcase` and discover a wide range of creative and innovative examples of data visualization.
- **Modeling:** Grasps the relationship between the elements present in data. To perform this task, you need tools taken from statistics, such as correlations, chi-square tests, linear regression, and many others that can reveal whether some values truly are different from others or just related. For instance, when analyzing expenditures in a supermarket, you can determine that people buying diapers also tend to buy beer. Statistical analysis finds these two products associated many times in the same baskets. (The association between diapers and beer is legendary in data analytics; see the old, but still relevant, short story in the *Forbes* article "Birth of a legend.": `www.forbes.com/global/1998/0406/0101102s1.html`)

Data analysis isn't magic. You perform transformations, cleansing, inspecting, visualizations and modeling by using mass summation and multiplication based on matrix calculus (which is nothing more than the long sequences of summation and multiplication that many people learn in school). The data analysis arsenal also provides basic statistical tools, such as mean and variance, that describe data distribution, or sophisticated tools, such as correlation and linear regression analysis, that reveal whether you can relate events or phenomena to one another based on the evidence (like buying diapers and beer). To discover more about such data techniques, both *Machine Learning For Dummies*, 2nd Edition, and *Python For Data Science For Dummies*, 3rd Edition, by John Paul Mueller and Luca Massaron (both published by Wiley), offer a practical overview and explanation of each of them.


REMEMBER

What sometimes complicates data analysis is the vast volume of data that requires special computing tools, such as Hadoop (`https://hadoop.apache.org`) and Apache Spark (`https://spark.apache.org`), which are two software tools used to perform massive data operations on multiple computers. Despite such advanced tools, it's still a matter of perspiration to manually prepare your data.

Understanding why analysis is important

Data analysis is essential to AI. In fact, no modern AI is possible without visualizing, cleansing, transforming, and modeling data before advanced algorithms, such as machine learning, *natural language processing (NLP)*, computer vision, or Generative AI enter the process and turn it into information of even higher value than before.

In the beginning, when AI consisted of purely algorithmic solutions and expert systems, scientists and experts carefully prepared the data to feed them. Therefore, for instance, if someone wanted to develop an algorithm to process information, a data expert would place the correct data into *lists* (ordered sequences of data elements) or in another structured data format (a *data structure*) that could appropriately contain the information and allow its desired manipulation. At such a time, data experts gathered and organized the data so that its content and form were exactly as expected, and crafting new data for the purpose required a lot of time and energy. Consequently, algorithms had to work with less information than is available today.

Attention has now shifted from data production to data preparation through data analysis. The idea is that various sources already produce data in such large quantities that you can find what you need without having to create special data for the task. More data also makes the algorithms smarter than before. Imagine wanting an AI based on computer vision to control your pet door to let cats and dogs in but keep other animals out. Modern AI algorithms learn from task-specific data,

which means processing many images showing examples of dogs, cats, and other animals. Such a huge set of images would come from the Internet, usually from social media platforms or image searches. Previously, accomplishing a similar task meant that algorithms would use just a few specific data inputs selected because they did a good job of illustrating shapes, sizes, and distinctive characteristics of the animals. However, the scarcity of data once restricted the algorithms to only a few specific tasks. Remarkably, there are no examples of AI systems that could power a pet door using traditional algorithms or expert systems. Today, however, there are several working solutions using the latest deep learning algorithms (see, for example: `gizmodo.com/petvation-smart-pet-door-facial-recognition-cat-dog-1849113959`).

Data analysis comes to the rescue of modern algorithms by removing bad examples and transforming it according to requirements, which provides further useful information. For example, if the data is about images retrieved from the Internet, data analysis enables the selection of the data based on image sizes, variety, number of colors, words used in the image titles, and so on. This is part of the process of inspecting the data, and, in this case, that's necessary before you can cleanse and transform it. For instance, data analysis can help you spot a photo of an animal erroneously labeled a cat (you don't want to confuse your AI) and provide you the information to transform the images to the same color format and the same size.

Reconsidering the value of data

With the explosion of data availability on digital devices (as discussed in Chapter 2), data assumes new nuances of value and usefulness beyond its initial scope of teaching and transmitting knowledge. The abundance of data, when provided to data analysis and complex algorithms, allows for new descriptive and predictive functions beyond mere reporting:

- **Data describes the world better because it presents a wide variety of facts, and in more detail, by providing nuances for each fact.** Data has become so abundant that it covers every aspect, and it can unveil how even apparently unrelated elements and facts relate to each other.
- **Data shows how facts are associated with events.** Given enough data to dig out the underlying general rules, you can predict how the world will change or transform over time.

Large amounts of scientific data (such as from physics, chemistry, or biology) can allow scientists to approach problems without hypotheses, instead analyzing the information found in data and using intelligent algorithms. This contrasts with the past, when scientists relied on uncountable observations and a multitude of

experiments to gather enough evidence to describe the physics of the universe using the scientific method. However, this new data-driven approach to science would merely complement, not replace, the scientific method that has proven so effective in allowing scientists to find many underlying laws of the world.

The ability to innovate using data and AI algorithms is a breakthrough in the scientific quest to understand the world. AI achievements such AlphaFold, described in "DeepMind solves 50-year-old 'grand challenge' with protein foldingAI" at CNBC.com (www.cnbc.com/2020/11/30/deepmind-solves-protein-folding-grand-challenge-with-alphafold-ai.html), allow great steps forward on the way to figuring out how proteins fold in space and how they function, without the need for long experimentation. For many other scientific tasks, data analysis pairs observations expressed as inputs and outputs. This technique makes it possible to predict how things work and to define, thanks to ML, approximate rules (laws) of our world without having to resort to using long observations and experimentations. Many aspects of the scientific process can now become faster and more automatic using data and AI algorithms.

DISCOVERING SMARTER AI DEPENDS ON DATA

More than simply powering AI, data makes AI possible. Some people would say that AI is the output of sophisticated algorithms of elevated mathematical complexity, and that's certainly true. Activities like vision and language understanding require algorithms that aren't easily explained in layman's terms and necessitate millions of computations to work. (Hardware plays a role here, too.)

Yet there's more to AI than algorithms. Dr. Alexander Wissner-Gross, an American research scientist, entrepreneur, and fellow at the Institute for Applied Computation Science at Harvard, provided his insights in an earlier interview at Edge.org ("Datasets Over Algorithms" at www.edge.org/response-detail/26587). The interview reflects on why AI technology took so long to take off, and Wissner-Gross concludes that it might have been a matter of the quality and availability of data rather than algorithmic capabilities.

Wissner-Gross reviews the timing of most breakthrough AI achievements in preceding years, showing how data and algorithms contribute to the success of each breakthrough and highlighting how each was fresh at the time the milestone was reached. Wissner-Gross shows how data is relatively new and always updated, whereas algorithms aren't new discoveries, but rather rely on the consolidation of older technology.

Wissner-Gross concludes that, on average, a successful algorithm is usually 15 years older than the data it uses. He points out that data is pushing AI's achievements forward and leaves the reader wondering what could happen if it were possible to feed the current algorithms with better data in terms of quality and quantity.

Defining Machine Learning (ML)

The pinnacle of data analysis is machine language. You can successfully apply ML only after data analysis provides correctly prepared input. However, only ML can associate a series of outputs and inputs, as well as determine the working rules behind the output in an effective way. Data analysis concentrates on understanding and manipulating the data so that it can become more useful and provide insights into the world, whereas ML strictly focuses on taking inputs from data and elaborating a working, internal representation of the world that you can use for practical purposes. ML enables people to perform activities such as forecasting the future, classifying things in a meaningful way, and determining the optimal rational decision in a given context.


REMEMBER

The central idea behind ML is that you can represent reality by using a mathematical function that the algorithm doesn't know in advance but can guess after seeing some data. You can express reality and all its challenging complexity in terms of unknown mathematical functions that ML algorithms find and make actionable. This concept is the core idea for all kinds of ML algorithms.

Learning in ML is purely mathematical, and it ends by associating certain inputs with certain outputs. It has nothing to do with understanding what the algorithm has learned (data analysis builds understanding to a certain extent), thus the learning process is often described as *training* because the algorithm is trained to match the correct answer (the output) to every question offered (the input). (*Machine Learning For Dummies,* 2nd Edition, by John Paul Mueller and Luca Massaron, describes in detail how this process works.)

Despite lacking deliberate understanding and being simply a mathematical process, ML can prove useful in many tasks. When learning occurs by using the right data, it provides the AI application the power to do the most rational thing given a certain context. The following sections help describe in more detail how ML works, what benefits you can hope to obtain, and the limits of using ML within an application.

Understanding how ML works

Many people are used to the idea that software applications start with writing a function that accepts data as input and then provides a result. For example, a programmer might create a function called `Add()` that accepts two values as input, such as 1 and 2, and provides the result, which is 3. The output of this process is a value. In the past, writing a program meant understanding the function used to manipulate data to create a given result with certain inputs. ML turns this process around. In this case, you know that you have inputs, such as 1 and 2, and that the desired result is 3. However, you don't know what function to apply to create the desired result. Training provides a learner algorithm with all sorts of examples of the desired inputs and results expected from those inputs. The learner then uses this input to create a function. In other words, training is the process whereby the learner algorithm tailors a function to the data. The output is typically a numeric value, such as a measure or a probability.

To give an idea of what happens in the training process, imagine a child learning to distinguish trees from other objects. Before the child can do so in an independent fashion, a teacher presents the child with a certain number of tree images, complete with all the facts that make a tree distinguishable from other objects of the world. Such facts could be features such as the tree's material (wood), its parts (trunk, branches, leaves or needles, roots), and location (planted into the soil). The child produces an idea of what a tree looks like by contrasting the display of tree features with the images of other, different objects, such as pieces of furniture that are made of wood but do not share other characteristics with a tree.

An ML classifier works in a similar way. Under the hood, it defines a mathematical formulation that processes all the given inputs in a way that distinguishes a tree from any other object. First, this process assumes the existence of a suitable mathematical representation for the task, often referred to as the *target function*. Next, the algorithm searches to identify or approximate this target function. The ability to identify a variety of mathematical formulations is known as the *representation capability* of an ML algorithm.


REMEMBER

A target function is assumed to exist for an ML algorithm to work, but it may not exist or it may prove unfeasible to find given the circumstances. Making an ML algorithm work involves dealing with the uncertainty of the results and a certain degree of complexity. In the end, the process of training an ML algorithm is more empirical than theoretical, requiring experimentation and a solid validation of the obtained results.

Using a mathematical perspective, you can express the representation process in ML by using the equivalent term *mapping.* Mapping happens when you figure out the construction of a function by observing its outputs and associating them with their respective inputs. A successful mapping in ML is similar to a child

internalizing the idea of an object. The child understands the abstract rules derived from the facts of the world in an effective way so that when the child sees a tree, for example, they immediately recognize it.

Such a representation, that is the abstract rules derived from real-world facts, is possible because the learning algorithm has many internal parameters, consisting of vectors and matrices of numeric values. Such parameters equate to the algorithm's memory for ideas that are suitable for its mapping activity that connects features to response classes. The dimensions and type of internal parameters delimit the type of target functions that an algorithm can learn. During the learning process, an optimization engine in the algorithm changes parameters from their initial values during learning to represent or approximate the target function.

During optimization, the algorithm searches through possible variants of its parameter combinations until it finds one that allows the most accurate mapping between features and classes. This process evaluates many potential candidate target functions from among those the learning algorithm can generate. The set of all the potential functions that the learning algorithm can discover is the *hypothesis space.* The resulting classifier with its set parameters is called a *hypothesis*, a way in ML to say that the algorithm has set parameters to approximate the target function and is now ready to define the correct classification in any new situation.

For an ML algorithm to be performing effectively, its hypothesis space must contain a large range of parameter variants allowing it to fit any unknown target function when solving a classification problem. Different algorithms can have different hypothesis spaces. What really matters is that the hypothesis space contains the target function or a suitable approximation, which is a different but similarly working function.

You can imagine this phase as the time when a child experiments with many different creative ideas by assembling knowledge and experiences (an analogy for the given features) in an effort to create a visualization of a tree. Naturally, the parents are involved in this phase, and they provide relevant environmental inputs. In ML, someone has to provide the right learning algorithms, supply some unlearnable parameters (called *hyperparameters*), choose a set of examples to learn from, and select the features that accompany the examples. Just as a child can't always learn alone to distinguish between right and wrong, so ML — and AI algorithms in general — need guidance from human beings to learn efficiently and correctly.

Understanding the benefits of ML

You find AI and ML used in a great many applications today. The technology works so effectively that often its presence goes unnoticed. In fact, you might be

surprised to find that many devices in your home already incorporate both technologies. Both technologies appear in your car and the workplace. Chapter 1 lists a few of the ways in which you might see AI used (fraud detection, resource scheduling, and others; see "Considering AI Uses" in that chapter), but that list doesn't even begin to scratch the surface. In reality, you can find AI used in many other ways, including some that you might not immediately associate with an AI:

- **Access control:** In many cases, access control is a yes-or-no proposition. An employee smart card grants access to a resource much like traditional keys have done for centuries. Though some locks do offer the capability to set times and dates that access is allowed, such coarse-grained control doesn't answer every need. By using ML and deep learning, it becomes possible to ascertain whether an employee should gain access to a resource based on role and requirements. For example, based on attribute-based access control (ABAC), powered by a deep learning algorithm, an employee can gain access to a training room when the training reflects an employee's role and needs.
- **Animal protection:** The ocean might seem large enough to allow animals and ships to cohabitate without a problem. Unfortunately, many animals get hit by ships each year. An ML algorithm, utilizing sensors and cameras as inputs, enables ships to avoid collisions with animals by learning the sounds and characteristics of both the animal and the ship. (It also prevents collisions with debris and other vessels: `www.researchgate.net/publication/361809180_A_Survey_of_Recent_Machine_Learning_Solutions_for_Ship_Collision_Avoidance_and_Mission_Planning`.)
- **Predicting wait times:** Most people don't like waiting when they have no idea how long the wait will be. In healthcare settings, accurately predicting waiting time is crucial for patients to make informed decisions. ML allows an application to determine waiting times based on staffing levels, workload, complexity of the situation and problems the staff is trying to solve, availability of resources, and so on.

Being useful; being mundane

Even though the movies suggest that AI is sure to make a huge splash and you do occasionally see extraordinary uses for AI in real life, most uses for AI are mundane and even boring. For example, Hilary Mason, previously general manager of ML at Cloudera, cites how ML is used in an international accounting firm to automatically fill in accounting questionnaires (see "Make AI Boring: The Road from Experimental to Practical" at `InformationWeek.com tinyurl.com/y6y93h54`). Conducting this analysis may appear dull compared to other sorts of AI activities, but it leads to cost savings for the accounting firm and improves the quality of the results.

Specifying the limits of ML

Currently, it's unclear whether ML can provide the sort of AI that the movies present. In reality, even the most sophisticated algorithms can't think, feel, display any form of self-awareness, or exercise free will. What ML can do is perform predictive analytics much faster than any human does. As a result, ML can help humans work more efficiently when handling vast amounts of information. The present state of AI involves just performing analysis and returning the results. Humans must still consider the implications of that analysis and make the required moral and ethical decisions.

The main point of confusion between learning and intelligence is people's assumption that simply because a machine gets better at its job (because it memorized it), it automatically displays intelligence and can handle any new task. However, nothing supports this view of ML. Similar confusion occurs when people assume that a computer is purposely causing problems for them. The computer can't experience emotions and, therefore, acts only on the input provided and the instructions contained within an application to process that input. A true AI will eventually emerge when computers can finally emulate the intricate combination of these processes observed in nature:

- **Genetics:** Slow adaptation of traits from one generation to the next
- **Learning:** Fast learning from organized and unorganized sources
- **Exploration:** Spontaneous learning through intentional curiosity and interactions with others
- **Creativity:** Picking up new learning by improvisation and creative response to situations

Apart from the fact that ML consists of mathematical functions optimized for a certain purpose, other weaknesses expose the limitations of ML. You need to consider these three important limits:

- **Limits in representation:** Representing some problems using mathematical functions isn't easy, especially with complex problems like mimicking a human brain. At the moment, ML can solve singular, well-defined problems that answer simple questions, such as "What is this?" and "How much is it?" and "What comes next?" Even the more advanced generative AI applications simply predict the next word or phrase in a sequence based on probability, lacking abstract or symbolic reasoning capabilities.
- **Overfitting:** ML algorithms can seem to learn what you care about, but they actually often don't. Frequently, their internal functions mostly memorize the data without learning any general rule. *Overfitting* occurs when your algorithm

learns too much from your data, up to the point of creating functions and rules that don't exist.

- **Lack of effective generalization because of limited data:** The algorithm learns what you show it. If you show too little data for the task, it won't learn to perform it. If you provide flawed, biased, or weird data, the algorithm will behave in unexpected and undesired ways.

As for representation, a learning algorithm can tackle various tasks, but not every algorithm is suited for every problem. Some algorithms are adaptable enough to learn to play chess, recognize faces on Facebook, and diagnose cancer in patients. Some algorithms, known as foundational models, are so versatile that they can be easily adapted to other tasks by means of further training. In contrast, other algorithms can only handle one task at a time, and they need to forget what they have previously learned before being ready for different activities.

The secret to ML is generalization. The goal is to generalize the output function so that it works on data beyond the training examples. However, the pursuit of generalization introduces new challenges such as overfitting and *biased* data (where certain elements are overweighted or overrepresented). For example, consider an ML-based spam filter. The English language is estimated to have about 170,000 words in current use, although an average adult English speaker typically utilizes only 20,000 to 35,000 words in their vocabulary. A limited training dataset of about 5,000 email examples must create a generalized function that can then find spam in all the possible combinations of words that can appear in a new email, which is an astronomical number that far exceeds the capacity of any computer to calculate. In such conditions, the algorithm, trained on such a limited choice of examples, will seem to learn the rules of the language, but in reality it won't do well. The algorithm may respond correctly to contexts similar to those used to train it, but it will be clueless in completely new situations. Or, it may even show biases in unexpected ways because of the kind of data used to train it.

For instance, long before the advent of OpenAI's ChatGPT, Microsoft trained its own AI, Tay, to chat with human beings on Twitter and learn from their answers. Unfortunately, the interactions went haywire because users exposed Tay to hate speech, raising concerns about the goodness of any AI powered by ML technology. (You can read some of the story at `tinyurl.com/4bfakpac`.) The problem was that the ML algorithm was fed bad, unfiltered data (Microsoft didn't use appropriate data analysis to clean and balance the input appropriately), which biased the result and forced Microsoft to retire the AI. Other AI trained to chat with humans, such as the award-winning Kuki (`www.kuki.ai`), aren't exposed to the same risks as Tay because their learning is strictly controlled and supervised by data analysis and human evaluation. As for current language models such as ChatGPT, Google Gemini, Anthropic Claude, and many others, much effort is dedicated to achieving

alignment — that is, ensuring the responses from the AI are aligned with human values and ethical principles.

Considering How to Learn from Data

Everything in ML revolves around algorithms. An *algorithm* is a procedure or formula used to solve a problem. The problem domain affects the kind of algorithm needed, but the fundamental premise is always the same: to solve some sort of problem, such as driving a car or playing dominoes. In the first case, the problems are complex and many, but the ultimate issue is one of moving a passenger from one place to another without crashing the car or breaking the law. Likewise, the goal of playing dominoes is simply to win in a game.

Learning to solve problems with ML comes in many different flavors, depending on the algorithm and its objectives. You can divide ML algorithms into three main groups, based on their purpose:

- Supervised learning
- Unsupervised learning
- Reinforcement learning

The following sections discuss in more detail how these groups approach and solve problems.

Supervised learning

Supervised learning occurs when an algorithm learns from sample data and associated target responses that can consist of numeric values or string labels, such as classes or tags, in order to later predict the correct response when given new examples. The supervised approach is similar to human learning under the supervision of a teacher. The teacher provides good examples for the student to memorize, and the student then derives general rules from these specific examples.

You need to distinguish between *regression* problems, whose target is a numeric value, and *classification* problems, whose target is a qualitative variable, such as a class or a tag. A regression task could determine the average prices of houses in a specific area, whereas an example of a classification task is distinguishing between kinds of iris flowers based on their sepal and petal measures. Table 5-1 shows some examples of supervised learning with important applications in AI described by their data input, their data output, and the real-world application they can solve.

TABLE 5-1 Machine Learning Real-World Applications

Data Input	Machine Learning Output	Real-World Application
History of customers' purchases	A list of products that customers would be willing to buy	Recommender system
Images depicting various objects	A list of areas in the image labeled with an object name	Image detection and recognition
English text in the form of questions and statements	English text in the form of answers	Chatbot, a software application that can converse
English text	German text	Machine language translation
Audio	Text transcript	Speech recognition
Image, sensor data	Steering, braking, or accelerating	Behavioral planning for autonomous driving

Unsupervised learning

Unsupervised learning occurs when an algorithm learns from plain examples without any associated response, leaving the algorithm to determine the data patterns on its own. This type of algorithm tends to restructure the data into something else, such as new features that may represent a class or a new series of uncorrelated values. The resulting data is quite useful in providing humans with insights into the meaning of the original data and new useful inputs to supervised ML algorithms.

Unsupervised learning resembles methods used by humans to determine that certain objects or events are from the same class, such as observing the degree of similarity between objects. Some recommender systems that you find on the web in the form of marketing automation are based on this type of learning. The marketing automation algorithm derives its suggestions from what you've bought in the past. The recommendations are based on an estimation of what group of customers you resemble the most and then inferring your likely preferences based on that group.

Reinforcement learning

Reinforcement learning occurs when you present the algorithm with examples that lack labels, as in unsupervised learning. However, you can accompany an example with positive or negative feedback according to the consequences of the solution that the algorithm proposes. Reinforcement learning is connected to applications for which the algorithm must make decisions (so the product is prescriptive, not just descriptive, as in unsupervised learning), and the decisions

bear consequences. In the human world, it's just like learning by trial and error. Errors help you learn because they have a penalty added (cost, loss of time, regret, pain, and so on), teaching you that a certain course of action is less likely to succeed than others. An interesting example of reinforcement learning occurs when computers learn to play video games by themselves.

In this case, an application presents the algorithm with examples of specific situations, such as having the gamer stuck in a maze while avoiding an enemy. The application lets the algorithm know the outcome of actions it takes, and learning occurs while trying to avoid what it discovers to be dangerous and to pursue survival. You can see how Google DeepMind created a reinforcement learning program that plays old Atari video games on YouTube ("Google DeepMind's Deep Q-learning playing Atari Breakout"). When watching the video, notice how the program is initially clumsy and unskilled but steadily improves with training until it becomes a champion. This process illustrates the core functioning of reinforcement learning, where an agent learns to make better decisions from its experience within an environment where it received feedback for its actions in the form of rewards or penalties.

IN THIS CHAPTER

- Using the tools of various tribes when learning from data
- Discovering how probability benefits AI
- Guessing using naïve Bayes and Bayesian networks
- Partitioning data into branches and leaves by decision trees

Chapter 6
Employing Machine Learning in AI

Learning has been an integral part of AI from the beginning because we humans want AI to emulate a human-like level of intelligence. Reaching a level of mimicry that effectively resembles learning has taken a long time and a variety of approaches. Today, machine learning (ML) can boast amazing advances in specific tasks, such as image classification or sound processing, and it's striving to reach a similar level of learning in many other tasks.

After discussing data analysis and its foundational role in AI and presenting ML in Chapter 5, here we explore the various families of ML algorithms that AI can use to learn from data. Each family of algorithms has specific ways of accomplishing tasks, and this chapter describes those methods. The goal is to understand how AI makes decisions and predictions. Like discovering the man behind the curtain in *The Wizard of Oz,* we will help you uncover the machinery and the operator behind AI in this chapter.

In addition, we focus on the functioning of three basic ML algorithms, which are frequently employed in AI applications — namely, naïve Bayes, Bayesian networks, and decision trees. We explore how they process information and generate results. Moreover, we also understand why ML cannot be completely automated.

Presently, automation requires large amounts of human-selected data with preliminary exploration by data analysis and extensive training under human supervision. It's like taking a child by the hand for those first steps.

Taking Many Different Roads to Learning

Just as human beings have different ways of learning from the world, so the scientists who approached the problem of AI learning took different routes. Each one believed in a particular recipe to mimic intelligence. Until now, no single model has proven superior to any other. The *no free lunch* theorem, which states that no algorithm can work optimally for all kinds of problems, is in full effect. Each of these efforts has proven effective in solving problems, but not all at one time. Because the algorithms are equivalent in the abstract (see the nearby "No free lunch" sidebar), no single algorithm consistently outperforms others across a number of practical problems. The following sections provide additional information about this concept of using different methods to learn.

NO FREE LUNCH

A common theorem in mathematical folklore is the no-free-lunch theorem, by David Wolpert and William Macready, which states that any two optimization algorithms are equivalent when their performance is averaged across all possible problems. Hence, for any search or optimization algorithm, any overperformance in one class of problems is paid back when dealing with another class. Essentially, no matter which optimization algorithm you use, there will be no advantage to using it across all possible problems. To gain an advantage, you must use it on those problems for which the algorithm excels. The same principle can be extended to supervised machine learning, too. The paper "Simple explanation of the no free lunch theorem of optimization," by Yu-Chi Ho and David L. Pepyne, at `ResearchGate.net`, provides an accessible but rigorous explanation of the theorem. It's also a good idea to review the discussion at `www.no-free-lunch.org` for more details about no-free-lunch theorems.

Recognizing five main approaches to AI learning

An *algorithm* is a kind of container — it provides a box for storing a method to solve a particular kind of problem. Algorithms process data through a series of well-defined steps. The steps need not be deterministic (in many algorithms, chance plays a role in finding the right solution), but the states are defined nonetheless. The sequence of states defines the range of mathematical solutions that the algorithm can grasp (technically referred to as the *space of hypothesis*). The goal is to create a sequence of states that solves a problem. In the supervised approach, the algorithm receives inputs with associated outputs, and the focus is finding a way to predict the outputs, given the inputs.

Algorithms must express the transitions between states using a well-defined and formal language that the computer can understand (usually, a computer language such as Python). In processing the data and solving the problem, the algorithm defines, refines, and applies a mathematical function. The function is always specific to the kind of problem being addressed.

As described in Chapter 1, each of the five tribes (schools of thought on the best mathematical models for AI) has a different technique and strategy for solving problems that result in unique algorithms. Pedro Domingos, in his book *The Master Algorithm*, argues that combining these algorithms should eventually lead to the master algorithm that will be able to solve any given problem. The following sections provide an overview of the five main algorithmic families, which include the Symbologists, the Connectionists, the Evolutionaries, the Bayseians, and the Analogizers.

The ultimate goal of ML is to combine the technologies and strategies embraced by the five tribes to create a single algorithm (the master algorithm) that can learn anything. Of course, achieving that goal is a long way off. Even so, scientists such as Pedro Domingos (`https://homes.cs.washington.edu/~pedrod`) are working toward that goal.

Symbolic reasoning

One of the earliest tribes, the Symbologists, believed that knowledge could be obtained by operating on *symbols* (signs that stand for a certain meaning or event) and deriving rules from them. By putting together complex systems of rules, you could attain a logical deduction of the result you wanted to know — thus, the symbologists shaped their algorithms to produce rules from data. In symbolic reasoning, *deduction* expands the realm of human knowledge, whereas *induction* raises the level of human knowledge. Induction commonly opens new fields of exploration, whereas deduction explores those fields.

Connections modeled on the brain's neurons

The Connectionists are perhaps the most famous of the five tribes. This tribe strives to reproduce the brain's functions by using silicon instead of biological neurons. Essentially, each of the algorithmic neurons (created as an algorithm that models the real-world counterpart) solves a small piece of the problem, and using many neurons in conjunction with them solves the problem. After receiving data, if the input signal is suitable, the artificial neuron activates and passes its solution along to the next neurons in line. The output created by just one neuron is only part of the whole solution. Each neuron passes information to the next neurons in line (the *feedforward* process) until the processed data reaches a group of neurons created to produce the definitive output. This method proved the most effective in human-like tasks such as recognizing objects, understanding written and spoken language, and chatting with humans.

The secret source in the Connectionists' model is the use of *backpropagation*, or backward propagation of errors. This optimization process minimizes the errors in the networks. Traversing backward from output to input all the node layers, backpropagation works by adjusting the *weights* (how much a particular input figures into the result) and *biases* (how features are selected) of the network. The goal is to continue changing the weights and biases through multiple iterations until the actual output matches the target output.

Evolutionary algorithms that test variation

The Evolutionaries rely on the principles of evolution to solve problems. In other words, this strategy is based on the survival of the fittest (removing any solutions that don't match the desired output). A fitness function determines the viability of each function in solving a problem. Using a tree structure, the solution method looks for the best solution based on function output. The winner of each level of evolution gets to build the next-level functions. The idea is that the next level will come closer to solving the problem but may not solve it completely, which means that another level is needed. This particular tribe relies heavily on recursion and languages that strongly support recursion to solve problems. An interesting output of this strategy has been algorithms that evolve: One generation of algorithms actually builds the next generation.

Bayesian inference

A group of scientists called Bayesians perceived that uncertainty was the key aspect to keep an eye on and that learning wasn't assured but rather took place as a continuous updating of previous beliefs that grew more and more accurate. This perception led the Bayesians to adopt statistical methods and, in particular, derivations from Bayes' theorem, which helps you calculate probabilities under specific conditions — for instance, the chance of seeing a card of a certain *seed*,

the starting value for a pseudorandom sequence, drawn from a deck after three other cards of the same seed have been drawn.

Systems that learn by analogy

The Analogyzers use kernel machines to recognize patterns in data. *Kernel machines* are a family of algorithms, used for pattern analysis in ML, that can operate on complex data by transforming it into a simpler form where patterns are more evident. By recognizing the pattern of one set of inputs and comparing it to the pattern of a known output, you can create a problem solution. The goal is to use similarity to determine the best solution to a problem. It's the kind of reasoning that determines that using a particular solution worked in a given circumstance at some previous time; therefore, using that solution for a similar set of circumstances should also work. One of the most recognizable outputs from this tribe is recommender systems. For example, when you buy a product on Amazon, the recommendation system comes up with other related products you might also want to buy.

Exploring the three most promising AI learning approaches

Later sections in this chapter explore the nuts and bolts of the core algorithms chosen by the Bayesians, Symbologists, and Connectionists. These tribes represent the present and future frontiers of learning from data because any progress toward a human-like AI derives from them, at least until a new breakthrough with new and more incredible and powerful learning algorithms occurs. The ML scenery is certainly much larger than these three algorithms, but the focus in this chapter is on these three tribes because of their current role in AI. Here's a synopsis of the approaches in this chapter:

- **Naïve Bayes:** This algorithm can be more accurate than a doctor in diagnosing certain diseases. In addition, the same algorithm can detect spam and predict sentiment from text. It's also widely used in the Internet industry to easily treat large amounts of data.
- **Bayesian networks (graph form):** This graph offers a representation of the complexity of the world in terms of probability.
- **Decision trees:** The decision tree type of algorithm best represents the Symbologists. The decision tree has a long history and is an example of how an AI can transparently make decisions because it operates through a series of nested decisions, which you can draw as a tree (hence the name).

Chapter 7 introduces neural networks, an exemplary type of algorithm proposed by the Connectionists and the real engine behind the current AI renaissance. Chapter 7 first discusses how a neural network works and then explains deep learning and why it's effective in learning.

REMEMBER

All these sections discuss types of algorithms. These algorithm types are further divided into subcategories. For example, decision trees come categorized as regression and classification trees. Furthermore, they serve as the foundation for boosted trees, bootstrap aggregation, and random forest algorithms. You can even drill down into more subtypes within these subcategories. In short, this book gives you an overview of a significantly more complex topic that could require many volumes to cover in detail. The takeaway is to grasp the type of algorithm and not get mired in complex details.

Awaiting the next breakthrough

In the 1980s, as expert systems ruled the AI scenery, most scientists and practitioners deemed ML to be a minor branch of AI that was focused on learning how to best answer simple predictions from the environment (represented by data) using optimization. Today, ML has the upper hand in AI, outweighing expert systems in many applications and research developments and powering AI applications that scientists previously regarded as impossible at such a level of accuracy and performance. Neural networks, the solution proposed by the Connectionists, made the breakthrough possible in the past few years by using a mix of increased hardware capacity, more suitable data, and the efforts of scientists such as Geoffrey Hinton, Yann LeCun, Yoshua Bengio, and many others. The generative AI revolution — represented by models such as ChatGPT, Google's Gemini, and other large language models frequently mentioned, as well as by Stable Diffusion and other image generation and manipulation techniques — is essentially an advancement in neural networks.

The capabilities offered by neural network algorithms (newly branded deep learning because of increased complexity) are increasing daily. Frequent news reports recount the fresh achievements in text and image generation, audio understanding, image and video recognition, language translation, and even lip reading. (And in terms of lip reading, it's been a few years now that deep learning achieved HAL 9000 performance, exceeding human capabilities. See "Google's DeepMind AI can lip-read TV shows better than a pro" at `www.newscientist.com`, which talks about a Google DeepMind and the University of Oxford's AI system for lip reading that surpasses experts.) The improvements are the result of intensive funding from large and small companies to engage researchers and of the availability of powerful tools, such as Google's TensorFlow (`www.tensorflow.org`) and JAX (`jax.readthedocs.io/en/latest`) and PyTorch, an open source ML library primarily developed by Facebook's AI Research (FAIR) lab. (See `pytorch.org`.)

These types of powerful tools give both scientists and practitioners access to the technology.

Look for even more sensational AI innovations in the near future. Of course, researchers could always encounter setbacks, as happened in the previous AI winters. Some are already debating that current text-generation models will soon hit a wall (read, for instance, Gary Marcus newsletter at `https://garymarcus.substack.com/p/evidence-that-llms-are-reaching-a`), but innovation in AI has proved unstoppable in recent times, as long as we believe in its potential and we put forth efforts to carry on.

No one can know whether AI will reach the human level using the present technology or whether someone will discover a master algorithm, as Pedro Domingos predicted in his TEDx talk "The Quest for the Master Algorithm" (at `www.youtube.com/watch?v=qIZ5PXLVZfo`), that will solve all AI problems (some of which we have yet to imagine). Nevertheless, ML is certainly not a fad driven by hype; it's here to stay, in either its present form or the form of new algorithms to come.

Exploring the Truth in Probabilities

Some websites and some Internet discussions would have you believe that statistics and machine learning are two completely different approaches and that the two methodologies are not only different but also downright hostile toward each other. Statistics, contrary to machine learning, was born in an age of limited computational power (you even had to solve calculations by hand at that time). Thus, statistics relies more on simplistic mathematical assumptions that render computations easier. Although statistics shows a more theoretical approach to problems, whereas ML is based purely on data, statistics and ML have a lot in common. Also, statistics represents one of the five tribes that make ML feasible.

Statistics often resorts to probabilities — which are a way to express uncertainty regarding world events — and so do ML and AI (to a larger extent than pure statistics). Not all problems are like the games of chess or Go, which let you take a large but limited number of actions when you decide to take them. If you want to learn how to move a robot in a corridor crowded with people or have a self-driving car successfully engage in a crossing, you have to consider that plans (such as for moving from point A to point B) don't always have a single outcome and that many results are possible, each one with a different likelihood. In a sense, probability supports AI systems in their reasoning, providing decision-making support and making what seem to be the best, most rational choices despite

uncertainty. Uncertainty can exist for various reasons, and AI should be made aware of the level of uncertainty by an effective use of probability:

1. Some situations can't offer certainty because they're random in nature. Similar situations are inherently stochastic. For instance, in card games, you can't be sure what hand you'll have after the dealer shuffles and deals the cards.
2. Even if a situation isn't random, not observing all its aspects (incomplete observation) creates uncertainty over how things will turn out. For instance, a robot walking down a corridor crowded with people can't know the intended direction of each person (it can't read their minds), but it can formulate a guess based on a partial observation of their behavior. As with any guess, the robot has a chance of being right and of being wrong.
3. Limits in the hardware that records world data (called *sensors*) and approximations in data processing can render uncertain the results produced from such data. Measuring is often subject to errors because of the tools used and how the measuring is done. In addition, humans are often subject to cognitive biases and easily fall prey to illusions or blind spots. Similarly, AI is limited by the quality of the data it receives. Approximations and errors introduce uncertainty into every algorithm.

Determining what probabilities can do

Probability tells you the likelihood of an event, and you express it as a number. For instance, if you throw a coin in the air, you don't know whether it will land as heads or tails, but you can tell the probability of both outcomes. The probability of an event is measured in the range from 0 (no probability that an event occurs) to 1 (certainty that an event occurs). Intermediate values such as 0.25, 0.5, and 0.75 say that the event will happen with a certain frequency when tried enough times. If you multiply the probability by an integer number representing the number of trials you're going to try, you get an estimate of how many times an event should happen on average if all the trials are tried. For instance, if you have an event occurring with probability p = 0.25 and you try 100 times, you're likely to witness that event happen around 0.25 * 100 = 25 times.

As it happens, the outcome of p = 0.25 is the probability of picking a certain suit when choosing a card randomly from a deck of cards. French playing cards make a classic example of explaining probabilities. The deck contains 52 cards equally divided into four suits: clubs and spades, which are black, and diamonds and hearts, which are red. So if you want to determine the probability of picking an ace, you must consider that there are four aces of different suits. The answer in terms of probability is p = 4/52, that is approximately 0.077.

Probabilities are between 0 and 1; no probability can exceed such boundaries. You define probabilities empirically from observations. Simply count the number of times a specific event happens with respect to all the events that interest you. Say that you want to calculate the probability of how many times fraud happens when doing banking transactions, or how many times people develop a certain disease in a particular country. After witnessing the event, you can estimate the probability associated with it by counting the number of times the event occurs and dividing by the total number of events.

You can count the number of times the fraud or the disease happens by using recorded data (mostly taken from records in databases or from direct observation) and then divide that figure by the total number of generic events or observations available. Therefore, you divide the number of frauds by the number of transactions in a year, or you count the number of people who fell ill during the year with respect to the population of a certain area. The result is a number ranging from 0 to 1, which you can use as your baseline probability for a certain event, given certain circumstances.

Counting all the occurrences of an event is not always possible, so you need to know about sampling. By *sampling*, which is an act based on certain probability expectations, you can observe a small part of a larger set of events or objects yet be able to infer approximately correct probabilities for an event, as well as exact measures such as quantitative measurements or qualitative classes related to a set of objects. For instance, if you want to track the sales of cars in the United States for the past month, you don't need to track every sale in the country. By using a sample composed of the sales from a few car sellers around the country, you can determine *quantitative* measures, such as the average price of a car sold, or *qualitative* measures, such as the car model sold most often.

Considering prior knowledge

Probability makes sense in terms of time and space, but certain other conditions also influence the probability you measure. The context is important. When you estimate the probability of an event, you may (sometimes wrongly) tend to believe that you can apply the probability you calculated to each possible situation. The term to express this belief is *a priori probability*, meaning the general probability of an event.

For example, when you toss a coin, if the coin is fair, the *a priori* probability of a head is about 50 percent (when you also assume the existence of a tiny likelihood of the coin's landing on its edge). No matter how many times you toss the coin, when faced with a new toss, the probability for heads is still about 50 percent. However, in some other situations, if you change the context, the *a priori* probability is no longer valid, because something subtle happened and changed it.

In this case, you can express this belief as an *a posteriori probability,* which is the *a priori* probability after something happened to modify the count.


REMEMBER

The Latin terms *a priori* and *a posteriori* derive from the treatise *Elements*, by the Greek mathematician Euclid (`https://mathcs.clarku.edu/~djoyce/java/elements/toc.html`). It describes *a priori* as what comes before and *a posteriori* as what comes after.

For instance, the *a priori* probability of a rainy day in the place you live during springtime could be 20 percent. (It depends on where you live on Planet Earth; elsewhere, probabilities may be different.) However, such probability may differ drastically if you consider only specific temperature and pressure ranges. For instance, when you notice that air pressure is turning low but the temperature is steadily high, the probability of rain drastically increases, and you have a high probability of experiencing a thunderstorm. Therefore, given a different context, the *a posteriori* probability is different from the expected *a priori* one. The following sections help you understand the usefulness of probability in more detail.

Conditional probability and naïve Bayes

You can view cases such as the weather-related ones mentioned in the previous section as *conditional probability,* and express them as p(y|x), which is read as the probability of event *y* happening, given that *x* has happened. Conditional probabilities are a powerful tool for ML and AI. In fact, when the *a priori* probability changes greatly because of certain circumstances, knowing the possible circumstances can boost your chances of correctly predicting an event by observing examples — which is exactly what ML is intended to do. For example, as mentioned, the expectation of a rainy day could be low in your location, depending on the current season. However, if you observe temperature, humidity, and atmospheric pressure, you find that certain combinations lead to an increased probability of rain. If the percentage of rainy days is high when certain conditions are met, contrary to the *a priori* probability, an ML algorithm, called *naïve Bayes,* can provide a probability estimation from knowing meteorological measurements.

In fact, the naïve Bayes algorithm takes advantage of boosting the chance of a correct prediction by knowing the circumstances surrounding the prediction. Everything starts with the Reverend Bayes and his revolutionary theorem of probabilities. In fact, as noted elsewhere in this book, one of the ML tribes is named after him (the Bayesians). Bayesians use various statistical methods to solve problems, all based on observing probabilities of the desired outcome in the right context, before and after observing the outcome itself. Based on these observations, they solve the sunrise problem (estimating the likelihood that the sun will rise tomorrow) by chaining repeated observations and continuously updating their estimate of the probability of the sun rising again proportionally to the number of times they have already witnessed a long series of dawns.

Data scientists have great expectations for the development of advanced algorithms based on Bayes' theorem. In addition, the foundations of Bayes' theorem aren't all that complicated, although they may be a bit counterintuitive if you normally consider, as most people do, only the *a priori* probabilities without considering *a posteriori* ones.

Considering Bayes' theorem

Apart from being a Presbyterian minister, the Reverend Thomas Bayes was also a statistician and philosopher who formulated his theorem during the first half of the 18th century. The theorem was never published while he was alive. Its eventual publication revolutionized the theory of probability by introducing the idea of conditional probability (mentioned in the previous section). Thanks to Bayes' theorem, predicting the probability of an outcome, like having a rainy day, given certain conditions, becomes easier when you apply his formula. Here's the formula used by Thomas Bayes:

```
P(B|A) = P(A|B)*P(B) / P(A)
```

Reading the formula using the previous example as input can provide a better understanding of an otherwise counterintuitive formula:

- **P(B|A):** The probability that an event B occurs, given that event A has already occurred (*a posteriori* probability). For example, B could represent raining and A could represent a situation of low atmospheric pressure. By calculating P(B|A), you can estimate the probability of rain given the observed low pressure.
- **P(A|B):** The probability of having low atmospheric pressure when it rains. This term refers to the probability of the event happening in the subgroup, which is itself a conditional probability. In this case, the figure is 90 percent, which translates to a value of 0.9 in the formula (*a priori* probability).
- **P(B):** The general probability of having a rainy day; that is, the *a priori* probability of the event. In this case, the probability is 20 percent.
- **P(A):** The general probability of measuring low atmospheric pressure. Here, it's another a priori probability, this time related to the observed event. In this formula, it's a 25 percent probability.

If you solve the previous problem using the Bayes' theorem and the values you have singled out, the result is `0.9 * 0.2 / 0.25 = 0.72`. This high probability indicates that, given the evidence of low atmospheric pressure, there's a good chance it will rain soon.

Another common example, which can raise some eyebrows and is routinely found in textbooks and scientific magazines, is that of the positive medical test. It's quite interesting for a better understanding of how *a priori* and *a posteriori* probabilities may indeed change a lot under various circumstances.

Say that you're worried that you have a rare disease experienced by 1 percent of the population. You take the test and the results are positive. Medical tests are never perfectly accurate, and the laboratory tells you that when you're ill, the test is positive in 99 percent of the cases, whereas when you're healthy, the test is negative in 99 percent of the cases. Now, using these figures, you immediately believe that you're ill, given the high percentage of positive tests when a person is ill (99 percent). However, the reality is quite different. In this case, these are the figures to plug into Bayes' theorem:

```
P(B|A) = P(A|B)*P(B) / P(A)
```

- 0.99 as P(A|B)
- 0.01 as P(B)
- 0.01 * 0.99 + 0.99 *0.01 = 0.0198 as P(A)

The calculations are then `0.99 * 0.01 / 0.0198 = 0.5`, which corresponds to just a 50 percent probability that you're ill. In the end, your chances of not being ill are more than you expected. This kind of result is called a *false positive paradox*, where the indicators seem to point to a positive result but the math says otherwise. You may wonder how this is possible. The fact is that the number of people seeing a positive response from the test is as follows:

- **Who is ill and gets the correct answer from the test:** This group holds the true positives, and it amounts to 99 percent of the 1 percent of the population who gets the illness.
- **Who isn't ill and gets the wrong answer from the test:** This group holds the 1 percent of the 99 percent of the population who get a positive response even though they aren't ill. Again, this is a multiplication of 99 percent and 1 percent. This group corresponds to the false positives.

If you look at the problem using this perspective, it becomes evident why the probability of actually being sick is only 50 percent. When limiting the context to people who receive a positive response to the test, the probability of being in the group of the true positives is the same as that of being in the false positives.

Envisioning the world as a graph

Bayes' theorem can help you deduce how likely something is to happen in a certain context, based on the general probabilities of the fact itself and the evidence you examine, and combined with the probability of the evidence given the fact. Seldom will a single piece of evidence diminish doubts and provide enough certainty in a prediction to ensure that it will happen. As a true detective, to reach certainty, you have to collect more evidence and make the individual pieces work together in your investigation. Noticing how atmospheric pressure has decreased isn't sufficient to determine whether it will rain. Adding data about humidity, season, and location can help increase confidence.

The naïve Bayes algorithm helps you arrange all the evidence you gather and reach a more solid prediction with a higher likelihood of being correct. Gathered evidence considered separately couldn't save you from the risk of predicting incorrectly, but all evidence summed together can reach a more definitive resolution. The following example shows how things work in a naïve Bayes classification. This is an old, renowned problem, but it represents the kind of capability you can expect from an AI. The dataset is from the paper "Induction of Decision Trees" by John Ross Quinlan. Quinlan is a computer scientist who contributed to the development of another ML algorithm, decision trees, in a fundamental way, but his example works well with any kind of learning algorithm. The problem requires that the AI guess the best conditions for playing tennis, given the weather conditions.

Here's the set of features described by Quinlan:

- **Outlook:** Sunny, overcast, or rainy
- **Temperature:** Cool, mild, or hot
- **Humidity:** High or normal
- **Windy:** True or false

The following table contains the database entries used for the example:

Outlook	Temperature	Humidity	Windy	Play Tennis
Sunny	Hot	High	False	No
Sunny	Hot	High	True	No
Overcast	Hot	High	False	Yes
Rainy	Mild	High	False	Yes

Outlook	Temperature	Humidity	Windy	Play Tennis
Rainy	Cool	Normal	False	Yes
Rainy	Cool	Normal	True	No
Overcast	Cool	Normal	True	Yes
Sunny	Mild	High	False	No
Sunny	Cool	Normal	False	Yes
Rainy	Mild	Normal	False	Yes
Sunny	Mild	Normal	True	Yes
Overcast	Mild	High	True	Yes
Overcast	Hot	Normal	False	Yes
Rainy	Mild	High	True	No

The option of playing tennis depends on the four arguments shown in Figure 6-1.

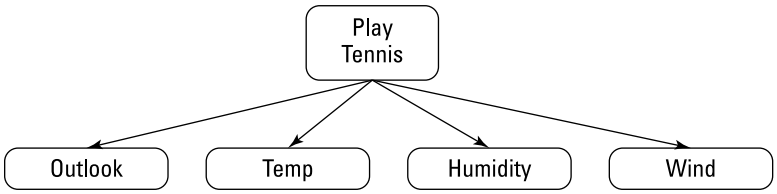

FIGURE 6-1: A naïve Bayes model can retrace evidence to the right outcome.

The result of this AI learning example is the decision whether to play tennis, given the weather conditions (the evidence). Using just the outlook (sunny, overcast, or rainy) won't be sufficient because the temperature and humidity might be too high or the wind might be strong. These arguments represent real-life conditions that have multiple causes, or causes that are interconnected. The naïve Bayes algorithm is skilled at guessing correctly when multiple causes exist.

The algorithm computes a score based on the probability of making a particular decision and multiplies it by the probabilities of the evidence connected to that decision. For instance, to determine whether to play tennis when the outlook is sunny but the wind is strong, the algorithm computes the score for a positive answer by multiplying the general probability of playing (9 played games out of 14 occurrences) by the probability of the day's being sunny (2 out of 9 played games) and of having windy conditions when playing tennis (3 out of 9 played games). The same rules apply for the negative case (which has different probabilities for not playing, given certain conditions):

```
likelihood of playing: 9/14 * 2/9 * 3/9 = 0.05
likelihood of not playing: 5/14 * 3/5 * 3/5 = 0.13
```

Because the score for the likelihood of not playing is higher, the algorithm decides that it's safer not to play under such conditions. It computes such likelihood by summing the two scores and dividing both scores by their sum:

```
probability of playing: 0.05 / (0.05 + 0.13) = 0.278
probability of not playing: 0.13 / (0.05 + 0.13) = 0.722
```

You can further extend naïve Bayes to represent relationships that are more complex than a series of factors that hint at the likelihood of an outcome using a *Bayesian network,* which consists of graphs showing how events affect each other. Bayesian graphs have nodes that represent the events, and arcs showing which events affect others, accompanied by a table of conditional probabilities that show how the relationships work in terms of probability. Figure 6-2 shows a famous example of a Bayesian network taken from a 1988 academic paper, "Local computations with probabilities on graphical structures and their application to expert systems," by Steffen L. Lauritzen and David J. Spiegelhalter, published by the *Journal of the Royal Statistical Society* (`https://rss.onlinelibrary.wiley.com/doi/10.1111/j.2517-6161.1988.tb01721.x`).

The depicted network is called Asia, as defined by Lauritzen and Spiegelhalter in their 1988 work on expert systems. It shows possible patient conditions and what-causes-what. For instance, if a patient has dyspnea, it might be an effect of tuberculosis, lung cancer, or bronchitis. Knowing whether the patient smokes, has traveled to Asia, or has received anomalous X-ray results (thus giving certainty to specific pieces of evidence, or *a priori,* in Bayesian language) helps infer the real-life (a posteriori) probabilities of having any of the pathologies in the graph.

Bayesian networks, though intuitive, have complex math behind them, and they're more powerful than a simple naïve Bayes algorithm because they mimic the world as a sequence of causes and effects based on probability. Bayesian networks are so effective that you can use them to represent any situation. They have varied applications, such as medical diagnoses, the fusing of uncertain data arriving from multiple sensors, economic modeling, and the monitoring of complex systems, such as cars. For instance, because driving in highway traffic may involve complex situations with many vehicles, the Analysis of MassIve Data STreams (AMIDST) consortium, in collaboration with the automaker Daimler, devised a Bayesian network that can recognize maneuvers by other vehicles and increase driving safety.

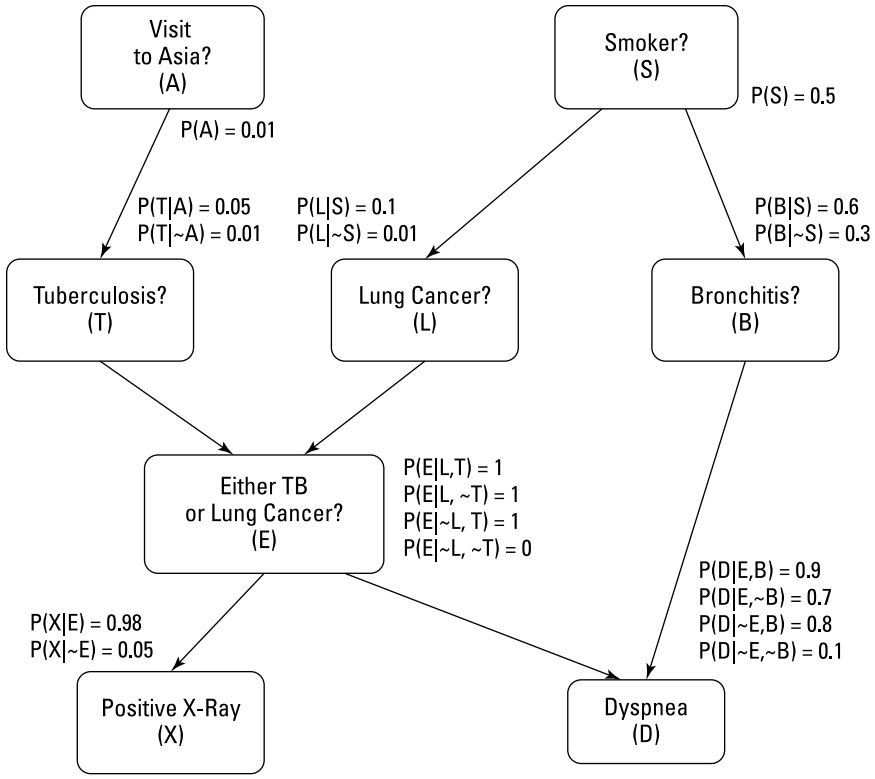

FIGURE 6-2: A Bayesian network can support a medical decision.

Growing Trees That Can Classify

A decision tree is another type of key algorithm in ML that contributes to AI implementation and learning. Decision tree algorithms aren't new, but they do have a long history. The first algorithm of its kind dates back to the 1970s (with many ensuing variants). When you consider experiments and original research, the use of decision trees goes back even earlier — they are as old as the perceptron, the forerunner of neural networks. As the core Symbologist algorithm, the decision tree has enjoyed long popularity because it's an intuitive type of algorithm. It's easy to translate the output into rules and therefore make the output easily understood by humans. Decision trees are also extremely easy to use. All these characteristics make them an effective and appealing no-brainer compared to models that require complex input data matrix transformations or extremely accurate tuning of hyperparameters.

REMEMBER

Symbolism is the AI approach based on logic statements and extensive use of deduction. *Deduction* expands knowledge from what we know, and *induction* formulates general rules starting from evidence.

Predicting outcomes by splitting data

If you have a group of measures and want to describe them using a single number, you use an arithmetic *mean* (summing all the measures and dividing by the number of measures). In a similar fashion, if you have a group of classes or qualities (for instance, you have a dataset containing records of many breeds of dogs or types of products), you can use the most frequent class in the group to represent them all, which is called the *mode.* The mode is another statistical measure like the mean, but it contains the value (a measure or a class) that appears most often. Both the mean and the mode strive to report a number or class that provides you with the most confidence in guessing the next group element, because they produce the fewest mistakes. In a sense, they're predictors that learn the most probable answer from existing data. Decision trees leverage means and modes as predictors by splitting the dataset into smaller sets whose means or modes are the best possible predictors of the problem at hand.

REMEMBER

Dividing a problem to arrive at a solution easily is also a common strategy in many *divide-and-conquer* algorithms. As with an enemy army in battle, if you can split your foe and fight it singularly, you can attain an easier victory.

Using a sample of observations as a starting point, the algorithm retraces the rules that generated the output classes (or the numeric values when working through a regression problem) by dividing the input matrix into smaller and smaller partitions until the process triggers a rule for stopping. Such retracing from particular toward general rules is typical of human inverse deduction, as treated by logic and philosophy.

The division enforces a simple principle: Each partition of the initial data must make predicting the target outcome easier, which is characterized by a different and more favorable distribution of classes (or values) than the original sample. The algorithm creates partitions by splitting the data. It determines the data splits by first evaluating the features. Then it evaluates the values in the features that could bring the maximum improvement of a special statistical measure — that is, the measure that plays the role of the cost function in a decision tree.

Several statistical measurements determine how to make the splits in a decision tree. All abide by the idea that a split must improve on the original sample, or another possible split, when it makes prediction safer. Among the most used measurements are Gini impurity, information gain, and variance reduction (for regression problems). These measurements operate similarly, so this chapter focuses on information gain because it's the most intuitive measurement and conveys how a decision tree can detect an increased predictive ability (or a reduced risk) in the easiest way for a certain split. John Ross Quinlan created a decision tree algorithm based on information gain (ID3) in the 1970s, and it's still quite popular, thanks to its recently upgraded version to C4.5. Information gain relies

on the formula for informative entropy (devised by Claude Shannon, an American mathematician and engineer known as the father of information theory), a generalized formulation that describes the expected value from the information contained in a message:

$$\text{Shannon Entropy } E = -\Sigma(p(x_i)\times\log2(p(x_i)))$$

In the formula, you consider all the classes one at a time, and you sum together the multiplication result of each of them. In the multiplication each class has to take, $p(x_i)$ is the probability for that class (expressed in the range of 0 to 1) and `log2` is the base 2 logarithm. Starting with a sample in which you want to classify two classes having the same probability (a 50/50 distribution), the maximum possible entropy is `Entropy = -0.5*log2(0.5) -0.5*log2(0.5) = 1.0`. However, when the decision tree algorithm detects a feature that can split the dataset into two partitions, where the distribution of the two classes is 40/60, the average informative entropy diminishes:

```
Entropy = -0.4*log2(0.4) -0.6*log2(0.6) = 0.97
```

Note the entropy sum for all the classes. Using the 40/60 split, the sum is less than the theoretical maximum of 1 (diminishing the entropy). Think of the entropy as a measure of the mess in data: The less mess, the more order, and the easier it is to guess the right class. After a first split, the algorithm tries to split the obtained partitions further, using the same logic of reducing entropy. It progressively splits any successive data partition until no more splits are possible because the subsample is a single example or because it has met a stopping rule.

Stopping rules are limits to the expansion of a tree. These rules work by considering three aspects of a partition: initial partition size, resulting partition size, and information gain achievable by the split. Stopping rules are important because decision tree algorithms approximate a large number of functions; however, noise and data errors can easily influence this algorithm. Consequently, depending on the sample, the instability and variance of the resulting estimates affect decision tree predictions.

Making decisions based on trees

As an example of decision tree use, this section uses the same John Ross Quinlan dataset discussed in the section "Envisioning the world as a graph," earlier in this chapter. Using this dataset lets us present and describe the ID3 algorithm, a method devised by Quinlan himself. The dataset is quite simple, consisting of only 14 observations relative to the weather conditions, with results that say whether playing tennis is appropriate.

The example contains four features: outlook, temperature, humidity, and wind, all expressed using qualitative classes instead of measurements (you could express temperature, humidity, and wind strength numerically) to convey a more intuitive understanding of how the weather features relate to the outcome. After these features are processed by the algorithm, you can represent the dataset using a tree-like schema, as shown in Figure 6-3. As the figure shows, you can inspect and read a set of rules by splitting the dataset to create parts in which the predictions are easier by looking at the most frequent class (in this case, the outcome, which is whether to play tennis).

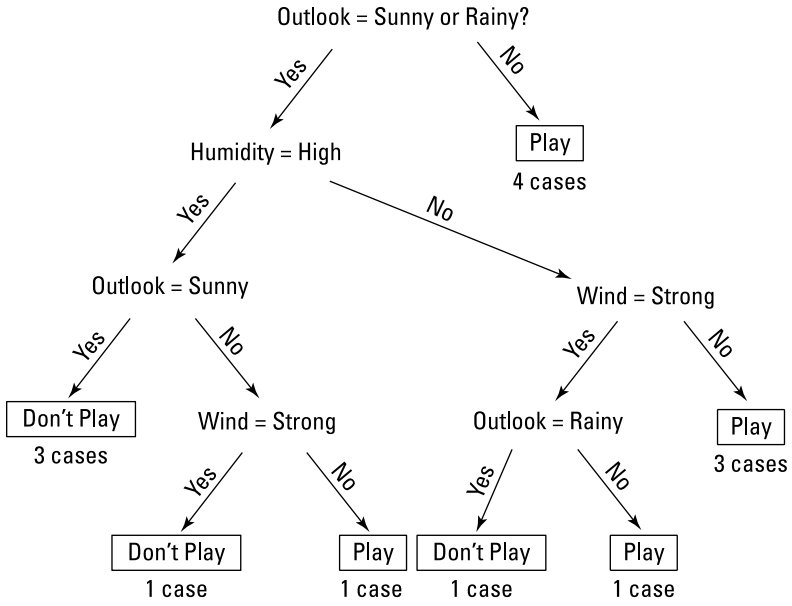

FIGURE 6-3: A visualization of the decision tree built from the play-tennis data.

To read the nodes of the tree, just start from the topmost node, which corresponds to the original training data; then start reading the rules. Note that each node has two derivations: The left branch means that the upper rule is true (the arrow is labeled "Yes"), and the right one means that it is false (the arrow is labeled "No").

To the right of the first rule, you see an important terminal rule (a terminal leaf), in a box, stating "Play", which means you can play tennis. According to this node, when the outlook isn't sunny or rainy ("Sunny or Rainy?"), it's possible to play. The numbers under the terminal leaf show how many cases applied to that path through the tree. Note that you could understand the rule better if the output simply stated that when the outlook is overcast, play is possible. Frequently, decision tree rules aren't immediately usable, and you need to interpret them before use. However, they are clearly intelligible (and much better than a coefficient vector of values).

On the left, the tree proceeds with other rules related to Humidity. On the left, when humidity is high and the outlook is sunny, the terminal leave is negative. You can play only when the outlook is not sunny and the wind is not strong. When you explore the branches on the right, where humidity is not high, you see that the tree reveals that play is possible when the wind isn't strong, or when the wind is strong but it doesn't rain.

Pruning overgrown trees

Even though the play-tennis dataset in the previous section illustrates the nuts and bolts of a decision tree, it has little probabilistic appeal because it proposes a set of deterministic actions. (It has no conflicting instructions.) Training with real-world data usually doesn't feature such sharp rules, thereby providing room for ambiguity, expressed by a probability for a specific outcome.

Decision trees have more variability in their estimations because of the noise they obtain from data during the learning process (an effect of overfitting). To overfit the data less, the example specifies that the minimum split has to involve at least five examples. Because the terminal leaves are numerically larger, the confidence that the tree is picking the correct signal increases because the evidence quantity is higher. Also, it prunes the tree. Pruning happens when the tree is fully grown.

Starting from the leaves, the example prunes the tree of branches that are showing little improvement in the reduction of information gain. By initially letting the tree expand, branches with little improvement are tolerated because they can unlock more interesting branches and leaves. Retracing from leaves to root and keeping only branches that have some predictive value reduces the variance of the model, making the resulting rules restrained.

IN THIS CHAPTER

- Shaping neural networks to resemble the human brain
- Mimicking a learning brain using math
- Introducing deep learning
- Detecting shapes in images and words in text using neural networks

Chapter 7

Improving AI with Deep Learning

Newspapers, business magazines, social networks, and nontechnical websites are all saying the same thing: AI is cool stuff that will revolutionize the world because of deep learning. Actually, AI is a far larger field than machine learning, and deep learning is just a small part of machine learning. Machine learning is a subset of AI, which focuses on learning from data and making predictions without being programmed to do so. Instead, deep learning is a type of machine learning that uses complex neural networks to learn from large amounts of data and can achieve results that other machine learning algorithms cannot.

It's important to distinguish the hype used to lure investors and show what deep learning technology can actually do. This chapter helps you understand deep learning from a practical and technical point of view, and what it can achieve in the near term by exploring its possibilities and limitations. We begin with the history and basics of neural networks, and then we move on to state-of-the-art results from convolutional neural networks, also known as ConvNets or CNNs. These neural architectures use specialized neurons to detect edges and shapes in images. Finally, we close the chapter by mentioning image challenges, which have driven advances in the field. Based on the same mechanism, similar challenges in many other tasks — from recognizing meaning in a text to associating images and text together and many others — are driving the current AI revolution.

Shaping Neural Networks Similar to the Human Brain

The following sections present a family of learning algorithms that derive inspiration from how the brain works. They're neural networks, the core algorithm of the Connectionists' tribe that best mimics neurons inside human brains at a smaller scale. In contrast to the human brain, which is estimated to have approximately 100 billion neurons and over 100 trillion synapses, neural networks vary incredibly in size. They may range from very small ones, composed of a handful of nodes, to massive models like ChatGPT that can boast having billions of numeric parameters, essentially artificial neurons. (See Chapter 1 for an overview of the five tribes of machine learning employed by various scientists.)

REMEMBER

Connectionism is the machine learning approach based on neuroscience, as well as the example of biologically interconnected networks.

Introducing the neuron

Human brains have billions of *neurons,* which are specialized cells responsible for receiving, processing, and transmitting both electric and chemical signals. Each neuron possesses a nucleus with filaments that act as inputs; *dendrites* that receive signals from other neurons; and a single output filament, the *axon,* that terminates with synaptic terminals devoted to outside communication. Neurons establish connections with one another at specialized junctions called synapses, allowing the transmission of information through chemical signals, whereas, within the neuron itself, information is processed electrically.

Reverse-engineering how a brain processes signals helps the Connectionists define neural networks based on biological analogies and their components. Connectionists use an abundance of brain terms such as neuron, activation, and connection as names for mathematical operations. Yet, despite the biological terms, neural networks resemble nothing more than a series of multiplications and summations when you check their math formulations. These algorithms are extraordinarily effective at solving complex problems such as image and sound recognition or machine language translation; using specialized hardware, they can execute prediction computations quickly.

SEEING DEEP LEARNING AS AUGMENTATION

Chapter 6 discusses Bayesian networks and includes an example of how such networks can provide diagnostic hints to a doctor. To do this, the Bayesian network requires well-prepared probability data. Deep learning can create a bridge between the capability of algorithms to make the best decision possible using all the required data and the data that is actually available, which is never in the best format for machine learning algorithms to understand. Photos, images, sound recordings, web data (especially from social networks), and company records all require data analysis to make the data suitable for machine learning purposes.

In contrast to Bayesian networks, deep learning algorithms need few instructions about the data they are working on. A deep learning algorithm could help doctors by matching extensive knowledge in medicine (using all available sources, including books, white papers, and the latest research from the National Institutes of Health) and patient information. The patient information, in turn, could come from previous diagnoses and medicine prescriptions, or even from social media evidence (so that doctors don't need to ask whether the patient has been in Asia, for example — the AI will detect it from photos on Instagram or Facebook). This scenario may sound like sci-fi, but the recent advances in deep learning truly demonstrate the potential of the technology in improving the efficiency and accuracy of pneumonia diagnosis, which is otherwise difficult to distinguish from other respiratory diseases, such as tuberculosis. This is especially helpful in resource-constrained settings or during public health emergencies, like the COVID-19 pandemic, opening opportunities for an imminent real-world clinical deployment.

Deep learning also appears in many applications. You find it in social networks where images and content are automatically classified; in search engines when queries are retrieved; in online advertising when consumers are targeted; in mobile phones and digital assistants for speech, language understanding, or translation tasks; in self-driving cars for obstacle avoidance and traffic navigation; and in a Go game by AlphaGo against a champion. In less widely known applications, deep learning can also power robotics and earthquake predictions.

Starting with the miraculous perceptron

The core of a neural network algorithm is the neuron (also called a neural node or unit). Many neurons are arranged, forming layers that, in an interconnected structure, make up a neural network. The neurons in each layer are linked to the inputs and outputs of the neurons in the following and preceding layers. Thus,

a neuron can input data from examples or transmit the results of other neurons, depending on its location in the neural network.

Frank Rosenblatt at the Cornell Aeronautical Laboratory created the first example of a neuron of this kind, the perceptron, a few decades ago. He devised the perceptron in 1957 under the sponsorship of the United States Naval Research Laboratory (NRL). Rosenblatt was a psychologist as well as a pioneer in the field of artificial intelligence. Proficient in cognitive science, his idea was to create a computer that could learn by trial and error, just as a human does.

Although hyped as a miraculous technology, the perceptron was just a smart way to trace a separating line in a simple space made by the input data. The perceptron could solve a simple problem, as shown in Figure 7-1, in which you have two features (in this case, the size and level of domestication of an animal) to use to distinguish two classes (dogs and cats, in this example). The perceptron formulation produces a line in a Cartesian space where the examples divide more or less perfectly into groups. The approach is like naïve Bayes, described in Chapter 6, which sums conditional probabilities multiplied by general ones in order to classify data.

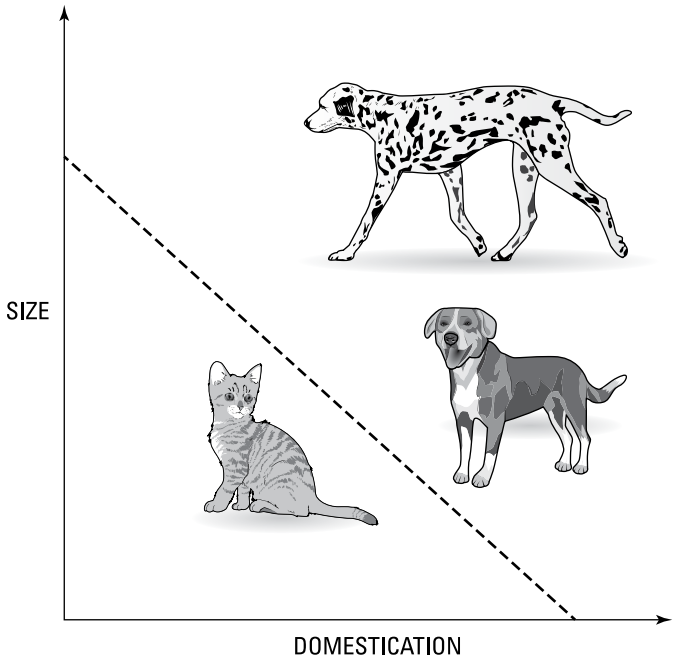

FIGURE 7-1: Example of a perceptron in simple and challenging classification tasks.

The perceptron didn't realize the full expectations of its creator or financial supporters. It soon displayed a limited capacity, even in its image-recognition specialization. The general disappointment ignited the first AI winter, the period when general disillusionment prevailed and funds were reduced thus slowing down any further progress in AI and resulting in the abandonment of connectionism until the 1980s. Yet, some research continued despite the loss of funding, providing key improvements for the renaissance of the neural network technology in the 1980s and 1990s.

In fact, the ideas prompted by the perceptron were here to stay. Later, experts tried to create a more advanced perceptron, and they succeeded. Neurons in a neural network are a further evolution of the perceptron: There are many, they connect to each other, and they imitate our neurons when they activate under a certain stimulus. In observing human brain functionalities, scientists noticed that neurons receive signals but don't always release a signal of their own. Releasing a signal depends on the amount of signal received. When a neuron acquires enough stimuli, it fires an answer; otherwise, it remains silent. In a similar fashion, algorithmic neurons, after receiving data, sum it up and use an activation function to evaluate the result. If the input they receive achieves a certain threshold, the neuron transforms and transmits the input value; otherwise, it simply dies.


TIP

Neural networks use special functions called *activation functions* to fire a result. All you need to know is that they are a key neural network component because they allow the network to solve complex problems using nonlinear patterns. They are like doors, letting the signal pass or stop. They don't simply let the signal pass, however; they transform it in a useful way. Deep learning, for instance, isn't possible without efficient activation functions such as the *r*ectified *l*inear *u*nit (ReLU), and thus activation functions are an important aspect of the story.

Mimicking the Learning Brain

In a neural network, you must consider the architecture first, which is the arrangement of the neural network components. The following sections discuss neural network architectural considerations.

Considering simple neural networks

Contrary to other algorithms, which have a fixed pipeline that determines how algorithms receive and process data, neural networks require that you decide how information flows by fixing the type and number of units (the neurons) and their distribution in layers called the *neural network architecture*, as shown in Figure 7-2.

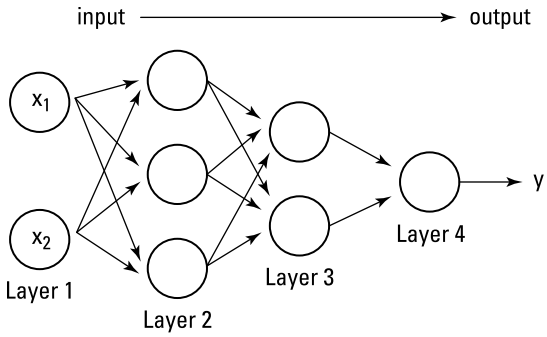

FIGURE 7-2: A neural network architecture, from input to output.

The figure shows a simple neural network architecture. While there are various other designs, this architecture is one of the earliest and is still commonly used today. Note how the layers filter and process information in a progressive way. This is a *feed-forward input* because data feeds one direction into the network. Connections exclusively link units in one layer with units in the following layer (information flows from left to right). No connections exist between units in the same layer or with units outside the next layer. Moreover, the information pushes forward (from the left to the right). Processed data never returns to previous neuron layers.

REMEMBER

In more advanced neural network applications, you also have to decide on the layer types you need and some parameters that will influence the layers' behavior. Neural networks are extremely flexible, and that aspect is a double-edged sword: You increase the power of the machine learning tool as complexity skyrockets.

Using a neural network is like using a stratified filtering system for water: You pour the water from above, and the water is filtered as it runs to the bottom. The water has no way to go back up; it just moves forward and straight down, and never laterally. In the same way, neural networks force data features to flow through the network and mix with each other as dictated by the network's architecture. By using the best architecture to mix features, the neural network creates newly composed features at every layer and helps achieve better predictions. Unfortunately, in spite of the efforts of academics to discover a theoretical rule, you have no way to determine the best architecture without empirically trying different solutions and testing whether output data helps predict your target values after flowing through the network. This need for manual configuration illustrates the *no free lunch* theorem (see Chapter 6) in action. The gist of it is that an architecture that works the best on one task won't necessarily perform successfully on other problems.

TIP

Sometimes, concepts can be understood better if directly tested in reality. Google offers a neural network playground (`playground.tensorflow.org`) in which you can hands-on experience how a neural network works, as shown in Figure 7-3. You see how the neural network builds a neural network by adding or removing layers and changing kinds of activations.

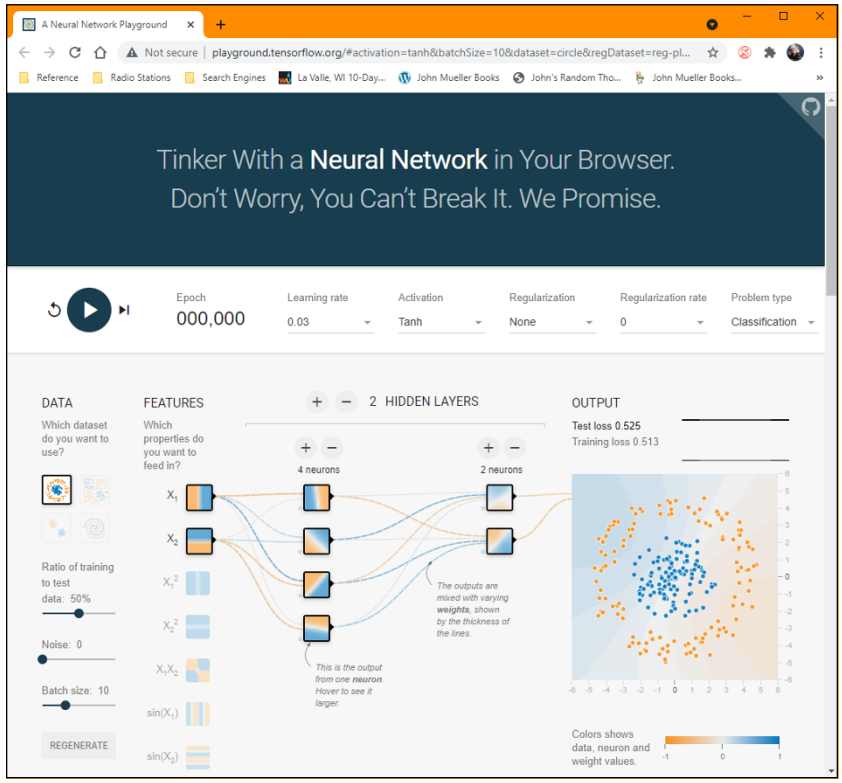

FIGURE 7-3: This neural network playground lets you see how modifying a neural network changes how it works.

Figuring out the secret is in the weights

Neural networks have different layers, with each one having its own weights. *Weights* represent the strength of the connections between neurons in the network. When some weights among the connections between two layers are small, it means that the network dumps values flowing between them and signals that taking certain routes isn't likely to influence the final prediction. Likewise, a large positive or negative value affects the values that the next layer receives, thus determining certain predictions. This approach is analogous to brain cells, which don't stand alone but connect with other cells. As someone grows in experience,

connections between neurons tend to weaken or strengthen to activate or deactivate certain brain network cell regions, causing other processing or activity (a reaction to danger, for instance, if the processed information signals a life-threatening situation).

Each successive layer of neural network units progressively processes values taken from features, as in a conveyor belt. As the network transmits data, it arrives at each unit as a summated value produced by the values present in the previous layer and weighted by connections in the present layer. When the data received from other neurons exceeds a certain threshold, the activation function opportunely increases or modifies the value stored in the unit; otherwise, it extinguishes the signal by reducing or canceling it. After activation function processing, the result is ready to push forward to the next layer's connection. These steps repeat for each layer until the values reach the end and you have a result.

The weights of the connections provide a way to combine the inputs in a new way, creating new features by mixing processed inputs in a creative way because of weights and activation functions. The activation, because of the transformation it applies, also renders nonlinear the resulting recombination of the inputs received by the connections. Both the weights and the activation function enable the algorithm to learn complex target functions that represent the relationship between the input features and the target outcome.

Understanding the role of backpropagation

Learning occurs in the human brain because of the formation and modification of synapses between neurons, based on stimuli received by experience, self-reflection, and reasoning. Neural networks provide a way to simulate this process as a mathematical formulation called *backpropagation.* Here's how this architecture of interconnected computing units can solve problems: The neurons in the network receive batches of examples, and if they don't make correct predictions, a process retraces the problem through the system of existing weights and adjusts them by changing certain values. This process, called backpropagation, is repeated many times across all the available data as the neural network improves its performance. A complete pass of the neural network over all the data is called an *epoch,* a name that fits perfectly because a neural network may need literally epochs (days or even weeks) of training to learn complex tasks.


TECHNICAL STUFF

Backpropagation math is quite advanced and requires knowledge of concepts such as derivatives. You can read a detailed-but-accessible math description in *Machine Learning For Dummies,* 2nd Edition (Wiley), by John Paul Mueller and Luca Massaron, and get an overview of the necessary calculations. Backpropagation as a concept is intuitive enough to grasp and convey because it resembles what people do when performing a task using iterated approximate trial and error.

Since the appearance of the backpropagation algorithm in the 1970s, developers have refined it many times and are now discussing whether to rethink it. (You can read the opinion of Geoffrey Hinton, one coauthor of the method, at `https://tinyurl.com/rrea42wz`.) Backpropagation is at the core of the present AI renaissance. In the past, each neural network learning process improvement resulted in new applications and a renewed interest in the technique. Also, the current deep learning revolution, which involves a revival of neural networks (abandoned at the beginning of the 1990s), resulted from key advances in the way neural networks learn from their errors.

Introducing Deep Learning

After backpropagation, the next improvement in neural networks led to deep learning. Research continued despite the AI winter, and neural networks overcame technical problems, such as the vanishing gradient, which limits the dimensionality of neural networks. Developers needed larger neural networks to solve certain problems, so large that creating such a large neural network wasn't feasible in the 1980s. Moreover, researchers started taking advantage of the computational developments in CPUs and GPUs (the graphic processing units better known for their application in gaming).

The vanishing-gradient problem occurs when you try to transmit a signal through a neural network and as the signal, passes through the layers, it quickly fades to near-zero values. When this happens, the subsequent neurons stop transmitting the signal through their activation functions. This happens because neural networks are chained multiplications. Each near-zero multiplication decreases the values rapidly, and activation functions need large enough values to let the signal pass. The farther neuron layers are from the output, the higher the likelihood that they'll get locked out of updates because the signals are too small and the activation functions will stop them. Consequently, your network stops learning as a whole, or it learns at an incredibly slow pace.

New solutions help avoid the problem of the vanishing gradient and many other technical problems, allowing larger deep networks in contrast to the simpler shallow networks of the past. Deep networks are possible thanks to the studies of scholars from the University of Toronto in Canada, such as Hinton, who insisted on working on neural networks, even when they seemed to most people to be an old-fashioned machine learning approach.

GPUs are powerful matrix- and vector-calculation computing units that speed up the computations for backpropagation. These technologies make training neural networks achievable in a shorter time and accessible to more people. Research

also opened a world of new applications. Neural networks can learn from huge amounts of data and take advantage of big data (images, text, transactions, and social media data), creating models that continuously perform better, depending on the flow of data you feed them.

Big players such as Google, IBM, Meta, and Microsoft spotted the new trend and have, since 2012, started acquiring companies and hiring experts in the new fields of deep learning. For instance, Yann LeCun, the French scientist who created convolutional neural networks, is vice president and chief AI scientist at Meta. Hinton has long been working at Google, although he recently left to be able to voice his concerns about AI systems' risks without having to consider the impact on the company he was working for: `https://arstechnica.com/information-technology/2023/05/warning-of-ais-danger-pioneer-geoffrey-hinton-quits-google-to-speak-freely`

UNDERSTANDING DEEP LEARNING ISSUES

As things stand now, people have an unrealistic idea of how deep learning can help society as a whole. You see a deep learning application beat someone at chess or Go and think, "If it can perform that truly amazing task, what other amazing things can it do?" The problem is that even its proponents don't fully understand deep learning. In technical papers about deep learning, the researchers often describe layers of nebulous processing organized into a network with no sort of discourse into what really happens in each of those boxes. Recent advances point out that deep learning networks are basically a way to memorize data and then retrieve relevant bits of it using similarity between the actual problem and the memorized data. (You can read an amazing scientific paper on the topic by Pedro Domingos at `https://tinyurl.com/46wfu3mr`)

The essential point to remember is that deep learning doesn't actually understand anything. It uses a massive number of examples to derive statistically based pattern matching using mathematical principles. When an AI wins a game involving a maze, it doesn't understand the concept of a maze; it simply knows that certain inputs manipulated in specific ways create certain winning outputs. In contrast to humans, deep learning must rely on a huge number of examples to discover specific relationships between inputs and outputs. When learning something new, deep learning requires special training to accomplish the task, and it would be easy to fool because examples beyond its training data may not be recognized.

Humans can also create hierarchies of knowledge without any sort of training. We know, for example, without much effort, that dogs and cats are both animals. In addition, in knowing that dogs and cats are animals, a human can easily make the leap to

see other animals as animals, even with no specific training. Deep learning would require separate training for each thing that is an animal. In short, deep learning can't transfer what it knows to other situations as humans can.

Even with these limitations, deep learning is an amazing tool, but it shouldn't be the only tool in the AI toolbox. Using deep learning to see patterns where humans can't is the perfect way to apply this technology. Patterns are an essential part of discovering new information. For example, human testing of compounds to battle cancer or fight a coronavirus pandemic could take an immense amount of time. By seeing patterns where humans can't, deep learning could make serious inroads toward a solution with a lot less effort than humans would require.

Deep learning versus simpler solutions

Deep learning may seem to be just a larger neural network that runs on more computers — in other words, just a mathematics and computational power technology breakthrough that makes larger networks available. However, something inherently qualitative changed in deep learning as compared to shallow neural networks. It's more than the paradigm shift of brilliant techs at work. Deep learning shifts the paradigm in machine learning from feature creation (features that make learning easier and that you have to create using data analysis) to feature learning (complex features automatically created based on the actual data). Such an aspect couldn't be spotted otherwise when using smaller networks but becomes evident when you use many neural network layers and lots of data.

When you look inside deep learning, you may be surprised to find a lot of old technology, but amazingly, everything works as it never has before. Because researchers finally figured out how to make some simple, good ol' solutions work together, big data can automatically filter, process, and transform data. For instance, new activations like ReLU aren't all that new; they've been known since the perceptron. Also, the image-recognition abilities that initially made deep learning hugely popular aren't new. Initially, deep learning achieved great momentum, thanks to CNNs. Discovered in the 1980s by LeCun (whose personal home page is at `http://yann.lecun.com`), such networks now bring about astonishing results because they use many neural layers and lots of data. The same goes for technology that allows a machine to understand human speech or translate from one language to another; it's decades-old technology that a researcher revisited and got to work in the new deep learning paradigm.

Of course, part of the difference is also provided by data (more about this topic later), the increased usage of GPUs, and computer networking. Together with *parallelism* (more computers put in clusters and operating in parallel), GPUs allow you to create larger networks and successfully train them on more data. In fact, a

GPU is estimated to perform certain operations many times faster than any CPU, allowing a cut in training times for neural networks from weeks to days or even hours.


TIP

GPUs aren't the only option for building effective deep learning solutions promptly: Special application-specific integrated circuits (ASIC) have made an appearance, and the designers have demonstrated that those circuits perform even better than GPUs. For instance, in 2015, Google started developing the *tensor processing unit (TPU),* a blazing-fast, application-specific integrated circuit to accelerate the calculations involved in deep learning when using Google's specialized computational library, TensorFlow. In 2018, Google made TPUs available in its cloud centers. See the "Working with Deep Learning Processors (DLPs)" section of Chapter 4 for details on other alternatives.

Finding even smarter solutions

Deep learning influences AI's effectiveness in solving problems in image recognition, machine translation, and speech recognition that were initially tackled by classic AI and machine learning. In addition, it presents new and advantageous solutions:

- Continuous learning using online learning
- Reusable solutions using transfer learning
- Simple straightforward solutions using end-to-end learning
- More democratization of AI using open source frameworks

The following sections describe these four new approaches.

Using online learning

Neural networks are more flexible than other machine learning algorithms, and they can continue to train as they work on producing predictions and classifications. This capability comes from optimization algorithms that allow neural networks to learn, which can work repeatedly on small samples of examples (called *batch learning*) or even on one example at a time (called *online learning*). Deep learning networks can build their knowledge step by step and be receptive to new information that may arrive (like a baby's mind, which is always open to new stimuli and learning experiences). For instance, a deep learning application on a social media website can be trained on cat images. As people post photos of cats, the application recognizes them and tags them with an appropriate label. When people start posting photos of dogs on the social network, the neural network doesn't need to restart training; it can continue by learning images of dogs as well.

This capability is particularly useful for coping with the variability of Internet data. A deep learning network can be open to novelty and adapt its weights to deal with it.

Using transfer learning

Flexibility is handy even when a network completes its training, but you must reuse it for purposes different from the initial learning. Networks that distinguish objects and correctly classify them require a long time and a lot of computational capacity to learn what to do. Extending a network's capability to new kinds of images that weren't part of the previous learning means transferring the knowledge to this new problem *(transfer learning)*.

For instance, you can transfer a network that's capable of distinguishing between dogs and cats to perform a job that involves spotting dishes of macaroni and cheese. You use the majority of the layers of the network as they are (you freeze them) and then work on the final, output layers *(fine-tuning)*, thus adapting an existing neural network to perform a new task. Recent advances have even made it possible to fine-tune all layers of a deep learning network to obtain better results: LoRA (low rank adaptation) is a new technique that leverages matrix multiplication to adapt an entire network using the least number of computations possible. In a short time, and with fewer examples, the network will apply to macaroni and cheese whatever it learned in distinguishing dogs and cats. It will perform even better than a neural network trained only to recognize macaroni and cheese.

Transfer learning, a concept new to most machine learning algorithms, opens up a possible market for transferring knowledge from one application to another, from one company to another. Google, Meta, and Microsoft are already doing this — actually sharing their immense research work by making public many of the networks they built. This is a step in democratizing deep learning by allowing everyone to access its potentiality.

Using open source frameworks

Today, networks can be accessible to everyone, including access to tools for creating deep learning networks. It's not just a matter of publicly divulging scientific papers explaining how deep learning works; it's a matter of programming. In the early days of deep learning, you had to build every network from scratch as an application developed in a language such as C++, which limited access to a few well-trained specialists. Scripting capabilities today (for instance, using Python; go to `www.python.org`) are better because of a large array of open source deep learning frameworks, such as TensorFlow (`www.tensorflow.org`) and JAX (`jax.readthedocs.io/en/latest`), by Google, or PyTorch (`pytorch.org/`), by Meta.

These frameworks allow the replication of the most recent advances in deep learning using straightforward commands.


REMEMBER

Along with many lights come some shadows. Neural networks need huge amounts of data to work, and data isn't accessible to everybody because larger organizations hold it. Transfer learning can mitigate the lack of data, but only partially because certain applications do require actual data. Consequently, the democratization of AI is limited. Moreover, deep learning systems require huge computational resources and are so complex that their outputs are both hard to explain (allowing bias and discrimination to flourish) and frail because tricks can fool those systems. Any neural network can be sensitive to *adversarial attacks*, which are input manipulations devised to deceive the system into giving a wrong response.

Using end-to-end learning

Finally, deep learning allows *end-to-end learning*, which means that it solves problems in an easier and more straightforward way than previous deep learning solutions and might therefore have more impact when solving problems. Say that you want to solve a difficult problem, such as having AI recognize known faces or drive a car. Using the classical AI approach, you would have to split the problem into more manageable subproblems to achieve an acceptable result in a feasible amount of time. For instance, if you wanted to recognize faces in a photo, previous AI systems arranged the problem into these parts:

1. Find the faces in the photo.
2. Crop the faces from the photo.
3. Process the cropped faces to have a pose similar to an ID card photo.
4. Feed the processed cropped faces as learning examples to a neural network for image recognition.

Today, you can feed the photo to a deep learning architecture and guide it to learn to find faces in the images and then classify them. You can use the same approach for language translation, speech recognition, or even self-driving cars (as discussed in Chapter 15). In all cases, you simply pass the input to a deep learning system and obtain the wanted result.

Detecting Edges and Shapes from Images

Convolutional neural networks, or CNNs, have fueled the recent deep learning renaissance. Practitioners and academics are persuaded that deep learning is a feasible technique because of its results in image recognition tasks. This success

has produced a sort of gold rush, with many people trying to apply the same technology to other problems. The following sections discuss how CNNs help detect image edges and shapes for tasks such as deciphering handwritten text.

Starting with character recognition

CNNs aren't a new idea. They appeared at the end of the 1980s as the work of LeCun when he worked at AT&T Labs-Research — together with Yoshua Bengio, Leon Bottou, and Patrick Haffner — on a network named LeNet5. You can see the network at `http://yann.lecun.com/exdb/lenet` or in this video, in which a younger LeCun himself demonstrates the network: `https://tinyurl.com/3rnwr6de`. At that time, having a machine able to decipher handwritten numbers was quite a feat, one that assisted the postal service in automating zip code detection and sorting incoming and outgoing mail.

Developers achieved some results earlier by connecting a number of images to a detection neural network. In their attempt, each image pixel was connected to a node in the network. The problem with this approach is that the network can't achieve translation invariance, which is the capability to decipher the number under different conditions of size, distortion, or position in the image, as exemplified in Figure 7-4. A similar neural network could detect only similar numbers — those that it has seen before. Also, it made many mistakes. Transforming the image before feeding it to the neural network partially solved the problem by resizing, moving, and cleaning the pixels and creating special chunks of information for better network processing. This technique, called *feature creation*, requires both expertise in the necessary image transformations as well as many computations in terms of data analysis. Image recognition tasks at that time were more the work of an artisan than of a scientist.

Convolutions easily solved the problem of translation invariance because they offer a different image-processing approach inside the neural network. Convolutions, which are the foundation of LeNet5, provide the basic building blocks for all actual CNNs performing these tasks:

- **Image classification:** Determining what object appears in an image
- **Image detection:** Finding where an object is in an image
- **Image segmentation:** Separating the areas of an image based on their content; for example, in an image of a road, separating the road itself from the cars on it and the pedestrians

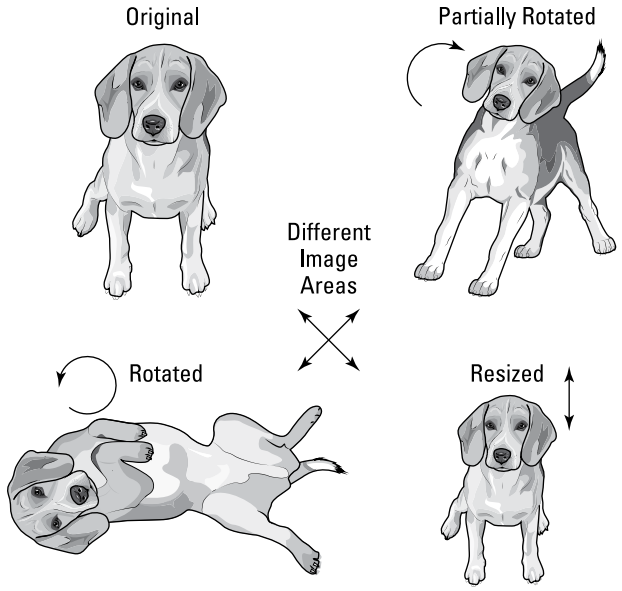

FIGURE 7-4: Using translation invariance, a neural network spots the dog and its variations.

Explaining how convolutions work

To understand how convolutions work, you start from the input, which is an image composed of one or more pixel layers, called *channels,* using values from 0 (the pixel is fully switched on) to 255 (the pixel is switched off). For instance, RGB images have individual channels for red, green, and blue colors. Mixing these channels generates the palette of colors as you see them on the screen.

The input data receives simple transformations to rescale the pixel values (for instance, to set the range from 0 to 1) and then pass on those values. Transforming the data makes the convolutions' work easier because convolutions are simply multiplication and summation operations, as shown in Figure 7-5. The convolution neural layer takes small portions of the image, multiplies the pixel values inside the portion by a grid of particularly devised numbers, sums everything derived from the multiplication, and projects it into the next neural layer.

Such an operation is flexible because backpropagation forms the basis for numeric multiplication inside the convolution, and the values that the convolution filters are image characteristics, which are important for the neural network to achieve its classification task. Some convolutions catch only lines, and others, only curves or special patterns, no matter where they appear in the image (and this is the translation invariance property of convolutions). As the image data passes through various convolutions, it's transformed, assembled, and rendered in increasingly complex patterns until the convolution produces reference images (for instance, the image of an average cat or dog), which the trained CNN later uses to detect new images.

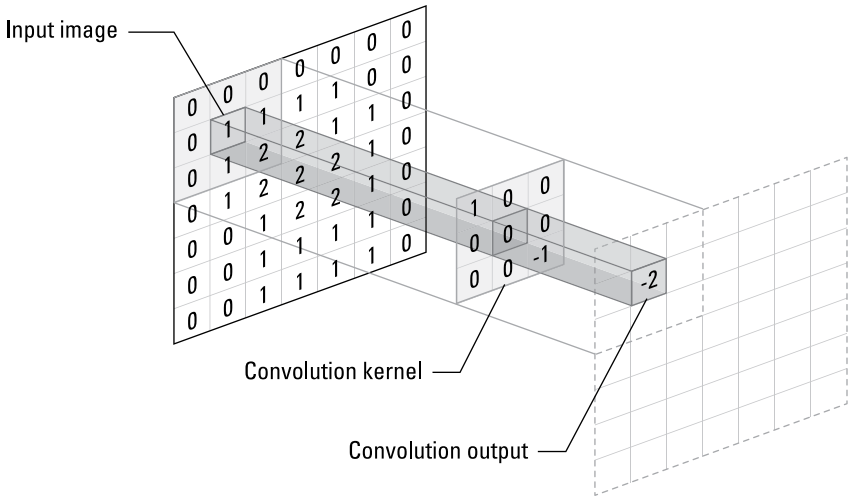

FIGURE 7-5: A convolution scanning an image.

TECHNICAL STUFF

If you want to know more about convolutions, you can check out a visualization created by some Google researchers from Research and Google Brain. The visualization is of the inner workings of a 22-layer network, developed by scientists at Google, called GoogleLeNet (see the paper at `https://tinyurl.com/6x8zuk5c`). In the appendix (`https://tinyurl.com/3d77zthf`), they show examples from the layers assigned to detect first edges, and then textures and then full patterns and then parts, and finally entire objects.

Interestingly, setting basic ConvNet architectures isn't hard. Just imagine that the more layers you have, the better (up to a certain limit, however). You set the number of convolution layers and some convolution behavior characteristics, like how the grid is made (filter, kernel, or feature detector values), how the grid slides in the image (stride), and how it behaves around the image borders (padding).

REMEMBER

Looking at how convolutions work hints that going deep in deep learning means that data goes into deeper transformations than it does under any machine learning algorithm or a shallow neural network. The more layers, the more transformations an image undergoes, and then the deeper it becomes.

Advancing using image challenges

The CNN is a smart idea. AT&T implemented LeNet5 into ATM check readers. However, another AI winter started in the mid-1990s, with many researchers and investors losing faith that neural networks could revolutionize AI. In addition, the data lacked complexity at the time. Researchers were able to achieve results comparable to LeNet5's using new machine learning algorithms called *support vector machines* (from the Analogizers tribe) and *random forests,* a sophistication of decision trees from the Symbologists tribe (both described in Chapter 6).

Only a handful of researchers, such as Hinton, LeCun, and Bengio, continued developing neural network technologies until a new dataset offered a breakthrough and ended the AI winter. For their efforts, they are often referred to as the "Godfathers of AI" and have been recognized with awards, such as the Turing Award by the Association for Computing Machinery. Meanwhile, 2006 saw an effort by Fei-Fei Li, then a computer science professor at the University of Illinois Urbana–Champaign (and later chief scientist at Google Cloud as well as a professor at Stanford) to provide more real-world datasets to better test algorithms. She started amassing an incredible number of images, representing a large number of object classes. She and her team achieved this monumental task by asking people on the Internet to complete microtasks (like classifying an image) for a small fee.

The resulting dataset, completed in 2009, was called ImageNet and contained 3.2 million labeled images, arranged into 5,247 hierarchically organized categories. You can learn more about the dataset at `https://image-net.org` or read the original paper that describes it at `https://tinyurl.com/yy98efcj`. ImageNet soon appeared at a 2010 competition in which neural networks proved their capability to correctly classify images arranged into exactly 1,000 classes.

In seven years of competition (the challenge closed in 2017), the winning algorithms raised the accuracy in predicting the images from 71.8 percent to 97.3 percent, which surpasses human capabilities (yes, humans make mistakes in classifying objects). At the beginning, researchers noticed that their algorithms started working better with more data (there was nothing like ImageNet at that time), and then they started testing new ideas and improved neural network architectures. That brought about a host of innovations in the way to process data, build layers, and connect them all together. Striving to achieve better results on the ImageNet competition had favorable impacts on all related fields of deep learning research.

Although the ImageNet competitions no longer take place, researchers are even today developing more CNN architectures, enhancing accuracy or detection capabilities as well as robustness. In fact, many deep learning solutions are still experimental and not yet applied to critical applications, such as banking or security, not just because of difficulties in their interpretability but also because of possible vulnerabilities.

WARNING

Vulnerabilities come in all forms. Researchers have found that by adding specially devised noise or changing a single pixel in an image, a CNN can radically change its answers, in attacks that are *nontargeted* (you just need to fool the CNN) or *targeted* (you want the CNN to provide a specific answer). The point is that CNNs aren't a safe technology yet. You can't simply use them in place of your eyes; you have to take great care with them.

3 Recognizing How We Interact with AI Every Day

IN THIS PART . . .

Enhance your own writing and creativity with Generative AI.

Work with AI in computer applications.

Use AI to automate common processes.

Define methods to allow human interaction.

IN THIS CHAPTER

- Familiarizing yourself with Generative AI
- Appreciating AI's magical smooth talk
- Getting a handle on how to use Generative
- Examining Generative AI's societal implications
- Evaluating a Generative AI app
- Figuring out how to make money with Generative AI

Chapter 8

Unleashing Generative AI for Text and Images

Generative AI, often shortened to GenAI, is revolutionizing how we humans create and interact with digital content. This technology is an evolution of the deep learning models discussed in Chapter 7. GenAI is based on neural network architectures and is built by training the internal weights of the networks on immense quantities of data (more than you can reasonably imagine). When given instructions in natural language, because there is no need for complex interfaces, the Generative AI technology produces text and images that closely match human creativity, providing significant innovation opportunities for many industries, including content creation, design, and research, by augmenting and accelerating human capabilities. However, this new technology also raises various concerns about ethics, intellectual property, the future of human creativity, and the potential impact on society, especially on clerical and creative work.

This chapter looks into the recent milestones achieved in Generative AI. It examines its increasingly widespread applications for text and images. We start by providing an overview of the technology and its evolution and retracing its origins in natural language models, generative adversarial networks, and reinforcement

learning. We conclude the chapter by discussing various applications and what we can expect from GenAI in the near future.

Getting an Overview of Generative AI

Similar to the AI models we discuss in earlier chapters, Generative AI algorithms learn patterns from existing data, not for the purpose of prediction but rather because they are designed to generate new content. Based on simple instructions, called *prompts,* which correspond to giving verbal orders, GenAI algorithms can produce text, images, videos, code, music, and data that is difficult to distinguish from what a human could have created. On one hand, GenAI has opened new avenues for artists, musicians, writers, programmers, and many other professionals whose creativity has been enhanced by these new tools. On the other hand, it has raised controversies and strong concerns about devaluing human creativity, violating intellectual property, disseminating and amplifying bias and discrimination, and producing false and misleading information.

What is certain about this technology is that it is undoubtedly revolutionary. Given its rapid progress, we can expect even more impact and changes derived from it in the future. Much of the GenAI revolution revolves around the San Francisco-based organization OpenAI (`openai.com`). Several scientists and entrepreneurs — including Elon Musk, Sam Altman, and Ilya Sutskever — founded the company at the end of 2015. OpenAI was initially a nonprofit research organization for safe AI, but later it became a commercial company. Notably, Musk is well known because of his successful business activities, ranging from space exploration to electric vehicles and much more, whereas Ilya Sutskever, along with Alex Krizhevsky and Geoffrey Hinton, actually co-invented AlexNet, one of the first revolutionary convolutional neural networks, as we discuss in Chapter 7.

The company immediately attracted the spotlight for its work on language models that could generate text and articles, which they named GPT, short for Generative Pre-trained Transformers. GPT-1, GPT-2, and GPT-3 succeeded each other from 2018 to 2020 and we have now reached GPT-4. In spite of factual imprecision and a tendency for the discourse they produced to easily go astray, these models amazed users with their creativity and soon made it to the headlines. However, their initial usage was limited to a few applications. One notable example was in gaming, specifically in text-based adventures like *Dungeon AI* (`https://play.aidungeon.com`).

The beginnings of this technology were certainly less than exceptional, but it was only a matter of time: When OpenAI launched ChatGPT in November 2022, the public's attention was drawn to its incredible capacity to create meaningful and to-the-point text most of the time. ChatGPT also excelled in its flexibility in

handling unexpected tasks, which was part of what become known as the *emergent capabilities* of this technology. The emergent capabilities of a generative algorithm may not have been directly programmed or anticipated by the developers but naturally emerge from the AI's learning and adaptation processes. It may sound like magic, but it is certainly part of being trained on such a large amount of data that comprises much more content than initially expected by those who devised such systems.

Besides AI models for text, some models are also capable of producing images, based on stable diffusion technology. These models, such as DALL-E 3 and Midjourney, combine the technology of large language models with vast amounts of image-text pairs and become capable of generating novel images from textual descriptions. Again, the technology initially produced simple images, which were easily recognizable as the work of an AI because of the obvious errors and visual noise, especially when drawing human hands. However, recent outputs by generative image AI have become so sophisticated that they win art competitions, produce realistic video clips, and cause serious concerns to artists because of AI capability to mimic any artistic style successfully. In Figure 8-1 you can see a few examples of images that can be easily created by OpenAI's DALL-E 3 technology based on a simple description of what you want to be represented.

FIGURE 8-1: A sample of images created with the DALL-E 3 technology from OpenAI.

A selection of images created with DALL-E 3

Here are some of the GenAI models available from various companies at the time of writing this book:

- **Amazon AWS:** Code Whisperer, Q
- **Anthropic:** Claude, Haiku
- **Cohere:** Command R+
- **Google:** Gemini, Gemma, Midjourney
- **Meta:** Llama 3
- **Mistral:** AI Mistral
- **OpenAI:** DALL-E, GPT-4o, SORA

The list is intended to provide you with an overview of the state of the art at the time we wrote this chapter, but it is far from exhaustive and it is destined to change rapidly in a short time. This is because of the intense competition between companies, the top researchers employed in the effort, and the large amount of funds invested in Generative AI companies. This reflects a present AI summer era, where the memory of AI winters is far away. The focus of the following sections is how we arrived at this stage of AI development, where we take a step back and investigate the technologies used to process text and images that become the building blocks of this new, amazing Generative AI deluge.

Memorizing sequences that matter

Understanding text is understanding sequences of words. One weakness of convolutional neural networks (CNNs), the neural networks we discuss in Chapter 7, is the lack of memory. CNNs do well with understanding a single picture, but trying to understand a picture in a context, like a frame in a video, translates into an inability to find the right answer to difficult AI challenges. Technically, a CNN can recognize a set of patterns, but without much distinction of how they are spatially arranged (hence their property of translation invariance). Instead, when the sequence in which patterns appear matters, CNNs offer no particular advantage. Many important problems are also sequences. If you want to understand a book, you read it page by page. The sequences are nested. Within a page is a sequence of words, and within a word is a sequence of letters. To understand a book, you must understand the sequence of letters, words, and pages and the same goes for a set of instructions or programming code for a computer. A new kind of neural network, the recurrent neural network (RNN), was the answer because it processes new inputs while keeping track of past ones. The network takes in sequences of inputs, capturing and retaining information from each element of the sequence. In this way, the network can model complex relationships between the elements in the sequence, making it particularly suitable at handling textual inputs.

If you feed a RNN a sequence of words, the network will learn that when it sees a word, preceded by certain other words, it can determine how to complete the phrase, something that previous natural language processing techniques, such as the bag of words model, could not easily achieve.

REMEMBER

Natural language processing (NLP) is a field of Artificial Intelligence that focuses on enabling computers to understand, interpret and generate human language by means of analyzing and interpreting text data.

RNN isn't simply a technology that can automate input compilation (such as when a browser automatically completes search terms as you type words). In addition, an RNN can feed sequences and provide a translation as output, such as the overall meaning of a phrase (so now AI can clarify phrases where wording is important) or translate text into another language (again, translation works in a context). This even works with sounds because it's possible to interpret certain sound modulations as words. RNNs allow computers and mobile phones to understand, with great precision, not only what you said (it's the same technology that automatically subtitles) but also what you meant to say, opening the door to computer programs that chat with you and to digital assistants such as Siri, Cortana, and Alexa.

RNNs have come a long way in recent years. When researchers and practitioners experienced how much more useful RNNs are than the previous statistical approach of analyzing text as a pool of words (the commonly used technical term is *bag of words*), they started using them en masse and, as they tested more and more applications, also discovered limitations that they tried to overcome.

As initially devised, the RNN had limits. In particular, it needed too much data to learn from and it couldn't accurately remember information that appeared earlier in a phrase. Moreover, many researchers reported that the RNN was just a look-back algorithm (also called *backjumping*) when processing text and that sometimes you need to look further into a phrase to make sense of what has been said before. Thus, to cope with the memory limitations of the RNN and the multiple relations of words in a phrase, researchers devised the long short-term memory (LSTM) and the gated recurrent unit (GRU) neural units, which can both remember and forget previous words in a smarter way. The researchers also made all these neural units read text bidirectionally, so they can pick a word from both the start and end of the phrase and make sense of everything.

TECHNICAL STUFF

Sepp Hochreiter, a computer scientist who made many contributions to the fields of machine learning, deep learning, and bioinformatics, and Jürgen Schmidhuber, a pioneer in the field of artificial intelligence, invented LSTMs. See "Long Short-Term Memory" in the MIT Press journal *Neural Computation*. The GRU first

appeared in the paper "Learning Phrase Representations using RNN Encoder-Decoder for Statistical Machine Translation" (`https://arxiv.org/pdf/1406.1078.pdf`).

RNNs have dominated the scenes of natural language processing until recently, when a new approach pioneered by Google researchers, the attention mechanism, has appeared. This breakthrough technology is at the core of the current large language models such as ChatGPT and Google Gemini. An *attention model* processes text sequences in a different way, thanks to a mechanism called self-attention, which helps the model focus on the important parts of the discourse, no matter where they're placed in a phrase. This contrasts with the unidirectionality of a RNN that can process the words of a phrase in only one direction, has limited memory, and can't retrace back if a word appearing later in the phrase modifies the initial meaning of the discourse. Take, for instance, a phrase such as "The bird perched on the branch, and it sang a song that echoed through the forest." A RNN model can progress only word by word, and it could not refer back to words in the phrase or figure out whether the word *it* refers to the bird or the branch.

Instead, an approach based on the self-attention mechanism would highlight words such as *bird* and *sang* and correctly identify that *it* refers to the bird that is singing the song. This mechanism is indeed more effective in problems such as machine translation, text summarization, and sentiment analysis, and it is at the root of recent GenAI models such as OpenAI ChatGPT, Google Gemini, and Meta's Llama.

Employing self-attention models

Before explaining what makes the attention mechanism special in a neural network, we need to first clarify what tokenization and embeddings are. The idea is to convert words into numbers, but you start from phrases or entire texts represented as strings, not numbers. A *tokenizer* is a piece of code that performs the initial transformation, the tokenization, of your text into a format that a neural network can process.

Tokenizing means splitting the text into smaller chunks, called tokens, based on some predefined rules — for instance, based on spaces, punctuation, and special characters such as the newline character. The process isn't just getting the words out of the text. Most advanced tokenizers can handle numbers and emojis, and they're proficient in multiple languages at once, from Arabic to French and from Chinese to Indian Devanagari and beyond. Even with English, the more sophisticated tokenizers don't simply split words, but they distinguish between the constant and variable parts of a word.

TIP

Tokenization is also a common procedure in natural language processing (NLP) in order to split text into tokens (elements of a phrase such as nouns, verbs, and adjectives) and remove any less useful or confounding information. The tokenized text is then processed using statistical operations or machine learning. For instance, NLP can help you tag parts of speech and identify words and their meaning, or determine whether one text is similar to another.

Once the text has been split by a tokenizer, it's not yet ready to be fed into a neural network — it has to be converted into numbers first. The numbers aren't randomly chosen but relate to each other in the same way as words relate by meaning. For example, you can assign the names of various foods into columns of numeric values (a matrix) in such a way that the words that show fruits can have a similar score in a particular column. In the same column, vegetables can score different values, but not too far from those of fruit. Finally, the names of meat dishes can be far away in value from fruits and vegetables. The values are similar when the words are synonymous or refer to a similar concept. This is called semantic similarity, *semantic* refers to the meaning of words.

This process of converting words into numerical representations is called *word embeddings*. Embeddings aren't new; they have a long history. The concept of embeddings appeared in statistical multivariate analysis under the name of *multivariate correspondence analysis.* In the 1970s, Jean-Paul Benzécri, a French statistician and linguist, along with colleagues from the French School of Data Analysis, discovered how to map a limited set of words into low-dimensional spaces (usually, 2D representations, such as a topographic map). This process turns words into meaningful numbers and projections. This discovery, which brought about many applications in linguistics and the social sciences, paved the way for the recent advancements in language processing using deep learning.

REMEMBER

The word *embedding* refers to nothing more than a mapping operation that transforms tokens into numeric sequences that are meaningful for a deep learning architecture. Using embeddings, a text can be converted into a multidimensional numeric matrix.

Initially, embeddings were standalone solutions. Popular word embeddings were Google's Word2Vec, Stanford's Global Vectors (GloVe), and Facebook's fastText, which were used to transform words into numeric sequences for RNNs. Then a series of pretrained networks appeared, making modeling language problems even easier. The first was the Google Bidirectional Encoder Representations from Transformers (BERT). Here's a link to the Google AI blog post describing the technique: `https://tinyurl.com/b7vhn8d6`. The GenAI revolution for text actually started from Google.

The interesting part of BERT was that it produced even more useful embeddings because it could map words into numbers differently based on the other words that appear with it in the phrase. Even if embeddings were just numbers, such developments demonstrated how machines could take an approach similar to how humans understand the meaning of words based on their context. BERT managed to understand the context of a word because it employed the attention mechanism — that is, it could focus on the most important parts of the sequence for the purpose of understanding the meaning of a phrase. In contrast to RNNs, the attention mechanism worked on all the sequence of words at one time and could be applied multiple times to grasp all nuances in the text. (This is referred to as the attention mechanism being *multi-head.*) In BERT, as well as in a sequence of following improved models such as Meta's RoBERTa, Google's DistilBERT and ALBERT, and Microsoft's DeBERTa, the attention mechanism is part of a more complex architecture called the transformer architecture. That's why you may hear all these models commonly referred to as *transformers*.

TIP

You can read an illustrated explanation of how transformers work from the *Financial Times* Visual Storytelling team at `https://ig.ft.com/generative-ai`.

Based on the same philosophy, the GPT neural network, created by OpenAI, a San Francisco–based artificial intelligence research laboratory, could achieve even more competitive results than the BERT. Even the first GPT models could answer questions, write and summarize essays, generate adventure games, translate languages, and even write computer code. Basically, the recipe from the first GPT to the most recent GPT-4o is the same: tokenization of a text and transformation of the tokens into a matrix of embeddings, and then the data passes through multiple layers based on the attention mechanism (we are talking about billions of neurons). All this architecture is then trained for a long time and on massive amounts of text to predict the likelihood of the next word in a sequence of words. To give a simple example, if the neural network is exposed during the training to many documents where the article *the* is followed by the word *world,* it will associate a high probability with the word *world* after the article *the.* A GPT model essentially learns what a word should be, given the other words preceding it.

There is nothing more in a GPT model, as well as in the other large language models (LLMs), to explain why they can chat with you and, apparently, solve complex problems. All such technology can perform extremely well in figuring out what the next word should be, given a starting text, which is called the *prompt.* After the initial input, the LLMs then continue predicting the next word, after having appended the previously predicted words, and they continue to do so until a stopping criterion is met. Even if some researchers claim that LLMs could reason and have consciousness, the naked truth is that LLMs are just sophisticated machines that can complete a phrase in the best way possible based on the text they have been trained on.

Discovering the Magic Smooth Talk of AI

A *chatbot* is software that can converse with you by way of two methods:

- Auditory (you speak with it and listen to answers)
- Textual (you type what you want to say and read the answers)

You may have heard of a chatbot under other names (conversational agent, chatterbot, and talkbot, for example), but the point is that you may already use one on your smartphone, computer, or special device. Siri, Cortana, and Alexa are all well-known examples. You may also exchange words with a chatbot when you contact a firm's customer service system by web or phone, or by way of an app on your mobile phone when using Twitter, Slack, Skype, or other applications for conversation.

Chatbots are big business because they help companies save money on customer service operators — maintaining constant customer contact and serving those customers — but the idea isn't new. Even if the name is recent (devised in 1994 by Michael Mauldin, the inventor of the Lycos search engine), chatbots are considered the pinnacle of AI. According to Alan Turing's vision, detecting a strong AI by talking with it shouldn't be possible. Turing devised a famous conversation-based test to determine whether an AI has acquired intelligence equivalent to a human being's.

The Turing test requires a human judge to interact with two subjects via a computer terminal: one human and one machine. The judge evaluates which one is an AI based on the conversation. Turing asserted that if an AI can trick a human into thinking that the conversation is with another human, it's possible to believe that the AI is at the human level of AI. Turing called this assessment the *imitation game* (see `https://academic.oup.com/mind/article/LIX/236/433/986238`). The problem is hard to solve because it's a matter not just of answering properly and in a grammatically correct way but also incorporating the context (place, time, and characteristics of the person the AI is talking with) and displaying a consistent personality (making the AI resemble a real-life persona, in both background and attitude).

Since the 1960s, challenging the Turing test has proved to be motivation for developing chatbots, which are based on the idea of *retrieval-based models* — that is, a natural language processing (NLP) algorithm parses language that is input by the human interrogator. Certain words or sets of words recall preset answers and feedback from chatbot memory storage.

Joseph Weizenbaum built the first chatbot of this kind, ELIZA, in 1966 as a form of computer psychotherapist. ELIZA was made of simple heuristics, which are base phrases to adapt to the context and keywords that triggered the software to recall an appropriate response from a fixed set of answers. You can try an online version of ELIZA at `https://tinyurl.com/3cfrj53y`, and you might even be surprised to read meaningful conversations such as the one produced by ELIZA with its creator (`https://tinyurl.com/j3zw42fj`) because the dialogue doesn't deviate from the rules embedded into the chatbot.

Retrieval-based models work fine when interrogated using preset topics, because they incorporate human knowledge, just as an expert system does (as discussed in Chapter 3); thus, they can answer with relevant, grammatically correct phrases. Problems arise when confronted with off-topic questions; the chatbot can try to fend off these questions by bouncing them back in another form (as ELIZA did) and be spotted as an artificial speaker. A later solution has been to create models that can autonomously generate completely novel answers to address requests. For instance, these later models include statistical models, machine learning, pretrained RNNs, or transformer-based models such as ChatGPT, which can generate human-like speech and even reflect the personality of a specific person.

GenAI models are so adept at creating reasonable and plausible text that they literally "broke the Turing test," as a *Nature* article stated (`www.nature.com/articles/d41586-023-02361-7`). Previously, the Lobner prize (`tinyurl.com/cwb2zr8c`), a competition in which Turing tests were applied to the current technology, was the place where you could assess the ability of chatbots, but it was discontinued a few years ago. Nowadays, chatbots are tested on a series of tasks regarding natural language understanding, dialogue management, common sense reasoning, and factual knowledge. There are various tests of this kind, and each new GenAI model can be immediately evaluated and compared with others. This sometimes leads to discussions because the set of tests used may be cherry-picked (selecting tests where a chatbot performs better) or there are doubts whether tests were correctly applied.

Sometimes, this situation is resolved by putting chatbots in competition in arenas, where human judges decide which one performs better in conversations and other real-world situations, like translating or writing poems, code, scripts, musical pieces, email, and letters. You can get an idea of the best chatbot by looking at contests such as LMSYS Chatbot Arena Leaderboard (see `chat.lmsys.org/?leaderboard` or read the paper explaining how it works: `arxiv.org/abs/2403.04132`), where a human judge decides what test to pose and then evaluates the answers. The contest is based on direct confrontations between two chatbots that are then converted into Elo scores. (An *Elo score* is a rating method used to calculate the relative skill levels of players in games where one player wins and the other loses, such as chess or tennis.)

REMEMBER

You have a weak AI when the AI shows intelligent behavior within specific boundaries but can't go beyond its limits or be self-conscious like a human being. A strong AI occurs when the AI can truly think like a human. Generative AI technologies such as ChatGPT are still a form of weak AI. However, they are quite effective and useful in conversation and many other tasks.

However, no matter how impressive ChatGPT and the other LLMs seem when chatting with you, there are open problems and doubts. First is the question of the ethical principles expressed by the chatbot, because it should avoid harmful or biased outputs, which can prove a difficult task, given the massive amount of text it has learned from. LLM chatbots often offer unacceptable answers, or you can trick them into providing inappropriate ones. This poses the endless problem of their *alignment,* which is the procedure to ensure that an LLM executes given instructions according to accepted ethical standards and the values and intentions of its creators.

In addition, LLMs suffer important limitations in the language they generate. They tend to produce predictable output. Many AI detectors work based on this principle, and the increased frequency of terms such as *delve, meticulously, intricate,* and *commendable* in writing, including scientific papers, is likely due to the widespread use of ChatGPT as a tool for preparing or polishing texts.

LLMs are also so predictable that they sometimes output the exact texts they were exposed to during training, thus leaking information their creators intended to keep secret or disseminating plagiarism. Finally, LLMs are intrinsically restricted in their reasoning by the type of tokenizer they use. Consequently, if they tokenize word by word, they cannot spell out words they don't know or count the number of specific letters in a word unless they have been explicitly instructed to do so for that word.

However, what is more revealing about their limitations is that they are quite weak in logical visual tests where, given a series of blocks on the screen, you have to detect patterns and regularities. Even when given simplified tests, they fail and perform significantly inferior to any human. Examples of such tests where LLMs fail are Francois Chollet's Abstraction and Reasoning Corpus (ARC), which you can find at `github.com/fchollet/ARC`, or the derived ConceptARC, by Arseny Moskvichev, Victor Vikram Odouard, and Melanie Mitchell (see `github.com/victorvikram/ConceptARC`). The poor results that LLMs achieve on such tests can certainly be explained by the fact that they have received no previous training on similar tasks. However, it also hints at their inability to abstract a newly encountered problem and find a solution, which is a key characteristic of intelligence in humans.

Creating generative adversarial networks

RNNs and transformers can make a computer converse with you. If you have no idea that the neural network is reactivating sequences of words it has previously learned, you get the idea that something related to intelligence is going on behind the scenes. In reality, no thought or reasoning goes behind it, though the technology doesn't simply recall preset phrases but is also fairly articulate.

Generative adversarial networks (GANs) represent another kind of deep learning technology that can give you an even stronger illusion that the AI can display creativity. They are the first attempt at an algorithm to generate an image, a predecessor of the present GenAI models that can produce images based on instructions. Again, this GAN technology relies on recalling previous examples and the machine's understanding that the examples contain rules — rules that the machine can play with as a child plays with toy blocks. (Technically, the rules are the statistical distributions underlying the examples.) Nevertheless, a GAN is an incredible type of technology that has displayed promise for a fairly large number of future applications, in addition to the uses today (see `tinyurl.com/na74p3uz` as an example).

GANs originated from the work of a few researchers at the Departement d'informatique et de recherche operationnelle at Montreal University in 2014, and the most notable among them is Ian Goodfellow (see the white paper at `tinyurl.com/4r65ca6e`). The proposed new deep learning approach immediately raised interest, and it is now one of the most researched technologies, with constant developments and improvements. Yann LeCun found generative adversarial networks "the most interesting idea in the last ten years in machine learning" (`tinyurl.com/y4j7ch6b`). In an interview with MIT Technology Review, Ian Goodfellow explains that level of enthusiasm with this intriguing statement: "You can think of generative models as giving artificial intelligence a form of imagination" (`tinyurl.com/zpzrsdpp`).

To see a basic GAN in action (there are now many sophisticated variants, and more are being developed), you need a reference dataset, usually consisting of real-world data, whose examples you want to use to teach the GAN. For instance, if you have a dog image dataset, you expect the GAN to learn from the dataset how a dog looks. After learning about dogs, the GAN can propose plausible, realistic images of dogs that differ from those in the initial dataset. (They'll be new images; simply replicating existing images is considered an error from a GAN.)

The dataset is the starting point. You also need two neural networks, each one specializing in a different task and both in competition with each other. One network is called the *generator;* it takes an arbitrary input (for instance, a sequence of random numbers) and generates an output (for example, a dog's image), which is an *artifact* because it's artificially created using the generator network. The second

network is the *discriminator*, which must correctly distinguish the products of the generator, the artifacts, from the examples in the training dataset.

When a GAN starts training, both the networks try to improve by using back-propagation, which we discussed in Chapter 7, based on the results of the discriminator. The errors the discriminator makes in distinguishing a real image from an artifact propagate to the discriminator (as with a classification neural network). The correct discriminator answers propagate as errors to the generator (because it was unable to make artifacts similar to the images in the dataset, and the discriminator spotted them). Figure 8-2 shows this relationship.

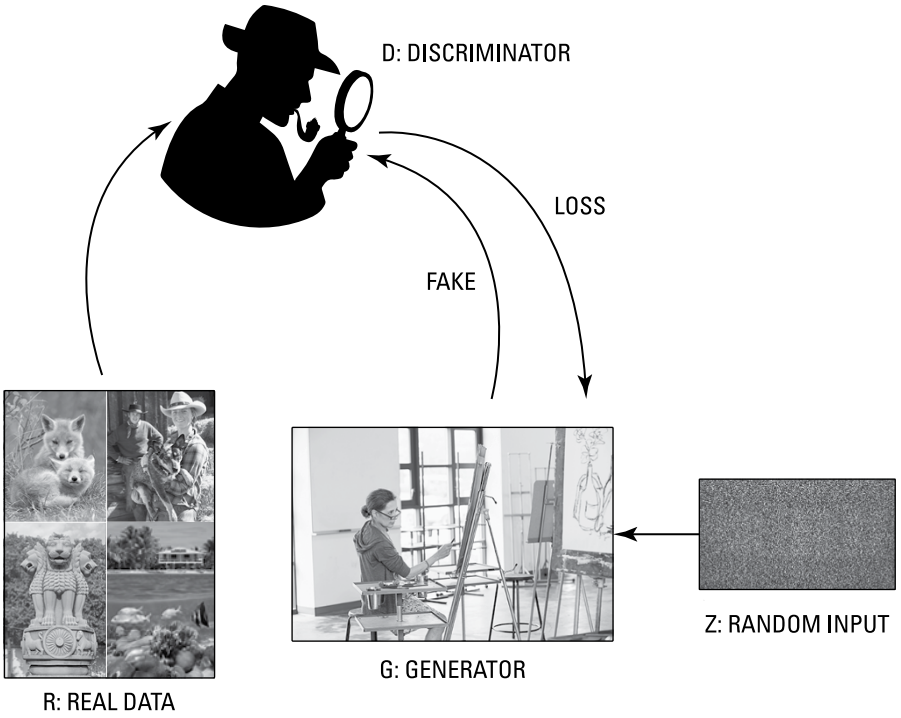

FIGURE 8-2: How a GAN network works, oscillating between generator and discriminator.

MrLeestudio/Shutterstock; Menno Schaefer/Shutterstock; iofoto/Shutterstock; dam/Adobe Stock Photos; Rana Faure/Corbis/VCG/Getty Images

The original images chosen by Goodfellow to explain how a GAN works are that of the art faker and the investigator. The investigator gets skilled in detecting forged art, but the faker also improves to avoid detection by the investigator.

You may wonder how the generator learns to create the right artifacts if it never sees an original. Only the discriminator sees the original dataset when it tries to distinguish real art from the generator artifacts. Even if the generator never

examines anything from the original dataset, it receives hints through the work of the discriminator. They're slight hints, guided by many failed attempts at the beginning from the generator. It's like learning to paint the *Mona Lisa* without having seen it and with only the help of a friend telling you how well you've guessed. The situation is reminiscent of the *infinite monkey* theorem, with some differences. In this theorem, you expect the monkeys to write Shakespeare's poems by mere luck (see `tinyurl.com/2t8v5bbr`). In the case of GANs, instead, the generator uses randomness only at the start, and then it's slowly guided by feedback from the discriminator. With some modifications of this basic idea, GANs have become capable of the following:

- Creating photorealistic images of objects such as fashion items, as well as interior or industrial designs based on a word description (you ask for a yellow-and-white flower and you get it, as described in this paper: `tinyurl.com/wu2n8nxn`)
- Modifying existing images by applying higher resolution, adding special patterns (for instance, transforming a horse into a zebra: `tinyurl.com/mbf5rwex`), and filling in missing parts (for example, to remove a person from a photo, a GAN replaces the gap with a plausible background, as in this image-completion neural architecture: `tinyurl.com/3ryvpzy2`)
- Many frontier applications, such as ones for generating movement from static photos; creating complex objects such as complete texts (which is called *structured prediction* because the output is not simply an answer, but rather a set of answers that relate to each other); creating data for supervised machine learning; or even generating powerful cryptography (`tinyurl.com/yzwhsa8c`)

Revolutionizing art with diffusion models

Diffusion models are another generative technology that has changed digital content creation. In a similar fashion to GPT models in text, diffusion models, given instructions, can rapidly generate photorealistic images and images in specific styles. Given their ease of use, because you just need to describe in words what you want them to create, models based on diffusion technology have made a significant impact on industries such as graphic design, gaming, and virtual reality.

Diffusion models are trained on massive datasets of images. To gain an advantage in competition, companies creating such models often directly download images from the Internet, including websites that collect images or illustrations, blogs, social networks, and shopping websites. Companies tend not to reveal where they found their images, to keep their recipe secret (data is often more important than the algorithm, as we have discussed) or to avoid contestations about usage and copyright. Alternatively, publicly available image databases provide access to

images *and* their descriptions. An example is the LAION dataset, which includes billions of image samples collected by a German nonprofit organization (`laion.ai`).

All these datasets are composed of images and their descriptions, allowing a model to associate images with words related to specific objects, colors, drawing or photographic styles, and image arrangements. However, the massive scale of the image collection makes it extremely difficult to verify whether the collected images are problematic, such as being private or sensitive or protected by copyright.

All the collected images are processed during the model's training in a way that progressively adds more noise to the image until it turns into just random noise; this is called the *forward diffusion* process. The model then learns to remove the noise from the images by determining at each noising step what denoising operation should be performed (the *reverse diffusion* process). At this point, the model can generate an image from an initial random noise image and is conditioned to do so based on the associated image description. This is accomplished by using a transformer architecture that can process language, called Contrastive Language-Image Pretraining, or CLIP (see Figure 8-3).

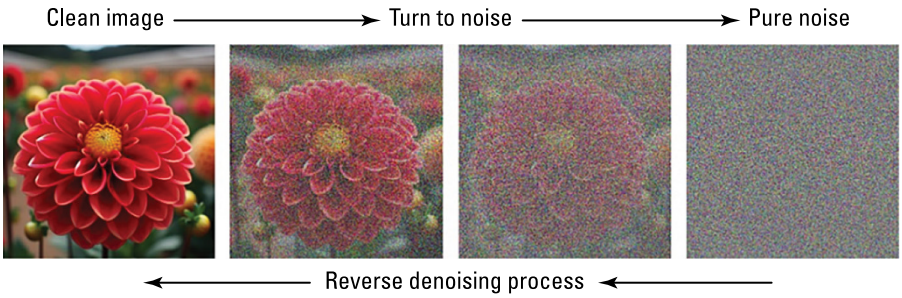

Image of Dahlia pinnata generated with DALL-E 3

FIGURE 8-3: How a diffusion model first adds noise and then learns to remove it.

Data and the diffusion model technique have been refined in fast iterations in recent years, going from the first tentative generated images to completely photorealistic results.

Applying reinforcement learning

Deep learning isn't limited to supervised learning predictions. You also use deep learning for unsupervised and reinforcement learning (RL). Unsupervised learning supports a number of established techniques, such as autoencoders and self-organizing maps (SOMs), which can help you segment your data into homogeneous groups or detect anomalies in your variables. Even though scientists are still

researching and developing unsupervised learning, reinforcement learning has recently garnered the lion's share of attention in both the academic papers and popularity among practitioners. RL achieves smarter solutions for problems such as parking a car, learning to drive in as little as 20 minutes (as this paper illustrates: `tinyurl.com/nr5wzvwx`), controlling an industrial robot, and more. Moreover, reinforcement learning is behind the efforts of Generative AI alignment because it is used to teach how a GenAI model should behave and execute instructions from humans.

RL provides a compact way of learning without gathering large masses of data, but it also involves complex interaction with the external world. Because RL begins with no data, interacting with the external world and receiving feedback defines the method used to obtain the data it requires. You could use this approach for a robot, moving in the physical world, or, for a bot, wandering in the digital world.

In RL, you have an agent (a robot in the real world or a bot in the digital one) interacting with an environment that can include a virtual world or another type of world with its own rules. The agent can receive information from the environment (called the *state*) and can act on it, sometimes changing it. More important, the agent can receive input from the environment, a positive or negative one, based on its sequence of actions or inactions. The input is a reward, even when negative. The purpose of RL is to have the agent learn how to behave to maximize the total sum of rewards received during its experience inside the environment.

Understanding how reinforcement learning works

You can determine the relationship between the agent and the environment from Figure 8-4. Note the time subscripts. If you consider the present instant in time as *t*, the previous instant is $t-1$. At time $t-1$, the agent acts and then receives both a state and a reward from the environment. Based on the sets of values relative to the action at time *t*, state at time $t-1$, and reward at time *t*, an RL algorithm can learn the action to obtain a certain environmental state.

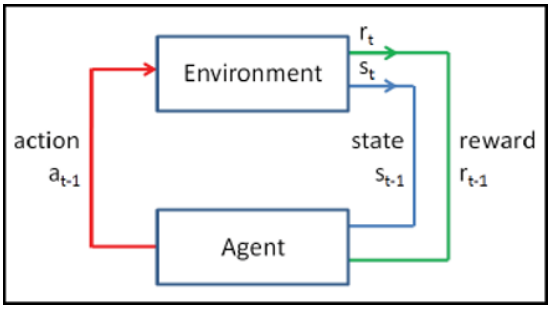

FIGURE 8-4: A schema of how an agent and an environment interact in RL.

Ian Goodfellow, the AI research scientist behind the creation of GANs, believes that better integration between RL and deep learning is among the top priorities for further deep learning advances. Better integration leads to smarter robots. Integration is now a hot topic, but until recently, RL typically had stronger bonds to statistics and algorithms than to neural networks, at least until the Google deep learning research team proved the contrary.

Progressing with Google AI and DeepMind discoveries

At Google DeepMind, a research center in London owned by Google, they took a well-known RL technique called Q-learning and made it work with deep learning rather than the classical computation algorithm. The new variant, named Deep Q-Learning, uses both convolutions and regular dense layers to obtain problem input and process it. At Google, they used this solution to create a Deep Q-Network (DQN), which has been successfully used to play vintage Atari 2600 games at an expert human level and win (see `tinyurl.com/t2u3dhf8`). The algorithm learned to play in a relatively short time and found clever strategies that only the most skilled game players use.

REMEMBER

The idea behind Deep Q-Learning is to approximately determine the reward of an agent after taking a certain action, given the present state of the agent and the environment. In a human sense, the algorithm simply associates state and actions with expected rewards, which is done using a mathematical function. The algorithm, therefore, can't understand whether it's playing a particular game; its understanding of the environment is limited to the knowledge of the reported state deriving from taken actions.

In recent years, the DeepMind team has continued exploring other possible RL solutions for playing Atari games. In particular, the team has tried to understand whether learning a model of the environment (in this case, the rules and characteristics of a specific Atari game) by image inputs could help the RL achieve even better results. In collaboration with Google AI and the University of Toronto, they finally introduced DreamerV2 (you can read more about it here: `tinyurl.com/3jjkdwne`), an RL agent-based application that achieves human-level performance on Atari games by means of creating a world model of the game itself through images of the game. In simple words, the DreamerV2 takes hints from provided images of the game and, on its own, figures out game object positions, trajectory, effects, and so on. Whereas DQN mapped actions and rewards, this RL agent goes beyond those tasks and creates an internal representation of the game in order to understand it even better. This is similar to what humans do when they develop internal images and ideas of the external world.

The dream of AI scientists is to create a general RL agent that can approach various problems and solve them, in the same spontaneous way as humans do. Recently, though, the most astonishing results have again occurred with task-specific problems that don't transfer easily to other situations.

Clear examples are the AI built to beat humans at games such as chess or Go. Chess and Go are both popular board games that share characteristics, such as being played by two players who move in turns and lack a random element (no dice are thrown, as in backgammon). Apart from that, they have different game rules and complexity. In chess, each player has 16 pieces to move on the board according to type, and the game ends when the king piece is stalemated or checkmated — unable to move further. Experts calculate that about 10^{123} different chess games are possible, which is a large number when you consider that scientists estimate the number of atoms in the known universe at about 10^{80}. Yet computers can master a single game of chess by determining the future possible moves far enough ahead to have an advantage against any human opponent. In 1997, Deep Blue, an IBM supercomputer designed for playing chess, defeated Garry Kasparov, the world chess champion.

REMEMBER

A computer cannot prefigure a complete game of chess using *brute force* (calculating every possible move from the beginning to the end of the game). The computer uses some heuristics and can look into a certain number of future moves. Deep Blue was a computer with high computational performance that could anticipate more future moves in the game than could any previous computer.

In Go, you have a 19-x-19 grid of lines containing 361 spots on which each player places a stone (usually, black or white in color) each time a player takes a turn. The purpose of the game is to enclose in stones a larger portion of the board than one's opponents. Considering that each player has, on average, about 250 possible moves at each turn, and that a game consists of about 150 moves, a computer would need enough memory to hold 250^{150} games, which is on the order of 10^{360} boards. From a resource perspective, Go is more complex than chess, and experts used to believe that no computer software would be able to beat a human Go master within the next decade using the same approach as Deep Blue. Yet a computer system called AlphaGo accomplished it using RL techniques.

DeepMind developed AlphaGo in 2016, which featured Go playing skills never attained before by any hardware or software solution. After setting up the system, DeepMind had AlphaGo test itself against the strongest Go champion living in Europe, Fan Gui, who had been the European Go champion three times. DeepMind challenged him in a closed-door match, and AlphaGo won all the games, leaving Fan Gui amazed by the game style displayed by the computer.

Then, after Fan Gui helped refine the AlphaGo skills, the DeepMind team — led by their CEO, Demis Hassabis, and chief scientist David Silver — challenged Lee

Sedol, a South Korean professional Go player ranked at the ninth dan, the highest level a master can attain. AlphaGo won a series of four games against Lee Sedol and lost only one. Apart from the match it lost because of an unexpected move from the champion, it actually led the other games and amazed the champion by playing unexpected, impactful moves. In fact, both players, Fan Gui and Lee Sedol, felt that playing against AlphaGo was like playing against a contestant coming from another reality: AlphaGo moves resembled nothing they had seen before.

TIP

The story behind AlphaGo is so fascinating that someone made a film out of it, named *AlphaGo*. It's well worth seeing: `tinyurl.com/58hvfs79`.

The DeepMind team that created AlphaGo didn't stop after the success of its solution; it soon retired AlphaGo and created even more incredible systems. First, the team built up AlphaGo Zero, which is AlphaGo trained by playing against itself. Then it created Alpha Zero, which is a general program that can learn to play chess and *shogi,* the Japanese chess game, by itself. If AlphaGo demonstrated how to solve a problem deemed impossible for computers, AlphaGo Zero demonstrated that computers can attain supercapabilities using self-learning (which is RL in its essence). In the end, its results were even better than with those starting from human experience: AlphaGo Zero has challenged the retired AlphaGo and won 100 matches without losing one. Finally, the DeepMind team even perfected Alpha Zero by further developing it into MuZero (see `tinyurl.com/bephn4e8`), an AI algorithm matching Alpha Zero's results in chess and *shogi,* but improving it in Go (thus setting a new world standard) and even Atari games.

REMEMBER

Alpha Zero managed to reach the pinnacle of performance starting with zero data. This capability goes beyond the idea that data is needed to achieve every AI target (as Alon Halevy, Peter Norvig, and Fernando Pereira stated just a few years ago in the white paper at `tinyurl.com/4et9hktx`). Alpha Zero is possible because we know the generative processes used by Go game players, and DeepMind researchers were able to re-create a perfect Go environment.

Understanding reinforcement learning from human feedback

Reinforcement learning from human feedback (RLHF) is a technique that works behind the scenes to make generative AI models, especially Large Language Models (LLMs), more acceptable because they align with human values and expectations. LLMs are trained on a large amount of data collected from the Internet, which cannot truly be completely curated. To give you an idea, Llama 3, the open-weight LLM developed by Meta, has been trained on a dataset of over 15 trillion tokens from publicly available sources, which is seven times larger than the dataset used for its predecessor, Llama 2. The same order of magnitude can certainly be expected from property models such as OpenAI's ChatGPT, Google's Gemini, and

many others. Given such data, it is impossible to have every text closely checked or curated.


REMEMBER

As a rule of thumb, a token corresponds to three-fourths of an English word, meaning that 100 tokens correspond to approximately 75 words. The average written sentence should have 15 to 20 words; a top results page on Google, about 1,500 words; and a best-selling book, around 50,000 to 80,000 words.

Due to the large amount of texts used and the fact that they cannot be easily selected or modified, much of the information going into the model isn't controlled in any way, which could lead to unwanted results. For instance, the model could generate unsuitable content because it is reflecting hate speech, harmful stereotypes or misinformation present in the training data.

Recapping the recent history of GenAI

Generative AI has seen many major advancements since 2016. Each new year brought innovations that pushed the boundaries of these technologies. At this point, we have discussed all the key innovations that contributed to this breakthrough AI technology, from the initial attempts with RNNs and GANs to the advances that brought us the self-attention mechanisms, transformers, GPT architectures, diffusion models, and the RLHF solution for aligning the technology with human values. Before proceeding to discuss the applications and implications of these technologies, let's recap the following milestones and provide a brief look at how Generative AI has evolved:

2013: Google researchers devised Word2vec for natural language processing and for learning word associations and showing the potentiality of embedding the text into a numeric matrix.

2014: Ian Goodfellow pioneered generative adversarial networks (GANs) for the generation of data and images.

2015: Dzmitry Bahdanau and others introduced the attention model for improved neural network performance in translation tasks.

2017: Google researchers proposed the Transformer architecture based on attention mechanisms.

2018: Alec Radford's work on Generative Pre-trained Transformer (GPT) showcases unsupervised learning capabilities. Google implemented transformers into Bidirectional Encoder Representations from Transformers (BERT), a model trained on over 3.3 billion words.

2019: OpenAI released GPT-2, a powerful language model for various applications.

2020: OpenAI released GPT-3, a model with 175 billion parameters, greatly improving its ability to generate human-like text.

2021: OpenAI introduced DALL-E, a model that could generate detailed digital images from text descriptions, demonstrating the potential of *multimodal* (using multiple modes, such as video and text) AI in creative fields. The emergence of diffusion models added a new dimension to Generative AI.

2022: ChatGPT, a conversational AI based on GPT technology by OpenAI, achieved rapid adoption. In addition, Stability AI's Stable Diffusion (a model that produces images based on text descriptions) made art creation more accessible and reduced costs.

2023: The emergence of Generative AI marked a new era of creativity and productivity for businesses and brands. Microsoft integrated ChatGPT technology into Bing, enhancing user experiences. OpenAI introduced GPT-4, further advancing language modeling capabilities. The release of GPT4's multimodal version, which is capable of understanding text and image inputs, illustrates AI's flexibility in handling and creating various content. Meta released the first version of Llama, its large language model, paving the way to multiple new language models based on retraining the Llama model. Microsoft released Phi, a language model built using extremely curated data, inaugurating the new category known as small language models (SLMs), that is, models with 3 billion parameters or fewer.

This timeline is far from being complete. At the time this book has been prepared, halfway through 2024, new models with enhanced capabilities were appearing month after month: GPT-4o (the *o* stands for *omni)*, which can chat in real-time using voice controls; Google's Gemma models, designed with responsible AI development in mind; and Gemini 1.5, Microsoft Phi-3, Meta's Llama 3, and many others.

All such rapid advancements in LLMs denote a blooming spring in AI, with practitioners and society at large trying to absorb and process this high bandwidth of innovation. However, discordant voices are pointing out that, despite the widespread use of Generative AI in many applications, its impact has not been as dramatic as expected (see, for instance, `www.msn.com/en-us/news/technology/openai-and-google-focus-chatbots-on-speed-as-ai-hype-fades/ar-BB1mv78A`).

Working with Generative AI

Generative AI has reshaped how we humans create and interact with digital content across many domains. By leveraging advanced machine learning models, these systems can generate new data mimicking human-like quality and

creativity. In the following list, we explore the primary types of outputs that Generative AI can produce — text, imagery, audio, and synthetic data:

- **Text:** Generative AI models, particularly those based on transformer architectures like GPT, have significantly impacted text generation. These models, trained on huge datasets, enable them to generate contextually relevant text based on input prompts. Applications include content creation for marketing, storytelling, automated customer support, and coding. The ability of these models to produce diverse forms of written content demonstrates their versatility and utility in various professional fields.
- **Imagery:** In visual content, Generative AI initially utilized models such as GANs and variational autoencoders (VAEs) to create detailed and almost realistic images from textual descriptions or modify existing images in novel ways. The field has been revolutionized by tools like Stable Diffusion 3, XL (SDXL) SDXL Turbo, and Adobe Firefly, which demonstrated the capabilities of AI in art and design to higher standards. This enables the generation of everything from product prototypes to abstract art and assists artists and designers in expanding their creative boundaries.
- **Audio:** Generative AI extends its capabilities to audio through models that can synthesize speech, music, and other sound effects. These models can generate realistic human voice simulations or new music compositions. It offers tools for creators in the entertainment and educational sectors. For example, AI-driven music generators can produce background scores for games and videos or assist musicians in exploring new music styles. The technology is also used to develop assistive technologies, such as generating synthetic voices for individuals with speech impairments.
- **Synthetic data:** One major application of Generative AI is generating synthetic data. This data type is crucial for training machine learning models where real data is scarce or sensitive. For example, synthetic AI-generated data in healthcare can simulate patient data for research purposes without compromising privacy. In addition, in autonomous vehicle development, synthetic data helps create varied driving scenarios for training purposes. For instance, GAIA-1 (see `wayve.ai/thinking/scaling-gaia-1`) can generate complete, realistic worlds for self-driving cars to learn how to handle different situations under various settings and weather conditions.

TIP

For more about self-driving vehicles, see Chapter 15.

Creating text using Generative AI

The incredible aspect of Generative AI for language is that such a complex technology can be easy to interact with, using an input field in a search-engine-like

interface or even by voice. However, besides the tricks of the trade that may not work under all circumstances (for instance, at a certain point, someone claimed that LLMs perform better if you promise them a tip: `www.superannotate.com/blog/llm-prompting-tricks`), large language models, when used to generate text and provide solutions to tasks, tend to perform best during these operations:

- **Generation of fresh text:** This involves generating text, ranging from predicting the next token or word to completing phrases and even generating text from instructions.
- **Extraction of elements from documents:** LLMs excel in tasks such as named entity recognition, sentence segmentation, keyword extraction, topic modeling, semantic relationship extraction, and more.
- **Classification of documents:** LLMs are adept at classifying text based on language, intention, sentiment, semantics, and even nuanced concepts such as sarcasm, irony, or negation.
- **Transformation of existing text:** LLMs can transform text through operations such as translation, correction, style modification, paraphrasing, and summarization.
- **Comprehension of text and problems:** LLMs can help comprehension, and they provide question answering, reasoning, and knowledge completion. Some applications, such as retrieval-augmented generation (RAG), allow the LLM to act as a search engine, retrieving information and then summarizing an answer for you, even to complex questions requiring a certain expertise and domain knowledge.
- **Coding:** LLMs can replace a programmer in various computer languages and operating systems when required to create simple computer programs or functions.

All these tasks are achieved by using a prompt, which contains explicit instructions, questions, or contextual information that you want to pose to the AI model in order to get an answer back. The process works as follows:

1. You may state a role for the AI.

   You can ask the AI to impersonate a skilled writer, programmer, or expert in ancient history. The required impersonation should be relevant to the task you need for the LLM. Behind the scenes, your request helps the model focus on only certain parts of its neural network, containing the information you may need.

2. You state your request.

As a best practice, try to be concise and clear. If you can state what you want without too many details or ambiguous words, it's easier for the LLM to execute your task. In addition, consider that — because you need to state in a clear way what you want — you should not forget to also state what you actually *don't* want, although affirmations tend to work better than negations.

3. If you're asking for a task, show some examples.

   This is called a one-shot request (if you're providing only one example) or a few-shot request. An example of what you expect as a result from the AI, helps the AI focus on only certain possible parts of its network and resulting outputs. If you aren't showing any example, this is a zero-shot request and you're relying on its own unique capabilities to disentangle your request.

4. Optionally, state guidance on how you expect the output.

   For instance, you may require the answer to be short, contain fewer than a certain number of characters, or even be formatted in a specific way, such as being enclosed in a data structure suitable for a programming language.

These are just general guidelines, but remember that each AI differs from the others and that not every prompt always works everywhere. Prompting still seems more an art than a science. Trial and error in various experiments may be necessary to obtain what you expect.

TIP

If you find yourself needing or wanting to know more about the ins and outs of effective prompting, check out *Generative AI For Dummies*, by Pam Baker (Wiley).

Creating images using Generative AI

As with text, you can also use instructions to create an image, following a similar approach as we have discussed with text. It's important to point out that you're working with image creation, and you have to consider creative aspects in your prompt, such as these:

- **Describe the image in detail**, including the setting, the object, and the subject and, if the subject is human, define the gender, age, mood, actions, and expressions for the best result.
- **Provide preferred framing and light details.** Framing options could be, for instance, dramatic, wide-angle, or close-up. As for light details, you could mention morning, daylight, evening, golden hour, darkness, firelight, or flashlight, for instance.

- **Specify the aesthetic style.** You might prefer, for example, watercolor, sculpture, digital art, or oil painting. You can also request specific artistic styles, such as impressionist, or specify an artist such as Monet. Please note that many contemporary artists are currently opposing GenAI companies, alleging that GenAI has plagiarized their work (watch the YouTube video "AI vs Artists — The Biggest Art Heist in History" to learn about their stance: `www.youtube.com/watch?v=ZJ59g4PV1AE`) and that certain outputs from an image generator may represent a problem for an artist.
- **Indicate the desired coloring and realism.** Point out the color palette you want and the level of realism, ranging from abstract to cartoonish to photorealistic.

As mentioned, when dealing with text generation, be prepared to experiment and test a lot. Consulting repositories of AI-generated images — such as Lexica (`lexica.art`), PromptMid (`midprompteria.com`), or ArtHub (`arthub.ai/library`) — may provide you with ideas and hints about specialized keywords to obtain the artistic nuances you look for in your image.

Understanding the Societal Implications of Generative AI

Generative AI is transforming many aspects of society, from creating and consuming content to managing data security. Its huge impact prompts discussions on its benefits and risks and the need for careful management. In the next several sections, we explore the societal implications of Generative AI.

Managing media hype

When new technology is introduced, people tend to fear the unforeseen consequences. This fear can lead to heightened expectations or unnecessary anxiety. The hype surrounding Generative AI can be managed by distinguishing between its real capabilities and its overhyped claims.

Media outlets and stakeholders in the AI industry must work to present an informative view that highlights the advancements and the limitations of Generative AI. This involves debunking myths and providing clear, accurate information to prevent misinformation.

Promoting positive uses

Generative AI holds great potential for positive impact across the entire world — in these areas, for example:

- **Content creation:** Generative AI enhances productivity and creativity, helping marketers, writers, and artists generate new ideas and material more quickly and effectively.
- **Healthcare:** Generative AI aids pharmaceutical development and patient diagnoses. It could potentially revolutionize medical research and treatment outcomes.
- **Education:** Generative AI can personalize learning and adapt content to fit individual learning styles, which would help learners worldwide succeed and improve their living standards.

Addressing security concerns

Security is always a concern when new technology is introduced. Bad actors are always willing to exploit something new. The following are two main concerns that people are grappling with regarding AI:

- **Deepfakes:** One of the most concerning security implications of Generative AI is the creation of *deepfakes* — these are highly realistic and convincing images, videos, or audio recordings manipulated to portray events or statements that never occurred. Indeed, although the technology can be used for misleading-yet-acceptable commercial practices, such as having your favorite seller always on sales livestreaming (`www.technologyreview.com/2023/09/19/1079832/chinese-ecommerce-deepfakes-livestream-influencers-ai`), there have already been cases of phone and video call fraud achieved using this technology.

  Deepfakes pose significant risks in spreading misinformation and influencing public opinion. To combat these risks, developing sophisticated detection technologies and promoting public awareness about the nature of deepfakes is crucial.

  
  TIP

  Legal frameworks and regulations should be updated to address the challenges posed by these technologies, ensuring accountability and preventing misuse.
- **Data privacy and cybersecurity risks:** Generative AI raises substantial data privacy and cybersecurity concerns. Technology can expose sensitive personal or corporate data if not properly managed. Organizations must implement strong data governance and cybersecurity measures, such as data encryption, secure data storage, and compliance with privacy regulations.

Attempting to mimic human creativity

Generative AI has made strides in mimicking human creativity, sparking debates about the nature of creativity and the role of AI in the creative process. The technology utilizes advanced machine learning algorithms to generate new content that imitates human-generated outputs in complexity and appeal.

REMEMBER

Generative AI's ability to imitate human creativity challenges traditional notions of art and authorship. Though it isn't a substitute for the human touch in creative works, it can act as a powerful assistant to expand the boundaries of what is possible.

Understanding the illusion of creativity

As you may have seen, Generative AI learns from huge datasets containing human-created content. Then it applies learned patterns to generate new works. This process can give the illusion of creativity. The AI can produce work that seems original to human observers. However, it's important to note that these systems don't possess personal experiences, emotions, or consciousness, which are integral to human creativity.

Reviewing human versus machine creativity

The debate about creativity often centers on whether AI truly "creates" or just repeats back modified versions of its training data. Though AI can produce art, music, and literary works that seem novel, these are often the results of probabilistic calculations and pattern recognition rather than a conscious, emotional response to the world. Various experiments have demonstrated that, under certain prompts, a GenAI model can just return the data it initially received during training. For instance, in this article, some iconic photos are easily re-created from image models such as DALL-E 3 and Midjourney v6, implying that they have been memorized: `petapixel.com/2024/03/07/recreating-iconic-photos-with-ai-image-generators`.

Enhancing human creativity

Despite these perceived limitations, Generative AI is a valuable tool for enhancing human creativity. Content creators use AI to overcome creative blocks and generate new ideas. This collaboration between humans and machines augments creativity, which allows for hybrid works that are innovative.

Defining the side effects

AI apps are never perfect. Here are several factors to watch for when using them:

- **Accuracy:** Accuracy in AI refers to the degree to which an AI model's predictions or outputs match expected outcomes. Though AI can achieve high levels of accuracy, especially in pattern recognition and predictive analytics, inaccuracies can still happen. This is due to factors like inadequate training data, model overfitting, or algorithmic limitations. These inaccuracies can lead to errors in the decision-making process, particularly in critical areas like healthcare, where they might result in incorrect diagnoses or faulty treatment recommendations.

  
  REMEMBER

  Overfitting happens when a model learns the details and noise in the training data to the extent that it negatively impacts the model's performance on new data.

- **Bias:** Bias arises when the algorithms produce prejudiced results due to biased training data or flawed algorithm design. This can be displayed in various forms, such as racial bias, gender bias, or socioeconomic bias. This leads to unfair outcomes in recruitment, law enforcement, loan approvals, and other significant areas of life.

- **Hallucinations:** AI hallucinations occur when AI systems generate false or misleading information. This can happen due to overfitting, insufficient or noisy training data, or the AI's inherent inability to understand context or reality. Some researchers, such as Andrej Karpathy, former AI director at Tesla and one of the initial OpenAI founders, claims that hallucinations are a characteristic of Generative AI — that is, they're intrinsic to the way they work — and that the problem cannot be solved in any way.

  Hallucinations are particularly problematic in fields requiring high accuracy and reliability, such as medical writing, legal documentation, and scientific research, where they can lead to misinformation and possibly dangerous outcomes. For a more in-depth look at the issue of hallucinations, see "What Are AI Hallucinations?" (`builtin.com/artificial-intelligence/ai-hallucination`).

- **Weird answers:** AI can sometimes produce bizarre or completely irrelevant responses to queries, often called "weird answers." These can result when the AI misinterprets the query, errors occur in data processing, or limitations pop up in the AI's understanding of complex or ambiguous language. Though these responses can be humorous, they can also be confusing. They may erode user trust in AI systems, especially when users rely on AI for accurate information or decision-making.

Deciding What Makes a Good Generative AI App

Evaluating a Generative AI application involves examining the aspects that contribute to its effectiveness and user satisfaction. In the next few sections, we look at some criteria you may consider when evaluating whether you have a good Generative AI app. They include accuracy, reliability, user experience, innovation, scalability and performance, and economic and ethical considerations. We look at each in turn.

Assessing accuracy and reliability

A fundamental criterion for any Generative AI application is its accuracy and reliability. These applications should produce correct and appropriate outputs that meet the user's needs.

REMEMBER

The reliability of AI tools ensures that professionals can trust them to make critical decisions. This involves rigorous testing and updates to adapt to new data and changing conditions to ensure that the AI's outputs remain accurate.

The implications of inaccuracies in AI outputs can be significant, particularly in critical domains such as healthcare and finance. For example:

- **Healthcare:** Inaccurate outputs can lead to misdiagnoses, inappropriate treatment plans, and possibly patient harm. For example, if an AI system incorrectly identifies a benign condition as malignant, it can cause unnecessary anxiety for the patient and lead to invasive treatments that are not needed.
- **Finance:** AI tools can be used for fraud detection and risk assessment tasks. Unreliable AI can result in false positives or negatives in fraud detection, leading to financial losses, damage to customer relationships, and possibly regulatory penalties.

WARNING

Constant monitoring is essential to ensure the accuracy and reliability of AI models. AI systems can drift over time due to changes in the underlying data they were trained on (known as *model drift*). As new data becomes available, AI models may no longer perform correctly unless updated to reflect these changes. Continuous monitoring helps detect this drift early and can prompt timely updates to the model.


REMEMBER

Updating AI models involves retraining them with new data, refining algorithms, or redesigning the system architecture to improve performance and accuracy. This process is crucial for maintaining the trust and dependability of AI applications across all sectors.

Enhancing the user experience

The user experience encompasses an application's ease of use, interface design, and overall satisfaction. A well-designed Generative AI app should have an intuitive interface that works for both novice and experienced users. You want to present easy navigation and a minimal learning curve. For example, AI-driven design tools should offer customizable templates and interactive elements to assist users in creating designs without needing extensive graphical design knowledge. User satisfaction is significantly enhanced when the application reduces complexity and makes technology accessible to a broader audience.

Implementing innovation

Innovation in Generative AI applications refers to introducing new capabilities or improving existing technologies. An innovative AI app might offer unique features that distinguish it from conventional tools, such as NLP capabilities to understand and generate human-like text based on contextual distinctions. For marketers, an innovative Generative AI could automatically create and optimize content across multiple platforms, adapting the tone and style to each audience segment. This pushes the boundaries of traditional content creation tools.

Monitoring stability and performance

A Generative AI application's performance efficiency and scalability are vital for long-term success. The app should handle expanding data sets and growing number of users without affecting performance. This involves optimizing algorithms for speed and efficiency and using scalable cloud infrastructure to manage workload increases. For example, an AI-powered analytics tool should process large datasets to deliver real-time insights, enabling businesses to quickly make informed decisions.

Looking at ethical considerations

Ethical considerations are crucial in the development and deployment of Generative AI applications. This includes addressing bias issues, where you must train an AI on diverse data to avoid perpetuating stereotypes.

Privacy is another critical concern. These applications should be designed to protect user data and comply with regulations like the General Data Protection Regulations (GDPR). Also, security measures must be powerful enough to prevent unauthorized data access. An ethically designed AI app encourages trust and ensures that the technology is used responsibly.

Identifying economic considerations

When assessing criteria, it's important to evaluate the economic feasibility and effectiveness of Generative AI applications. You should consider the following financial factors that directly impact the overall value and sustainability of the investment; these considerations are particularly relevant for business users who need to justify the costs of using these technologies against the expected benefits:

- **Assessing cost-effectiveness:** Cost-effectiveness is key in assessing Generative AI applications. This evaluation includes examining the direct and indirect costs of deploying and operating the AI system.
- **Understanding direct costs:** Direct costs are tied to the AI system's development, implementation, and maintenance. This encompasses software acquisition and hardware investments (if necessary) and the costs of training the AI models with sufficient data. These factors should also be considered if the AI application requires ongoing licensing fees or subscriptions.
- **Evaluating indirect costs:** Indirect costs are often less obvious but can significantly impact the total cost of ownership. These costs may include the time employees spend interacting with and training the AI system, potential downtime or disruptions during integration, and any long-term maintenance or unexpected updates. If the AI application leads to inefficiencies or requires additional oversight, these factors also contribute to the indirect costs.

Maximizing ROI potential

Another critical economic consideration is the potential for a return on investment (ROI). For Generative AI applications, there are several ways to consider accomplishing it:

- **Enhancing direct revenue generation:** Some Generative AI applications can directly contribute to revenue generation. For example, AI-driven personalization in e-commerce can increase sales by suggesting products customized to user preferences. Also, AI applications in marketing can generate new leads or enhance customer engagement through personalized campaigns. These can directly impact the bottom line.

- **Implementing efficiency improvements:** Efficiency improvements are a more indirect form of ROI but are equally important. Generative AI can automate routine tasks, reduce the need for manual labor, and speed up processes. This lowers operational costs and improves service delivery. For example, AI in customer service can handle routine inquiries without human contact, allowing staff to focus on higher-priority issues. This reduces labor costs and can also improve response times and customer satisfaction.
- **Leveraging strategic advantages:** Beyond measurable financial gains, Generative AI can provide strategic advantages that, though harder to quantify, contribute to long-term ROI. These include enhanced decision-making capabilities from predictive analytics, improved product innovation through data-driven insights, and stronger competitive positioning by leveraging advanced technology.


TIP

For businesses, investing in Generative AI technology should involve a careful analysis of both the costs and the potential returns. This includes considering the solution's scalability, the compatibility with current systems, and the ability to adapt to upcoming needs.

Commercializing Generative AI

The commercialization of Generative AI represents a shift in the view of technology and business. It offers new opportunities for innovation, enhanced efficiency, and user experiences. Companies need to develop a strong understanding of their capabilities and challenges to deliver the power of Generative AI.

Viewing the GPT store

The GPT Store, launched by OpenAI, is a marketplace where developers and businesses can explore, utilize, and share GPT models. This platform is important for commercializing Generative AI because it provides a centralized location to access a diverse range of GPT models developed by OpenAI's partners and the community. Users can browse categories such as DALL-E3, writing, research, programming, and education.


TIP

The store enables the discovery of innovative GPT models and provides a mechanism for developers to monetize their apps. By submitting their GPT models to the store, developers can reach a wider audience and potentially earn money based on their application's usage.

CONSIDERING STRATEGIC APPROACHES

Businesses can capitalize on the benefits of Generative AI in several ways. Consider these strategic approaches when planning to commercialize your app:

- **Investing in quality data:** Building or acquiring high-quality datasets to train AI models, which is crucial for generating accurate and relevant output
- **Focusing on niche applications:** Identifying specific problems or opportunities where Generative AI can provide significant advantages or innovations
- **Looking at partnerships and collaboration:** Engaging with technology providers, research institutes, and industry partners to share knowledge, resources, and best practices
- **Utilizing continuous learning and adaptation:** Staying updated with AI advancements and continually adapting strategies in response to technological and market developments
- **Creating an ethical AI framework:** Proactively developing a framework to address ethical considerations, which ensures transparency, accountability, and public trust in AI applications

Looking at basic app creation techniques

Creating a Generative AI app involves several key steps that leverage the capabilities of AI to generate unique content or solutions tailored to specific user needs:

- **Defining the problem:** Developers must first define the problem they want to solve.
- **Collecting the data:** Once the problem is defined, they need to gather relevant data to inform the AI model.
- **Choosing the model:** Following data collection, the next step involves choosing the AI model and algorithm that best fits the application. This could range from text generation to code generation or image creation.
- **Training the model:** Developers need to train the model. They should make sure it learns the appropriate patterns and nuances of the data.
- **Testing performance:** After training, the model should be tested and refined to optimize performance and accuracy.
- **Deploying the app:** The app is deployed, allowing users to interact with the AI in a real-world setting. Throughout this process, user interface design, functionality, and user experience are critical to ensuring the app's success and usability.


TIP

For an in-depth discussion about Generative AI app creation, see "Deploying an application with Generative AI best practices" on the Google for Developers channel (`www.youtube.com/watch?v=dRf4DdA1o5c`).

Monetizing your Generative AI app

Monetizing a Generative AI app can be approached in several ways, depending on the application's characteristics and target market. Here are several models to consider:

- **Subscription:** In this model, users pay to access the app or specific features. This model is appropriate for apps that offer substantial value for productivity enhancements or capabilities that are unavailable elsewhere.

  
  TIP

  You can offer multiple tiers to cater to user needs and budgets when using a subscription app. Consider including a trial period to allow users to experience the full capabilities before committing to a subscription. This makes it easier for them to buy.

- **Freemium:** This represents a model where the basic app is free but users pay for premium features. This method can initially attract a larger user base, converting users to paid plans when they want more advanced features.

  
  REMEMBER

  For freemium apps, make sure to differentiate between free and premium features. Make the transition from free to premium seamless and help customers understand the value of upgrading.

- **In-app:** Developers can implement in-app advertising or sponsorships, especially if the app attracts many users. This method can be effective if the app's content is regularly updated and keeps users engaged.

- **Licensing:** You can license your technology to other businesses. This model is for apps with unique algorithms or capabilities you can integrate into different products.


TIP

Choosing the right monetization strategy for your Generative AI app depends on knowledge of your target market, the unique value your app provides, and the way users interact with your app.

Addressing the regulatory environment in commercializing Generative AI

The regulatory environment is a crucial aspect of commercializing Generative AI that requires careful consideration. Governments worldwide are increasingly

focusing on creating frameworks to ensure that these technologies are safe and ethical and do not infringe on personal rights. The next few sections look at why regulatory considerations are essential.

Complying with data protection laws

Generative AI relies on massive amounts of data to train and operate effectively, which raises important concerns about privacy and data protection. For example, regulations like the General Data Protection Regulation (GDPR) in the European Union and the California Consumer Privacy Act (CCPA) in the United States impose strict data collection, processing, and storage guidelines. Developers must ensure that their AI applications comply with these and similar regulations to avoid substantial fines and reputational damage.

Reviewing intellectual property issues

Generative AI can create content that infringes on existing intellectual property (IP) rights. For example, an AI that generates music, art, or written content could replicate copyrighted material without authorization. Navigating IP law is crucial to ensure that generative applications are deployed in a way that respects existing copyrights and trademarks. This could require mechanisms to attribute original creators or avoid generating copyrighted content.

Navigating sector-specific regulations

Depending on the application of AI, sector-specific regulations may apply. For instance, AI tools used in healthcare must comply with laws such as the Health Insurance Portability and Accountability Act (HIPAA) in the United States or the Medical Device Regulation (MDR) in the EU. Also, financial applications must adhere to regulations governing financial conduct and data handling.

Meeting international standards

International standards and norms also become important as AI technologies cross borders by way of global services. Compliance with international guidelines, such as those developed by the International Organization for Standardization (ISO) or the International Electrotechnical Commission (IEC), can help standardize the deployment of AI technologies globally.

REMEMBER

Companies that proactively engage with these issues can create more sustainable AI solutions.

IN THIS CHAPTER

- Defining and using AI in applications
- Using AI for corrections and suggestions
- Tracking down potential AI errors

Chapter 9
Seeing AI Uses in Computer Applications

You have likely used AI in some form in many of the computer applications you rely on for your work. For example, talking to your smartphone requires the use of a speech recognition AI. Likewise, an AI filters out all that junk mail that could arrive in your Inbox. The first part of this chapter discusses AI application types, many of which will surprise you, and the fields that commonly rely on AI to perform a significant number of tasks. You also learn about a source of limitations for creating AI-based applications, which helps you understand why sentient robots may not ever happen — or not with the currently available technology, at least.

However, regardless of whether AI ever achieves sentience, the fact remains that AI does perform a significant number of useful tasks. The two essential ways in which AI currently contributes to human needs are through corrections and suggestions. You don't want to take the human view of these two terms. A correction isn't necessarily a response to a mistake. Likewise, a suggestion isn't necessarily a response to a query. For example, consider a driving-assisted car (one in which the AI assists rather than replaces the driver). As the car moves along, the AI can make small corrections that allow for driving and road conditions, pedestrians, and a wealth of other issues in advance of an actual mistake. The AI takes a proactive approach to an issue that may or may not occur. Likewise, the AI can suggest to the human driving the car a certain path that may present the greatest

likelihood of success, only to change the suggestion later based on new conditions. The second part of this chapter considers corrections and suggestions separately.

The third main part of this chapter discusses potential AI errors. An error occurs whenever the result is different from the one that's expected. The result may be successful, but it might remain unexpected. Of course, outright errors occur, too: An AI may not provide a successful result. Perhaps the result even runs counter to the original goal (possibly causing damage).


TIP

If you get the idea that AI applications provide gray, rather than black or white, results, you're well on the road to understanding how AI modifies typical computer applications, which do in fact provide either an absolutely correct or absolutely incorrect result.

Introducing Common Application Types

Just as the only thing that limits the kinds of procedural computer application types is the imagination of the programmer, so many AI applications appear in any venue for just about any purpose, most of which no one has thought of yet. In fact, the flexibility that AI offers means that some AI applications may appear in places other than those for which the programmer originally defined them. Someday, AI software may well even write its own next. However, to obtain a better idea of just what makes AI useful in applications, it helps to view the most commonly applied uses for AI today (and the potential pitfalls associated with those uses), as described in the sections that follow.

Using AI in typical applications

You might find AI in places where it's hard to imagine using an AI. For example, your smart thermostat for controlling home temperature could contain an AI if the thermostat is complex. The use of AI, even in these particularly special applications, truly does make sense when the AI is used for tasks that AI does best, such as tracking preferred temperatures over time to automatically create a temperature schedule. Here are some of the more typical uses of AI that you'll find in many places:

- Artificial creativity
- Computer vision, virtual reality, and image processing
- Diagnosis

AI EXPLOITS

Not every use of AI is aboveboard and honest. Hackers can use AI hacks to attack AI applications to force them to perform in ways the creator never envisioned.

One of the AI exploits that has the potential for creating serious problems, however, is the *deep fake* (the impersonation of someone by an AI to say or do things the real person would never do). The article "The Year Deepfakes Went Mainstream" at `www.technologyreview.com/2020/12/24/1015380/best-ai-deepfakes-of-2020/` describes the technology in some detail. However, reading about a deep fake and seeing one in action are two different experiences. Watch the deep fake of former President Obama at `www.youtube.com/watch?v=AmUC4m6w1wo` and you begin to understand the truly evil purposes to which some people can apply AI. Of course, this new use of AI is creating serious problems for the court system, as described in "Courts and lawyers struggle with the growing prevalence of deepfakes" at `www.abajournal.com/web/article/courts-and-lawyers-struggle-with-growing-prevalence-of-deepfakes`.

- Face recognition
- Game artificial intelligence, computer game bot, game theory, and strategic planning
- Handwriting recognition
- Natural language processing, translation, and chatterbots
- Nonlinear control and robotics
- Optical character recognition
- Speech recognition

Realizing AI's wide range of fields

Applications define specific kinds of uses for AI. You can also find AI used more generically in specific fields of expertise. The following list contains some fields where AI commonly makes an appearance:

- Artificial life
- Automated reasoning
- Automation

- Biologically inspired computing
- Concept mining
- Data mining
- Email spam filtering
- Hybrid intelligent system
- Intelligent agent and intelligent control
- Knowledge representation
- Litigation
- Robotics: behavior-based, cognitive, cybernetic, developmental (epigenetic), and evolutionary
- Semantic web

Seeing How AI Makes Applications Friendlier

You can view the question of application friendliness addressed by AI in a number of different ways. At its most basic level, an AI can provide anticipation of user input. For example, when the user has typed just a few letters of a particular word, the AI guesses the remaining characters. By providing this service, the AI accomplishes several goals:

- The user becomes more efficient by typing fewer characters.
- The application receives fewer errant entries as the result of typos.
- The user and application both engage in a higher level of communication by prompting the user with correct or enhanced terms that the user might not otherwise remember, avoiding alternative terms that the computer may not recognize.

An AI can also learn from previous user input in reorganizing suggestions in a way that works with the user's method of performing tasks. This next level of interaction falls within the realm of suggestions described in the "Making Suggestions" section, later in this chapter. Suggestions can also include providing the user with ideas that the user might not have considered otherwise.

WARNING

Even in the area of suggestions, humans may begin to believe that the AI is thinking, but it isn't — the AI is performing an advanced form of pattern matching as well as analysis to determine the probability of the need for a particular input.

Using an AI also means that humans can now exercise other kinds of intelligent input. The example of voice is almost overused, but it remains one of the more common methods of intelligent input. However, even if an AI lacks the full range of senses, as described in Chapter 4, it can provide a wide variety of nonverbal intelligent inputs. An obvious choice is visual, such as recognizing the face of its owner or a threat based on facial expression. However, the input could include a monitor, possibly checking the user's vital signs for potential problems. In fact, an AI could use an enormous number of intelligent inputs, most of which aren't even invented yet.

Currently, applications generally consider just these first three levels of friendliness. Aristotle identified three distinct levels of friendship, each with unique characteristics and contributions to our lives:

1. **Friendships of utility:** These relationships are based on mutual benefits and practical support, such as coworkers who help each other with tasks or neighbors who help with chores.
2. **Friendships of pleasure:** These friendships are formed around shared enjoyment and activities, like friends who bond over hobbies, sports, or social events, providing entertainment and companionship.
3. **Friendships of the good:** The highest form of friendship, based on mutual respect and admiration for each other's virtues, where both individuals inspire and support each other to grow morally and ethically.

As AI intelligence increases, however, it becomes essential for an AI to exhibit friendly artificial intelligence (FAI) behaviors consistent with an artificial general intelligence (AGI) that has a positive effect on humanity. AI has goals, but those goals may not align with human ethics, and the potential for misalignment now causes angst. An FAI would include logic to ensure that the AI's goals remain aligned with humanity's goals, similar to the three laws found in Isaac Asimov's books, which we cover in more detail in Chapter 13. However, many experts say that the three laws are just a good starting point and that we need further safeguards.

TIP

Of course, all this discussion about laws and ethics could prove quite confusing and difficult to define. A simple example of FAI behavior is that the FAI might refuse to disclose personal user information unless the recipient has a need to know. In fact, an FAI could go even further by pattern-matching human input and locating potential personal information within it, notifying the user of the

potential for harm before sending the information anywhere. The point is that an AI can significantly change how humans view applications and interact with them.

Performing Corrections Automatically

Humans constantly correct everything. It isn't a matter of everything being wrong. Rather, it's a matter of making (or at least trying to make) everything slightly better. Even when humans manage to achieve just the right level of rightness at a particular moment, a new experience brings that level of rightness into question because now the person has additional data by which to judge the whole question of what constitutes right in a particular situation. To fully mimic human intelligence, AI must also have this capability to constantly correct the results it provides, even if the current results are already fine. The following sections discuss the issue of correctness and examine how automated corrections sometimes fail.

Considering the kinds of corrections

When most people think about AI and correction, they think about the spell checker or grammar checker. A person makes a mistake (or at least the AI thinks so), and the AI corrects this mistake so that the typed document is as accurate as possible. Of course, humans make lots of mistakes, so having an AI to correct them is a good idea.

Corrections can take all sorts of forms, and they don't necessarily mean that an error has occurred or will occur in the future. For example, a car might assist a driver by making constant lane position corrections. The driver might be well within the limits of safe driving, but the AI could provide these micro-corrections to help ensure that the driver remains safe.

Taking the whole correction scenario further, imagine that the car in front of the car containing the AI makes a sudden stop because of seeing a deer in the road. The driver of the current car hasn't committed any sort of error. However, the AI can react faster than the driver can and can act to stop the car as quickly and safely as possible to address the now-stopped car in front of it.

Seeing the benefits of automatic corrections

When an AI sees the need for a correction, it can either ask the human for permission to make the correction or make the change automatically. For example, when

someone uses speech recognition to type a document and makes an error in grammar, the AI should ask permission before making a change, because the human may have actually meant the word or the AI may have misunderstood what the human meant.

However, sometimes the AI *must* provide a robust enough decision-making process to perform corrections automatically. For example, when considering the lane position scenario from the previous section, the AI doesn't have time to ask permission: It must apply the brake immediately or else the human could die from the crash. Automatic corrections have a definite place when working with an AI, assuming that the need for a decision is critical and the AI is robust.

Understanding why automated corrections don't always work

AI can't actually understand anything. Without understanding, it doesn't have the capability to compensate for an unforeseen circumstance. In this case, the unforeseen circumstance relates to an unscripted event, one in which the AI can't accumulate additional data or rely on other mechanical means to solve. A human can solve the problem because a human understands the basis of the problem and usually enough of the surrounding events to define a pattern that can help form a solution. In addition, human innovation and creativity provide solutions where none are obvious by other means. Given that an AI currently lacks both innovation and creativity, the AI is at a disadvantage in solving specific problem fields.

To put this issue into perspective, consider the case of a spelling checker. A human types a perfectly legitimate word that doesn't appear in the dictionary used by the AI for making corrections. The AI often substitutes a word that looks close to the specified word but is still incorrect.


REMEMBER

Even after the human checks the document, retypes the correct word, and then adds it to the dictionary, the AI is still apt to make a mistake. For example, the AI could treat the abbreviation *CPU* differently from *cpu* because the former appears in uppercase and the latter in lowercase. A human would see that the two abbreviations are the same and that, in the second case, the abbreviation is correct but may need to appear in uppercase instead.

Making Suggestions

A suggestion is different from a command. Even though some humans seem to miss the point entirely, a *suggestion* is simply an idea put forth as a potential solution to a problem. Making a suggestion implies that other solutions might exist

and that accepting a suggestion doesn't mean automatically implementing it. In fact, the suggestion is only an idea — it may not even work. Of course, in a perfect world, all suggestions would be good suggestions — at least possible solutions to a correct output, which is seldom the case in the real world. The following sections describe the nature of suggestions as they apply to an AI.

Getting suggestions based on past actions

The most common way an AI creates a suggestion is by collecting past actions as events and then using those past actions as a dataset for making new suggestions. For example, someone purchases a Half-Baked Widget every month for three months. It makes sense to suggest buying another one at the beginning of the fourth month. In fact, a truly smart AI might make the suggestion at the right time of the month. For example, if the user makes the purchase between the third and fifth days of the month for the first three months, it pays to start making the suggestion on the third day of the month and then move on to something else after the fifth day.

Humans output an enormous number of clues while performing tasks. Unlike the average human, an AI actually pays attention to every one of these clues and can record them in a consistent manner to create *action data*. The action data varies by the task being performed; it can include info like interactions with a device, sequences for making selections, body position, facial expression, manner of expression (such as attitude), and so on. By collecting action data consistently, an AI can provide suggestions based on past actions with a high degree of accuracy in many cases.

Getting suggestions based on groups

Another common way to make suggestions relies on group membership. In this case, group membership need not be formal. A group can consist of a loose association of people who have some minor need or activity in common. For example, a lumberjack, a store owner, and a dietician could all buy mystery books. Even though they have nothing else in common, not even location, the fact that all three like mysteries makes them part of a group. An AI can easily spot patterns like this that might elude humans, so it can make good buying suggestions based on these rather loose group affiliations.

Groups can include ethereal connections that are temporary at best. For example, all the people who flew flight 1982 out of Houston on a certain day could form a group. Again, no connection whatsoever exists between these people except that they appeared on a specific flight. However, by knowing this information, an AI

could perform additional filtering to locate people within the flight who like mysteries. The point is that an AI can provide good suggestions based on group affiliation even when the group is difficult (if not impossible) to identify from a human perspective.

Obtaining the wrong suggestions

Anyone who has spent time shopping online knows that websites often provide suggestions based on various criteria, such as previous purchases or even searches. Unfortunately, these suggestions are often wrong because the underlying AI lacks understanding. For example, if you're an author of a book and you look at your book's statistics on Amazon, the Amazon AI will consistently recommend that you buy copies of your book no matter what you might want to do about it.

As another example, when someone makes a once-in-a-lifetime purchase of a Super-Wide Widget, a human would likely know that the purchase is indeed once in a lifetime because it's extremely unlikely that anyone will need two. However, the AI doesn't understand this fact. So, unless a programmer specifically creates a rule specifying that a Super-Wide Widget is a once-in-a-lifetime purchase, the AI may choose to keep recommending the product because sales are understandably small. In following a secondary rule about promoting products with slower sales, the AI behaves according to the characteristics that the developer provided for it, but the suggestions it makes are outright wrong.

Besides rule-based or logic errors in AIs, suggestions can become corrupted by data issues. For example, a GPS might make a suggestion based on the best possible data for a particular trip. However, road construction might make the suggested path untenable because the road is closed. Of course, many GPS applications do consider road construction, but they sometimes don't consider other issues, such as a sudden change in the speed limit or weather conditions that make a particular path treacherous. Humans can overcome a lack of data by way of innovation, such as by using the less traveled road or understanding the meaning of detour signs.

When an AI manages to get past the logic, rule, and data issues, it sometimes still makes bad suggestions because it doesn't understand the correlation between certain datasets in the same way a human does. For example, the AI may not know to suggest paint after a human purchases a combination of pipe and drywall when making a plumbing repair. The need to paint the drywall and the surrounding area after the repair is obvious to a human because a human has a sense of aesthetics that the AI lacks. The human makes a correlation between various products that isn't obvious to the AI.

Considering AI-Based Errors

An outright error occurs when the result of a process, given specific inputs, isn't correct in any form. The answer doesn't provide a suitable response to a query. It isn't hard to find examples of AI-based errors. The point is that AI still has a high error rate in some circumstances, and the developers working with the AI are usually unsure why the errors even occur.

The sources of errors in AI are many. However, as noted in Chapter 1, AI can't even emulate all eight forms of human intelligence, so mistakes are not only possible but also unavoidable. Much of the material in Chapter 2 focuses on data and its impact on AI when the data is flawed in some way. In Chapter 3, you also find that even the algorithms that AI uses have limits. Chapter 4 points out that an AI lacks access to the same number or types of human senses.

A major problem that's becoming more and more evident is that corporations often gloss over or even ignore problems with AI. The emphasis is on using AI to reduce costs and improve productivity, which may not be attainable. One of the more interesting, but disturbing, examples of a corporate entity going too far with AI, which happened several years ago, is Microsoft's Tay. Tay was maliciously trained to provide racist, sexist, and pornographic remarks in front of a large crowd during a presentation (see "Microsoft's chatbot gone bad, Tay, makes MIT's annual list of biggest technology fails" at GeekWire.com).

REMEMBER

The valuable nugget of truth to take from this section isn't that AI is unreliable or unusable. In fact, when coupled with a knowledgeable human, AI can make its human counterpart fast and efficient. AI can enable humans to reduce common or repetitive errors. In some cases, AI mistakes can even provide a bit of humor in the day. However, AI doesn't think, and it can't replace humans in many dynamic situations today. AI works best when a human reviews important decisions or the environment is so static that good results are predictably high (well, as long as a human doesn't choose to confuse the AI).

IN THIS CHAPTER

- Using AI to meet human needs
- Making industry more efficient
- Developing dynamic safety protocols using AI

Chapter 10
Automating Common Processes

Chapter 9 considers the use of AI in an *application,* which is a situation in which a human interacts with the AI in some meaningful way, even if the human is unaware of the presence of the AI. The goal is to help humans do something faster, easier, or more efficiently, or to meet some other need. A *process* that includes an AI is different because the AI is now working to assist a human or perform some other task without direct intervention. The first section of this chapter addresses how processes help humans. Given that boredom is possibly the worst-case human scenario (just think of all the negative things that happen when humans are bored), this chapter views the AI process for humans from a boredom perspective.

One of the ways AI has been in use the longest is industrial utilization, such as manufacturing processes, to allow for Industry 4.0 implementation. Industry 4.0 refers to the fourth industry revolution, which includes technology like the Internet of Things and cloud computing (see "What is Industry 4.0?" at `www.twi-global.com`).

Consider all the robots that now power factories across the world. Even though AI-powered automation replaces humans, it also keeps humans safer by performing tasks generally considered dangerous. Oddly enough, one of the most significant causes of industrial accidents and a wealth of other problems is boredom, as

explained in "Boredom at work" at www.bps.org.uk/psychologist/boredom-work. The article "How to make your boredom work for you" at www.fastcompany.com does try to turn things around, but still, boredom can be — and is — dangerous. Robots can perform those repetitive jobs consistently and without getting bored (although you might see an occasional yawn).

Just in case you haven't read enough about boredom yet, you can read something about it in the third section of this chapter, which discusses some of the newest areas in which AI excels — making environments of all sorts safer. In the automotive industry alone, in fact, you can find myriad ways in which the use of AI is making things better.


REMEMBER

The point of this chapter is that AI works well in processes, especially those processes during which humans tend to get bored, causing them to make mistakes when the AI likely wouldn't. Of course, an AI can't eliminate every source of lost efficiency, disinterest, and safety. For one thing, humans can choose to ignore the AI's help, but the nature of the limitations goes much deeper than that. As discussed in earlier chapters (especially Chapter 9), an AI doesn't understand; it can't provide creative or innovative solutions to problems, so some problems aren't solvable by an AI, no matter how much effort someone puts into creating it.

Developing Solutions for Boredom

Polls often show what people *think* they want, rather than what they do want, but they're still useful. When college graduates were polled to see what kind of life they wanted, not one of them said, "Oh, please, let me be bored!" In fact, you could possibly poll just about any group and not come up with a single boring response. Most humans (saying "All humans" would likely result in an avalanche of email, with examples) don't want to be bored. In some cases, AI can work with humans to make life more interesting — for the human, at least. The following sections discuss solutions for human boredom that AI can provide (and a few that it can't).

Making tasks more interesting

Any occupation, whether it's personal or for an organization, has certain characteristics that attract people and make them want to participate in it. Some occupations, such as taking care of your own children, obviously, pay nothing, but the satisfaction of doing so can be incredibly high. Likewise, working as a bookkeeper may pay quite well but offer little in the way of job satisfaction. Various polls and articles reflecting on the balance of money and satisfaction agree that after a

human makes a certain amount of money, satisfaction becomes the key to maintaining interest in the occupation (no matter what that occupation might be). Of course, figuring out what comprises job satisfaction is nearly impossible, but interest remains high on the list. An interesting occupation will always have higher satisfaction potential.


TIP

The problem, then, is not one of necessarily changing jobs. One way to increase job satisfaction could be to alleviate boredom. An AI can effectively help this process by removing repetition from tasks. However, examples such as Amazon's Alexa and Google's Home do provide other alternatives. The feeling of loneliness that can pervade the home, workplace, car, and other locations is a strong creator of boredom. When humans begin to feel alone, depression sets in, and boredom is often just a step away. Creating applications that use the Alexa interface (see `developer.amazon.com/en-US/alexa`) to simulate human interaction of the appropriate sort can improve the workplace experience. More importantly, developing smart interfaces of this sort can help humans perform a wealth of mundane tasks quickly, such as researching information and interacting with smart devices, not just light switches (see "How to control your lights with Amazon Echo" at `iMore.com` and `store.google.com/product/google_home` for details).

Helping humans work more efficiently

Most humans, at least the forward-thinking ones, have some idea of how they'd like an AI to make their lives better by eliminating tasks they don't want to do. Many of the tasks are mundane, but notice that ones like detecting when a significant other is unhappy and sending flowers probably won't work — though it's an interesting idea nonetheless.

The point is that humans will likely provide the most interesting ideas on how to create an AI that specifically addresses their needs. In most cases, serious ideas will work well for other users, too. For example, several companies now offer extensive application programming interfaces, or APIs, and scripting capabilities that enable organizations to customize how trouble tickets are generated, categorized, and processed.

Examining how AI reduces boredom

Boredom comes in many packages, and humans view these packages in different ways. There is the boredom that comes from not having the required resources or knowledge or other needs met. Another kind of boredom comes from not knowing what to do next when activities follow no specific pattern. An AI can help with the first kind of boredom; it can't help with the second. This section considers the first kind of boredom. (The next section considers the second kind.)

COUNTERINTELLIGENCE IN WORK

Few people like their work to be difficult; most of us want to ease into work and come out with a sense of satisfaction each day. However, some new articles and white papers seem to indicate that adding AI to the workplace actually makes things harder. Consider this article from *The Atlantic:* "AI Is Coming for Your Favorite Menial Tasks." However, the article isn't actually about menial tasks. It's more about AI sucking all the fun out of a person's job and leaving only the most stressful elements that only a human can effectively deal with. The article considers the other side of the coin: instances when automation makes a person's job significantly more difficult and definitely less satisfying, and the human isn't even getting paid more to do it. More importantly, the human's chance of making the right decision because all the decisions are hard ones also drops, which can then give management the impression that a worker is suddenly losing interest or simply not focusing. At some point, a balance will have to be struck between what AI does and what humans do to maintain job satisfaction. Current AI design doesn't even consider this aspect of human need, but it will be a requirement in the future.

REMEMBER

Access to resources of all sorts helps reduce boredom by allowing humans to be creative without the mundane necessity of acquiring needed materials. Here are some ways in which an AI can make access to resources easier:

- Searching for needed items online
- Ordering and reordering needed items automatically
- Performing sensor and other data-acquisition monitoring
- Managing data
- Carrying out mundane or repetitive tasks

Recognizing that AI can't reduce boredom

As noted in earlier chapters, especially Chapters 4 and 9, an AI is not creative or intuitive. So, asking an AI to think of something for you to do is unlikely to produce satisfying results. Someone could program the AI to track the top ten things you like to do and then select one of them at random, but the result still won't be satisfying because the AI can't take aspects like your current state of mind into account. In fact, even with the best facial expression recognition software, an AI will lack the capability to interact with you in a manner that will produce any sort of satisfying result.

Neither can an AI motivate you. Think about what happens when a friend offers to help motivate you (or you motivate the friend). The friend relies on a combination of intrapersonal knowledge (empathizing by considering how it feels to be in your situation) and interpersonal knowledge (projecting creative ideas on how to obtain a positive emotional response from you). An AI will have none of the first kind of knowledge and have only extremely limited amounts of the second kind of knowledge, as described in Chapter 1. Consequently, an AI can't reduce your boredom through motivational techniques.


TIP

Boredom may not always be a bad circumstance, anyway. A number of recent studies have shown that boredom helps *promote* creative thought, which is the direction that humans need to go. (For example, see "Being Bored Can Be Good for You — If You Do It Right" at `time.com/5480002/benefits-of-boredom`) Despite the myriad articles describing how AI will eliminate jobs, it's important to consider that the jobs that AI is eliminating are, in themselves, often boring and leave humans no time to create. Even today, humans can find productive, creative jobs to do if they stop and think seriously about it. The article "7 Surprising Facts About Creativity, According to Science" at `www.fastcompany.com/3063626/7-surprising-facts-about-creativity-according-to-science`) discusses the role of daydreaming when bored in enhancing creativity. In the future, if humans truly want to reach for the stars and do other amazing things, creativity will be essential, so the fact that AI can't reduce your boredom is actually a good thing.

Working in Industrial Settings

Any industrial setting is likely to have safety hazards, no matter how much time, effort, and money is thrown at the problem. You can easily find articles such as this one, "A Guide to the Most Common Workplace Hazards" at (`www.highspeedtraining.co.uk/hub/hazards-in-the-workplace`), which describes common safety hazards found in industrial settings. Although humans cause many of these problems and boredom makes them worse, the actual environment in which the humans are working causes a great many issues. The following sections describe how automation can help humans live longer and better lives.

Developing various levels of automation

Automation in industrial settings is a lot older than you might think. Many people think of Henry Ford's assembly line as the starting point of automation. In fact, the basics of automation began at least as early as 1104 CE in Venice where 16,000 workers were able to build an entire warship in a single day. Americans repeated the feat of building warships extremely fast with modern ships during World War

II by relying heavily on automation. In fact, four industrial revolutions have taken place so far (listed later in this chapter), according to the Institute of Entrepreneurship Development. So automation has been around for a long time.

What hasn't been around for a long time is an AI that can actually help humans within the automation process. In many cases, a human operator now begins by outlining how to perform the task, creating a *job*, and then turns the job over to a computer. An example of one of several fairly new kinds of job is robot process automation (RPA), which allows a human to train software to act in the stead of a human when working with applications. Many companies are now offering RPA services, such as UiPath (`www.uipath.com/rpa/robotic-process-automation`). This process differs from scripting, such as the use of Visual Basic for Applications (VBA) in Microsoft Office, in that RPA isn't application-specific and doesn't require coding. Many people find it surprising that there are ten levels of automation, nine of which can rely on an AI — the level you choose is dependent on your application:

1. A human operator creates a job and turns it over to a computer to implement.
2. An AI helps the human determine job options.
3. The AI determines the best job options and then allows the human to accept or reject the recommendation.
4. The AI determines the options, uses them to define a series of actions, and then turns over the list of actions to a human for acceptance or rejection of individual actions before implementation.
5. The AI determines the options, defines a series of actions, creates a job, and then asks for human approval before submitting the job to the computer.
6. The AI automatically creates the job and submits it to the computer's job queue, with the human operator acting as an intermediary in case the selected job requires termination before actual implementation.
7. The AI creates and implements the job and then tells the human operator what it did in case the job requires correction or reversal.
8. The AI creates and implements the job, telling the human what it did only when the human asks.
9. The AI creates and implements the job while providing no feedback unless a human needs to intervene, such as when an error occurs or the result isn't what was expected.
10. The AI initiates the need for the job rather than wait for the human to tell it to create the job. The AI provides feedback only when a human must intervene, such as when an error occurs. The AI can provide a level of error correction and manage unexpected results on its own.

Using more than just robots

When thinking about industry, most people think about automation: robots making stuff. However, society is in at least its *fourth* industrial revolution; we've had steam, mass production, automation, and now communication. Some people are already talking about moving toward a fifth level, personalization. (See this LinkedIn post, "Industry 5.0-Future of Personalisation.") An AI requires information from all sorts of sources in order to perform tasks efficiently. It follows that the more information an industrial setting can obtain from all sorts of sources, the better an AI can perform (assuming that the data is also managed properly). With this multisource idea in mind, industrial settings of all sorts now rely on an industrial communications engine (ICE) to coordinate communication between all the various sources an AI requires.

Robots do perform much of the actual work in an industrial setting, but you also need sensors to assess potential risks, such as storms. However, coordination is becoming ever more important to ensuring that operations remain efficient. For example, ensuring that trucks with raw materials arrive at the proper time while other trucks that haul off finished goods are available when needed are essential tasks for keeping warehouse floors running efficiently. The AI needs to know about the maintenance status of all equipment to ensure that the equipment receives the best possible care (to improve reliability and reduce repair costs); the AI also needs to know the times when the equipment is least needed (to improve efficiency). The AI would also need to consider issues such as resource cost. Perhaps gaining an advantage is possible by running certain equipment during evening hours when power is less expensive.

Relying on automation alone

Early examples of human-free factories include specialty settings, such as chip factories that required exceptionally clean environments. However, automation has spread. Because of the dangers to humans and the cost of using humans to perform certain kinds of industrial tasks, you can now find many instances of common factories that require *no* human intervention (See "No Humans, Just Robots" at `SingularityHub.com` for examples.) The term for that type of industry is *lights-out manufacturing.*


REMEMBER

A number of technologies will at some point enable the performance of all factory-related tasks without human intervention. (See `https://locusrobotics.com/blog/14-manufacturing-trends-2022` for examples.) The point is that society eventually will need to find jobs, other than repetitive factory jobs, for humans to perform.

Creating a Safe Environment

One of the most-often-stated roles for AI, besides automating tasks, is keeping humans safe in various ways. Articles such as "7 Reasons You Should Embrace, Not Fear, Artificial Intelligence" at `futurism.com/7-reasons-you-should-embrace-not-fear-artificial-intelligence`) describe an environment in which AI acts as an intermediary, taking the hit that humans would normally take when a safety issue occurs. Safety takes all sorts of forms. Yes, AI will make working in various environments safer, but it'll also help create a healthier environment and reduce risks associated with common tasks, including surfing the Internet. The following sections offer an overview of the ways in which AI might provide a safer environment.

Considering the role of boredom in accidents

From driving or being at work, boredom increases accidents of all sorts. In fact, anytime someone is supposed to perform a task that requires any level of focus and instead acts like they're half asleep, the outcome is seldom good. The problem is so serious and significant that you can find a wealth of articles on the topic. Solutions come in the form of articles like "Modeling job rotation in manufacturing systems: The study of employee's boredom and skill variations" at `ResearchGate.net`. Whether an accident actually occurs (or was a close call) depends on random chance. Imagine actually developing algorithms that help determine the probability of accidents happening because of boredom under certain conditions.

Seeing AI to avoid safety issues

No AI can prevent accidents stemming from human causes, such as boredom. In a best-case scenario, when humans decide to follow the rules that AI helps create, the AI can only help avoid potential problems. Science fiction author Isaac Asimov formulated the Three Laws of Robotics in his writings. Unlike with Isaac Asimov's robots, there are no three-laws protections in place in any environment; humans must choose to remain safe. With this reality in mind, an AI can help in these ways:

- Suggest job rotations (whether in the workplace, in a car, or even at home) to keep tasks interesting
- Monitor human performance in order to better suggest downtime because of fatigue or other factors

- Assist humans in performing tasks to combine the intelligence that humans provide with the quick reaction time of the AI
- Augment human detection capabilities so that potential safety issues become more obvious
- Take over repetitive tasks so that humans are less likely to become fatigued and can participate in the interesting aspects of any job

Accepting that AI cannot eliminate safety issues

Ensuring complete safety implies an ability to see the future. Because the future is unknown, the potential risks to humans at any given time are also unknown because unexpected situations can occur. An unexpected situation is one that the original developers of a particular safety strategy didn't envision. Humans are adept at finding new ways to get into predicaments, partly because we're both curious and creative. Finding a method to overcome the safety provided by an AI is in human nature because humans are inquisitive; we want to see what will happen if we try something — generally something stupid. Unpredictable situations aren't the only problems an AI faces. Even if someone were to find every possible way in which a human could become unsafe, the processing power required to detect the event and determine a course of action would be astronomical. The AI would work so slowly that its response would always occur too late to make any difference. Consequently, developers of safety equipment that actually requires an AI to perform the required level of safety have to deal in probabilities and then protect against the situations that are most likely to happen.

IN THIS CHAPTER

- Communicating in new ways
- Sharing ideas
- Employing multimedia
- Improving human sensory perception

Chapter 11

Relying on AI to Improve Human Interaction

People interact with each other in myriad ways. Few people realize, in fact, just how many different ways communication occurs. When many people think about communication, they think about writing or talking. However, interaction can take many other forms, including eye contact, tonal quality, and even scent. An example of the computer version of enhanced human interaction is the electronic "nose," which relies on a combination of electronics, biochemistry, and artificial intelligence to perform its task and has been applied to a wide range of industrial applications and research (see `tinyurl.com/488jfzut`). In fact, the electronic nose can even "sniff out" diseases (see `tinyurl.com/28cfcjek`). This chapter concentrates more along the lines of standard communication, however, including body language. You gain a better understanding of how AI can enhance human communication through means that are less costly than building your own electronic nose.

AI can also enhance the manner in which people exchange ideas. In some cases, AI provides entirely new methods of communication, but in many cases, AI provides a subtle (or sometimes not so subtle) method of enhancing existing ways to exchange ideas. Humans rely on exchanging ideas to create new technologies, build on existing technologies, or learn about technologies needed to increase an individual's knowledge. Ideas are abstract, which makes exchanging them particularly difficult at times, so AI can provide a needed bridge between people.

At one time, if someone wanted to store their knowledge to share with someone else, they generally relied on writing. In some cases, they could also augment their communication by using graphics of various types. However, only some people can use these two forms of media to gain new knowledge; many people require more, which is why online sources such as YouTube have become hugely popular. Interestingly enough, you can augment the power of multimedia, which is already substantial, by using AI, and this chapter tells you how.

The final section of this chapter helps you understand how an AI can give you almost superhuman sensory perception. Perhaps you want that electronic nose after all; it does provide significant advantages in detecting scents that are significantly less aromatic than humans can smell. Imagine being able to smell at the same level as a dog does (which uses 100 million aroma receptors, versus the 1 million aroma receptors that humans possess). It turns out there are two ways to achieve this goal: monitors that a human accesses indirectly and direct stimulation of human sensory perception.

Developing New Ways to Communicate

Communication involving a developed language initially took place between humans via the spoken versus written word. The only problem with spoken communication is that the two parties must appear near enough together to talk. Consequently, written communication is superior in many respects because it allows time-delayed communications that don't require the two parties to ever see each other. The three main methods of human nonverbal communication rely on

- **Alphabets/Iconographs:** The abstraction of components of human words or symbols
- **Language:** The stringing together of words or symbols to create sentences or convey ideas in written form
- **Body language:** The augmentation of language with context

The first two methods are direct abstractions of the spoken word. They aren't always easy to implement, but people have been implementing them for thousands of years. The body-language component is the hardest to implement because you're trying to create an abstraction of a physical process. Writing helps convey body language using specific terminology, such as that described at `tinyurl.com/27newjbf`. However, the written word falls short, so people augment it with symbols, such as emoticons and emojis (you can read about their differences at `tinyurl.com/9jyc5n4n`). The following sections discuss these issues in more detail.

Creating new alphabets

The introduction to this section mentions two new alphabets used in the computer age: emoticons and emojis (tinyurl.com/wjsw8te5 and emojipedia.org). The sites where you find these two graphical alphabets online can list hundreds of them. For the most part, humans can interpret these iconic alphabets without much trouble because the alphabets resemble facial expressions; an application lacks the human sense of art, however, so computers often require an AI just to figure out which emotion a human is trying to convey by using the little pictures. Fortunately, you can find standardized lists, such as the Unicode emoji chart at tinyurl.com/j4bdmm3m.

The emoticon is an older technology, and many people are trying their best to forget it (but likely won't succeed because emoticons are easy to type, though you might recall the movie titled *The Emoji Movie*). You can also turn your selfies into emojis (see "The 7 Best Free Apps to Turn Selfies Into Emojis, Stickers, and More" at MakeUseOf.com). Many people have a hard time figuring out emojis, so you can check Emojipedia to see what they mean.


REMEMBER

Humans have created new alphabets to meet specific needs since the beginning of the written word. Emoticons and emojis represent two of many alphabets that you can count on humans creating as the result of the Internet and the use of AI. In fact, it may actually require an AI to keep up with them all. However, it's equally important to remember that some characters are lost as time progresses. For example, check out the article "12 Characters that Didn't Make the Alphabet" at www.mentalfloss.com/article/31904/12-letters-didnt-make-alphabet.

Working with emojis and other meaningful graphics

Many text references are now sprinkled with emojis and other iconography. Most of the references you see online today deal with emojis and emoticons, either removing them or converting them to text.

It's not uncommon to find bits and pieces of other languages sprinkled throughout a text, and these words or phrases need to be handled in a meaningful way. The problem with translating certain languages into a form where they can act as input to a natural language processing (NLP) model is that the concept of the language differs from English. For example, when working with Chinese, you deal with ideas rather than with pronunciation, as you do with English.

Some situations also require that you process meaningful graphics because part of the text meaning is in the graphic. This sort of translation need commonly arises

in technical or medical texts. The article "How Image Analysis and Natural Language Processing Can Be Combined to Improve Precision Medicine," by Obi Igbokwe, at Medium.com, discusses how to accomplish this task.


REMEMBER

The point of these various translations of nontext into a textual form is that humans communicate in many ways, and AI can help make such communication easier and improve comprehension. In addition, using AI to perform NLP makes it possible to look for patterns, even in text that is heavily imbued with nontext elements.

Automating language translation

The world has always had a problem with the lack of a common language. Yes, English has become pervasive — though it's still not universal. Having someone translate between languages can be expensive, cumbersome, and error-prone, so translators, though necessary in many situations, aren't necessarily the ideal answer, either. For those who lack the assistance of a translator, dealing with other languages can be quite difficult, which is where applications such as Google Translate come into play.

Google Translate offers to automatically detect the language for you. What's interesting about this feature is that it works extremely well in most cases. Part of the responsibility for this feature is the Google Neural Machine Translation (GNMT) system. It can examine entire sentences to make sense of them and provide better translations than applications that use phrases or words as the basis for creating a translation (see tinyurl.com/8by975xx for details).


TECHNICAL STUFF

What is even more impressive is that GNMT can translate between languages even when it has no specific translator, using an artificial language, an *interlingua.* However, you should realize that an interlingua doesn't function as a universal translator; it's more of a universal bridge. Say that the GNMT doesn't know how to translate between Chinese and Spanish. However, it can translate between Chinese and English and between English and Spanish. By building a 3D network representing these three languages (the interlingua), GNMT is able to create its own translation between Chinese and Spanish. Unfortunately, this system doesn't work for translating between Chinese and Martian because no method is available yet to understand and translate Martian in any other human language. Humans still need to create a base translation for GNMT to do its work.

Incorporating body language

A significant part of human communication occurs with body language, which is why the use of emoticons and emojis is important. However, people are becoming

more used to working directly with cameras to create videos and other forms of communication that involve no writing. In this case, a computer could possibly listen to human input, parse it into tokens representing human speech, and then process those tokens to fulfill a request, similar to the way Alexa and Google Home (and others) work.


REMEMBER

Unfortunately, merely translating the spoken word into tokens won't do the job, because the whole issue of nonverbal communication remains. In this case, the AI must be able to read body language directly. The article "Computer Reads Body Language" from Carnegie Mellon University discusses some of the issues that developers must solve to make reading body language possible. The picture at the beginning of the article gives you some idea of how the computer camera must capture human positions to read the body language, and the AI often requires input from multiple cameras to make up for such issues as having part of the human anatomy obscured from the view of a single camera. The reading of body language involves interpreting these human characteristics:

- Posture
- Head motion
- Facial expression
- Eye contact
- Gestures

Of course, other characteristics must be considered, but if an AI can even get these five areas down, it can go a long way toward providing a correct body-language interpretation. In addition to body language, current AI implementations consider characteristics like tonal quality, which makes for an extremely complex AI that still doesn't come close to doing what the human brain does seemingly without effort.


TECHNICAL STUFF

After an AI can read body language, it must also provide a means to output it when interacting with humans. Given that reading body language (facial expressions, body position, placement of hands, and other factors) is in its infancy, robotic or graphical presentation of body language is even less developed.

Exchanging Ideas

An AI doesn't have ideas, because it lacks both intrapersonal intelligence and the ability to understand. However, an AI can enable humans to exchange ideas in a manner that creates a whole that is greater than the sum of its parts. In many

cases, the AI isn't performing any sort of exchange. Instead, the humans involved in the process perform the exchange by relying on the AI to augment the communication process. The following sections provide additional details about how this process occurs.

Creating connections

A human can exchange ideas with another human, but only as long as the two humans know about each other. The problem is that many experts in a particular field don't actually know each other — at least, not well enough to communicate effectively. An AI can perform research based on the flow of ideas that a human provides and then create connections with other humans who have that same (or similar) flow of ideas.

One way in which this communication creation occurs is in social media sites such as LinkedIn, where the idea is to create connections between people based on a number of criteria. A person's network becomes the means by which the AI deep inside LinkedIn suggests other potential connections. Ultimately, the purpose of these connections from the user's perspective is to gain access to new human resources, make business contacts, create a sale, or perform other tasks that LinkedIn enables using the various connections.

Augmenting communication

To exchange ideas successfully, two humans need to communicate well. The only problem is that humans sometimes don't communicate well, and sometimes they don't communicate at all. The issue is one of translating not only words but also ideas. The societal and personal biases of individuals can preclude the communication because an idea for one group may not translate at all for another group. For example, the laws in one country might make someone think in one way, but the laws in another country could make the other human think in an entirely different manner.

Theoretically, an AI could help communication between disparate groups in numerous ways. Of course, language translation (assuming that the translation is accurate) is one of these methods. However, an AI could provide cues to what is and isn't culturally acceptable by prescreening materials. Using categorization, an AI could also suggest aids like alternative graphics and other elements to help communication take place in a manner that helps both parties. For example, you could replace an image of a Red Cross with a Red Crescent or both to represent first aid in different cultures.

Defining trends

Humans often base ideas on trends. To visualize how the idea works, however, other parties in the exchange of ideas must also see those trends, and communicating using this sort of information is notoriously difficult. AI can perform various levels of data analysis and present the output graphically. The AI can analyze the data in more ways and faster than a human can so that the story the data tells is specifically the one you need it to tell. The data remains the same; the presentation and interpretation of the data change.

Studies show that humans relate better to graphical output than to tabular output, and graphical output definitely makes trends easier to see. You generally use tabular data to present only specific information; graphics always work best for showing trends (see `tinyurl.com/3hwsjwcy`). Using AI-driven applications can also make creating the right sort of graphical output for a particular requirement easier. Not all humans see graphics in precisely the same way, so matching a graphical type to your audience is essential.

Using Multimedia

Most people learn by using multiple senses and multiple approaches. A doorway to learning that works for one person may leave another completely mystified. Consequently, the more ways in which a person can communicate concepts and ideas, the more likely it is that other people will understand what the person is trying to communicate. Multimedia normally consists of sound, graphics, text, and animation, though some multimedia does more.

AI can help with multimedia in numerous ways. One of the most important is in the creation, or *authoring,* of the multimedia. You find AI in applications that help with everything from media development to media presentation. For example, when translating the colors in an image, an AI may provide the benefit of helping you visualize the effects of those changes faster than trying one color combination at a time (the brute force approach).

After using multimedia to present ideas in more than one form, those receiving the ideas must process the information. A secondary use of AI relies on the use of neural networks to process the information in various ways. Categorizing the multimedia is now an essential use of the technology. However, in the future, you can look forward to using AI to help in 3D reconstruction of scenes based on 2D pictures. Imagine police personnel being able to walk through a virtual crime scene with every detail faithfully captured.

MULTIMEDIA AND ADDRESSING PEOPLE'S FUNCTIONAL NEEDS

Most people have some particular functional need relating to how they take in and understand information. Considering such needs as part of people's use of multimedia is important. The whole intent of multimedia is to communicate ideas in as many ways as possible so that just about everyone can understand the ideas and concepts you want to present. Even when a presentation as a whole uses multimedia successfully, individual ideas can become lost when the presentation uses only a single method to communicate them. For example, communicating a sound only aurally almost guarantees that only those with excellent hearing will receive the idea. A subset of those with the required hearing level still won't get the idea because it may appear as only so much noise to them, or they simply won't learn through the limited method offered in the presentation. Using as many methods as possible to communicate each idea is essential if you want to reach as many people as possible. Even if you get the information in one way, also getting it another way provides useful confirmation that you understood correctly.

People used to speculate that various kinds of multimedia would appear in new forms. For example, imagine a newspaper that provides Harry Potter–like dynamic displays. Most of the technology pieces are available today, but the issue comes down to the market: For a technology to become successful, it must have a market — that is, a means for paying for itself.

Embellishing Human Sensory Perception

One way that AI truly excels at improving human interaction is by augmenting humans in one of two ways: by allowing them to use their native senses to work with augmented data or by augmenting the native senses to do more. The following sections discuss both approaches to enhancing human sensing and therefore improving communication.

Shifting data spectrum

When performing various kinds of information gathering, humans often employ technologies that filter or shift the data spectrum with regard to color, sound, touch, or smell. The human still uses native capabilities, but some technology changes the input such that it works with that native capability. One of the most common examples of spectrum shifting is astronomy, in which shifting and filtering light enables people to see astronomical elements, such as nebula, in ways that the naked eye can't — thereby improving our understanding of the universe.

Teaching a robot to feel by touch is in its infancy, as described at tinyurl.com/ukjscsye and tinyurl.com/y998s2h8. Most efforts now focus on helping the robot work better by using tactile responses as part of manipulating its machinery, such as the light touch needed to grasp an egg versus the heavier touch required to lift a barbell. As this technology moves far enough forward, it might become possible for various AIs to communicate with humans via direct touch or the description of various kinds of touch.

Shifting and filtering colors, sounds, touches, and smells manually can require a great deal of time, and the results can disappoint even when performed expertly, which is where AI comes into play. An AI can try various combinations far faster than a human can, and can locate the potentially useful combinations with greater ease because an AI performs the task in a consistent manner.

The most intriguing technique for exploring our world, however, is completely different from what most people expect. What if you could smell a color or see a sound? The occurrence of *synesthesia,* which is the use of one sense to interpret input from a different sense, is well documented in humans — see tinyurl.com/2s9tb284. For more about the general understanding of the current state of synesthesia, see www.psychologytoday.com/us/basics/synesthesia.

Augmenting human senses

As an alternative to using an external application to shift a data spectrum and somehow make that shifted data available for use by humans, you can augment human senses. In augmentation, a device, either external or implanted, enables a human to directly process sensory input in a new way. The idea is an old one: Use tools to make humans ever more effective at performing an array of tasks. In this scenario, humans receive two forms of augmentation: physical and intelligence.

Physical augmentation of human senses already takes place in many ways, and it's guaranteed to increase as humans become more receptive to various kinds of implants. For example, night vision glasses now allow humans to see at low levels, with high-end models providing color vision controlled by a specially designed processor. In the future, eye augmentation or replacement may allow people to see any part of the spectrum. This augmentation or replacement would be controlled by the person's thoughts so that people would see only that part of the spectrum needed to perform a specific task.

Intelligence augmentation requires more intrusive measures but also promises to allow humans to exercise far greater capabilities. Unlike AI, intelligence augmentation (IA) has a human actor at the center of the processing — the human provides the creativity and intent that AI now lacks.

4 AI Applied in Industries

IN THIS PART . . .

Consider how AI addresses medical needs.

Engage in robotic mayhem.

Fly everywhere with drones.

Let an AI do the driving for you.

IN THIS CHAPTER

- Monitoring patients more effectively
- Assisting humans in various tasks
- Analyzing patient needs locally and remotely
- Performing surgery and other tasks by medical professionals

Chapter 12
Using AI to Address Medical Needs

Medicine is complicated. There's a reason it can take 15 or more years to train a doctor, depending on specialty. The creation of new technologies, approaches, and other factors all conspire to make the task even more complex. At some point, it becomes impossible for any lone person to become proficient in even a narrow specialty. This is a prime reason that an irreplaceable human requires consistent, logical, and unbiased help in the form of an AI. The process begins by helping the doctor monitor patients in ways that humans would simply find impossible. That's true because the number of checks is high, the need to perform them in a certain order and in a specific way is critical, and the potential for error is monumental.

Fortunately, people have more options today than ever before for doing many medical-related tasks on their own. For example, the use of games enables a patient to perform some therapy-related tasks alone yet receive guidance from an application to help the person perform the task appropriately. Improved prosthetics and other medical aids also enable people to become more independent of professional human assistance.

Today, a doctor can fit a patient with a monitoring device, perform remote monitoring, and then rely on an AI to perform the analysis required for diagnosis — all without the patient's spending more than one visit at the doctor's office (the one

required to attach the monitoring device). In fact, in some cases, such as glucose monitors, the patient may even be able to buy the required device at the store so that the visit to the doctor's office becomes unnecessary as well. One of the more interesting additions to the healthcare arsenal during medical emergencies, such as pandemics, is the use of *telepresence,* which enables the doctor to interact with a patient without physically being in the same room.

Implementing Portable Patient Monitoring

A medical professional isn't always able to tell what's happening with a patient's health by simply listening to their heart, checking vital signs, or performing a blood test. The body doesn't always send out useful signals that let a medical professional learn anything at all. In addition, some body functions, such as blood sugar, change over time, so constant monitoring becomes necessary. Going to the doctor's office every time you need one of these vitals checked would prove time-consuming and possibly not all that useful. Older methods of determining certain body characteristics required manual, external intervention on the part of the patient — an error-prone process in the best of times. For these reasons, and many more, an AI can help monitor a patient's statistics in a manner that's efficient, less error-prone, and more consistent, as described in the following sections.

Wearing helpful monitors

All sorts of monitors fall into the helpful category. In fact, many of these monitors have nothing to do with the medical profession yet produce positive results for your health. Consider the Moov monitor (`welcome.moov.cc`), which monitors both heart rate and 3D movement. The AI for this device tracks these statistics and provides advice on how to create a better workout. You actually get advice on, for example, how your feet are hitting the pavement during running and whether you need to lengthen your stride. The point of devices like these is to ensure that you get the sort of workout that will improve your health without risking injury.

Mind you, in case a watch-type monitoring device is too large, Oura (`ouraring.com/oura-experience`) produces a ring that monitors about the same number of stats that Moov does, but in a smaller package. This ring even tracks how you sleep to help you get a good night's rest. Interestingly enough, many of the pictures on the Oura site look nothing like a fitness monitor, so you can have fashion and health all in one package.

Of course, if your only goal is to monitor your heart rate, you can buy devices such as Apple Watch (`support.apple.com/en-us/HT204666`) that also provide some level of analysis using an AI. All these devices interact with your smartphone, so you can possibly link the data to still other applications or send it to your doctor as needed.

Relying on critical wearable monitors

A problem with some human conditions is that they change constantly, so checking intermittently doesn't really get the job done. Glucose, the statistic measured for diabetics, is one statistic that falls into this category: The more you monitor the rise and fall of glucose each day, the easier it becomes to change medications and lifestyle to keep diabetes under control. Devices such as the K'Watch (`www.pkvitality.com/ktrack-glucose`) provide this type of constant monitoring, along with an app that a person can use to obtain helpful information on managing their diabetes. Of course, people have used intermittent monitoring for years; this device simply provides that extra level of monitoring that can help make having diabetes more of a nuisance than a life-altering issue. (The number of remote patient-monitoring devices produced by various companies is growing; see the article at `tinyurl.com/c52uytse` for details.)

Some devices are truly critical, such as the wearable cardioverter defibrillator (WCD), which senses your heart condition continuously and provides a shock should your heart stop working properly (see `tinyurl.com/jkzbv3x8` for details). This short-term solution can help a doctor decide whether you need the implanted version of the same device. There are pros and cons to wearing one, but then again, it's hard to place a value on having a shock available when needed to save a life. The biggest value of this device is the monitoring it provides. Some people don't actually need an implantable device, so monitoring is essential to prevent unnecessary surgery.

MEDICAL DEVICES AND SECURITY

A problem with medical technology of all sorts is the lack of security. Having an implanted device that anyone can hack is terrifying. The article at `https://tinyurl.com/rjnathrw` describes what could happen if someone hacked any medical device. Fortunately, according to many sources, no one has died yet.

However, imagine your insulin pump or implanted defibrillator malfunctioning as a result of hacking, and consider what damage it could cause. The Federal Drug

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Administration (FDA) has finally published guidance on medical device security, as described in the article at `https://tinyurl.com/w24cvfc7`, but these guidelines apparently aren't enforced. In fact, this article goes on to say that the vendors are actively pursuing ways to avoid securing their devices.

The AI isn't responsible for the lack of security these devices possess, but the AI could get the blame should a breach occur. The point is that you need to view all aspects of using AI, especially when it comes to devices that directly affect humans, such as implantable medical devices.

Using movable monitors

The number and variety of AI-enabled health monitors on the market is staggering. For example, you can buy an AI-enabled toothbrush that monitors your brushing habits and provides you with advice on better brushing technique (`tinyurl.com/6ft7u37y`). Oral B also has a number of toothbrushes that benefit from the use of AI: `tinyurl.com/35xdarjj`. When you think about it, creating a device like this presents a number of hurdles, not the least of which is keeping the monitoring circuitry happy inside the human mouth. Of course, some people may feel that the act of brushing their teeth has little to do with good health, but it does (see `tinyurl.com/6mfzc4hk`).

Creating movable monitors generally means making them both smaller and less intrusive. Simplicity is also a requirement for devices designed for use by people with little or no medical knowledge. One device in this category is a wearable electrocardiogram (ECG). Having an ECG in a doctor's office means connecting wires from the patient to a semiportable device that performs the required monitoring. The KardiaMobile (`kardia.com/?sscid=31k8_y6azo`) provides the ECG without using wires, and someone with limited medical knowledge can easily use it. As with many devices, this one relies on your smartphone to provide needed analysis and make connections to outside sources as needed.

REMEMBER

Current medical devices work just fine, but many aren't portable. The point of creating AI-enabled apps and specialized devices is to obtain much-needed data when a doctor actually needs it rather than have to wait for that data. Even if you don't buy a toothbrush to monitor your technique or an ECG to monitor your heart, the fact that these devices are small, capable, and easy to use means that you may still benefit from them at some point.

Making Humans More Capable

Many of the current techniques for extending the healthy range of human life (the segment of life that contains no significant sickness), instead of just increasing the number of years of life, depends on making humans more capable of improving their own health in various ways. You can find any number of articles that tell you 30, 40, or even 50 ways to extend this healthy range, but often it comes down to a combination of eating right, exercising enough and in the right way, and sleeping well. Of course, with all the advice out there, figuring out just which food, exercise, and sleep technique would work best for you could be nearly impossible. The following sections discuss ways in which an AI-enabled device might make the difference between having 60 good years and 80 or more good years. (In fact, it's no longer hard to find articles that discuss human lifespans of 1,000 or more years in the future because of technological changes.)

Using games for therapy

A gaming console can serve as a powerful and fun physical therapy tool. Both Nintendo Wii and Xbox 360 see use in many different physical therapy venues. The goal of these and other games is to get people moving in certain ways. The game automatically rewards proper patient movements, and a patient receives therapy in a fun way. Making the therapy fun means that the patient is more likely to do it and get better faster. You can now find informative studies about the use of games and their combination with telehealth strategies at `tinyurl.com/b6bt29r7` and `etsplaytherapy.org/collections/video-games-in-play-therapy`.

Of course, movement alone, even when working with the proper game, doesn't ensure success. In fact, someone could develop a new injury when playing these games. The Jintronix add-on for the Xbox Kinect hardware standardizes the use of this game console for therapy (`tinyurl.com/uzetv2tc` and `tinyurl.com/y42rmh4v`), increasing the probability of a positive outcome.

BIAS, SYMPATHY, AND EMPATHY

Getting good care is the initial aim of anyone who enters any medical facility. The assumption is that the care is not only the best available but also fair. An AI can help in the medical field by ensuring that technical skills remain high and that no bias exists whatsoever — at least, not from the AI's perspective.

Humans will always exhibit bias because humans possess intrapersonal intelligence (as described in Chapter 1). Even the kindest, most altruistic person will exhibit some form

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of bias — generally subconsciously — creating a condition in which the caregiver sees one thing and the patient another (see the section in Chapter 2 about considering the five mistruths in data). However, the people being served will almost certainly notice, and their illness will likely amplify the unintended slight. Using an AI to ensure even-handedness in dealing with patient issues is a way to avoid this issue. The AI can also help caregivers discover mistruths (unintended or otherwise) on the part of patients in relating their symptoms, thereby enhancing care.

The medical field can be problematic at times because technical skill often isn't enough. People frequently complain of the lack of a good bedside manner on the part of medical staff. The same people who want fair treatment also somehow want empathy from their caregivers (making the care unfair because it's now biased). Empathy differs from sympathy in context. People exhibit *empathy* when they're able to feel (almost) the same way the patient does and build a frame of reference with the patient. (It's important to note that no other person feels precisely the same way as you do because no other person has had precisely the same experiences you've had.) Two exercises in the "Considering the software-based solutions" section, later in this chapter, help you understand how someone could build a frame of reference to create empathy. An AI could never build the required empathy because an AI lacks the required sense awareness and understanding to create a frame of reference and the intrapersonal intelligence required to utilize such a frame of reference.

Unfortunately, empathy can blind a caregiver to true medical needs because the caregiver is now engaging in the mistruth of perspective by seeing only from the patient's point of view. So medical practitioners often employ *sympathy,* through which the caregiver looks in from the outside, understands how the patient might feel (rather than how the patient does feel), and doesn't build a frame of reference. Consequently, the medical practitioner can provide needed emotional support but also see the need to perform tasks that the patient may not enjoy in the short term. An AI can't accomplish these tasks because an AI lacks intrapersonal intelligence and doesn't understand the concept of perspective well enough to apply it appropriately.

Considering the use of exoskeletons

One of the most complex undertakings for an AI is to provide support for an entire human body. That's what happens when someone wears an *exoskeleton* (essentially a wearable robot). An AI senses movements (or the need to move) and provides a powered response to the need. The military has excelled in the use of

exoskeletons and is actively seeking more (see tinyurl.com/3sawszrb and tinyurl.com/tu525nuw for details). Imagine being able to run faster and carry significantly heavier loads as a result of wearing an exoskeleton. The video at tinyurl.com/p489dvj gives you just a glimpse of what's possible. The military continues to experiment, and those experiments often feed into civilian uses. The exoskeleton you eventually see (and you're almost guaranteed to see one at some point) will likely have its origins in the military.

Industry has also gotten in on the exoskeleton technology. In fact, the use of exoskeletons is becoming ever more important as factory workers age (tinyurl.com/9h9j8sh9). Factory workers currently face a host of illnesses because of repetitive stress injuries. In addition, factory work is incredibly tiring. Wearing an exoskeleton not only reduces fatigue but also reduces errors and makes the workers more efficient. People who maintain their energy levels throughout the day can do more with far less chance of being injured, damaging products, or hurting someone else.

The exoskeletons in use in industry today reflect their military beginnings. Look for the capabilities and appearance of these devices to change in the future to look more like the exoskeletons shown in movies such as *Aliens* (tinyurl.com/krhh8b5k). The real-world examples of this technology are a little less impressive but will continue to gain in functionality.

Exoskeletons can enhance people's physical abilities in downright amazing ways. For example, a *Smithsonian* magazine article discusses using an exoskeleton to enable a child with cerebral palsy to walk (tinyurl.com/nyb5p3kd). Not all exoskeletons used in medical applications provide lifelong use, however. For example, an exoskeleton can help a person who experienced a stroke walk without impediment (tinyurl.com/439syr72). As the person regains skills, the exoskeleton provides less support until the wearer no longer needs it. Some users of the device have even coupled their exoskeleton with other products, such as Amazon's Alexa (see tinyurl.com/tp3kyxfk for details).


REMEMBER

The overall purpose of wearing an exoskeleton isn't to make you into Iron Man. Rather, it's to cut down on repetitive stress injuries and help humans excel at tasks that currently prove too tiring or just beyond the limits of their body. From a medical perspective, using an exoskeleton is a win because it keeps people mobile longer, and mobility is essential to good health.

IMAGINING THE DARK SIDE OF EXOSKELETONS

Despite an extensive search online, few nefarious uses for exoskeletons turned up, unless you consider the military applications negative. However, destroying is easier than creating. Somewhere along the way, someone will come up with negative uses for exoskeletons (and likely every other technology mentioned in this chapter). For example, imagine high-stakes thieves employing exoskeletons to obtain some sort of advantage during the theft of heavy objects (`tinyurl.com/46tfte7c`).

Even though this book is about clearing away the hype surrounding AI and presenting some positive uses for it, the fact remains that the smart individual does at least consider the dark side of any technology. This strategy becomes dangerous when people raise an alarm with no facts to support a given assertion. Yes, thieves could run amok with exoskeletons, which should provide incentive to properly secure them, but it also hasn't happened yet. Ethical considerations of potential uses, both positive and negative, always accompany creating a technology such as AI.

Throughout this book, you find various ethical and moral considerations in the positive use of AI to help society. It's definitely important to keep technology safe, but you also want to keep in mind that avoiding technology because of its negative potential is truly counterproductive.

Addressing Special Needs

The creation of highly specialized prosthetics and other devices, many of them AI-enabled, has been a game changer for many people. For example, these days, some people can run a marathon or go rock climbing, even if they've experienced paralysis or the loss of a limb (`tinyurl.com/ce958ms9`). Then again, some people are using exoskeletons for an arguably less-than-productive use like "dancing" (`tinyurl.com/tt9rvxdj`).

REMEMBER

It's a fact of life that just about everyone faces a challenge in terms of capabilities and skills. At the end of a long day, someone with 20/20 vision might benefit from magnifying software to make text or graphical elements larger. Color-translation software can help someone who sees the full spectrum of human color take in details that aren't normally visible. As people age, they tend to need assistance to hear, see, touch, or otherwise interact with common objects. Likewise, assistance with tasks such as walking could keep someone in their own home for their entire life. The point is that using various kinds of AI-enabled technologies can significantly help everyone to have a better life, as discussed in the sections that follow.

THE GRIT AND PERSEVERANCE BEHIND THE AI DEVICE

The people you see online who are especially adept at having an amazing life with assistance from prosthetics or other devices have usually worked hard to get where they are now. Using an AI-enabled device can get you a foot in the door, but to enter, you must be willing to do whatever it takes to make the device work for you, which usually requires hour upon hour of therapy. This chapter doesn't seek to make light of the incredible amount of work that these amazing people have put into making their lives better; rather, it spotlights the technologies that help make their achievements possible. If you want to see something extraordinary, check out the ballerina at `tinyurl.com/37vn8bfd`. The article and its video make plain the amount of work required to make these various technologies work.

Considering the software-based solutions

Many people using computers today rely on some type of software-based solution to meet specific needs. One of the most famous of these solutions is a screen reader called Job Access With Speech (JAWS) (`tinyurl.com/nwjn8jmb`), which tells you about display content using sophisticated methods. As you might imagine, every technique that both data science and AI rely on to condition data, interpret it, and then provide a result likely occurs within the JAWS software, making it a good way for anyone to understand the capabilities and limits of software-based solutions. The best way to see how this works for you is to download and install the software and then use it while blindfolded to perform specific tasks on your system. (Avoid anything that will terrify you, though, because you'll make mistakes.)


TIP

Accessibility software helps people who live with particular challenges perform incredible tasks. It can also help others understand what it would be like to maneuver through life with that specific challenge. A considerable number of such applications are available, but for one example, check out Vischeck at `tinyurl.com/y6z7x8xs`. This software lets you see graphics in the same way that people with specific color issues see them. (Note that the site may not work well with very large images or during times of high usage rates.) It's not that people with these conditions don't see color — in fact, they see it just fine. But a given color is simply shifted to a different color, so saying *color shifted* is likely a better term, and a term like *color blindness* doesn't apply.

Relying on hardware augmentation

Many kinds of human activity challenges require more than just software to address adequately. The "Considering the use of exoskeletons" section, earlier in this chapter, tells you about the various ways in which exoskeletons see use today in preventing injury, augmenting natural human capabilities, or addressing specific needs (such as enabling a person with paraplegia to walk). However, many other kinds of hardware augmentation address other needs, and the vast majority require some level of AI to work properly.

Consider, for example, the use of eye-gaze systems (`eyegaze.com`). The early systems relied on a template mounted on top of the monitor. A person with quadriplegia could look at individual letters and that action would be picked up by two cameras (one on each side of the monitor) and then typed into the computer. By typing commands this way, the person could perform basic tasks at the computer.

Some of the early eye-gaze systems connected to a robotic arm through the computer. The robotic arm could do extremely simple but important actions, such as help users pour a drink or scratch their nose. Modern systems actually help connect a user's brain directly to the robotic arm, making it possible to perform tasks such as eating without assistance. In addition, some newer systems are doing things like restoring a person's sense of touch (`www.wired.com/story/this-brain-controlled-robotic-arm-can-twist-grasp-and-feel`).

Completing Analysis in New Ways

Using AI in a manner that best suits its capabilities maximizes the potential for medical specialists to use it in a meaningful way. Data analysis is one area in which AI excels. In fact, entire websites are devoted to the role that AI plays in modern medicine, such as the one at `tinyurl.com/amanphxc`.

Merely taking a picture of a potential tumor site and then viewing the result might seem to be all that a specialist needs to make an accurate diagnosis. However, most techniques for acquiring the required snapshot rely on going through tissue that isn't part of the tumor site, thereby obscuring the output. In addition, a physician wants to obtain the best information possible when viewing the tumor in its smallest stages.

Using AI to help perform the diagnosis not only assists in identifying tumors when they're small and with greater accuracy but also speeds up the analysis process immensely. Time is critical when dealing with many diseases.

As impressive as the detection and speed capabilities of AI are in this area, what truly makes a difference is the capability to combine AI in various ways to perform Internet of Things (IoT) data compilations. When the AI detects a condition in a particular patient, it can automatically check the patient's records and display the relevant information onscreen with the diagnosed scans, as shown in the article at www.ncbi.nlm.nih.gov/pmc/articles/PMC10740686. Now the doctor has every last piece of pertinent information for a patient before making a diagnosis and considering a particular path.

TIP

To see other amazing uses of AI in medicine, check out the site at tinyurl.com/275mztss.

Relying on Telepresence

In the future, you may be able to call on a doctor to help with a problem and not even visit the hospital or clinic to do it. For that matter, you may be able to call on just about any other professional in the same way. The use of telepresence in all sorts of fields will likely increase as the availability of professionals in specific areas decreases due to continuing specialization. The following sections discuss telepresence and describe how it relies largely on AI in some respects.

Defining telepresence

The term *telepresence* simply means to be in one place and seem as though you're in another. The ScienceDirect article at tinyurl.com/xs2sb6sa talks about how telepresence and augmented reality walk side by side to provide special kinds of experiences. Though augmented or virtual reality exists essentially in artificial worlds, telepresence exists in the real world. For example, using telepresence, you might be able to see the Grand Canyon more or less directly without actually being there. The thing that separates telepresence from simply using a camera is that, through the use of sensors, a person experiences telepresence through their own senses. It's almost, but not quite, the same as being there in person.

When the person is also able to interact with the other environment, perhaps through a robot-like device, many people call it *teleoperation.* A gray area exists in this case because it's hard to tell in many cases precisely where telepresence ends and teleoperation begins. However, the central idea in both cases is that it feels as though you're actually there.

Considering examples of telepresence

One of the most common uses of telepresence is to reduce costs in hospitals in various ways. For example, a robot might monitor a patient in ways that monitoring equipment can't, and then alert either a nurse or a doctor to changes in a patient's condition that the robot isn't designed to handle (tinyurl.com/ypzw52pt). Telepresence means being able to monitor patients from essentially anywhere, especially in their homes, making nursing home stays less likely (tinyurl.com/26tav7zv). In addition, telepresence allows a patient to visit with family when such visits wouldn't be possible for any of a number of reasons.

Telepresence is also making an appearance in factories and office buildings (www.robots4good.com.au/blog/how-telepresence-robots-will-transform-the-way-we-work-robots4good). A security guard is safer in a secured room than walking the rounds. Using a telepresence robot allows the guard to patrol the premises without getting tired. In addition, it's possible to fit a robot with special vision to see things a human guard can't see.

Enforced use of telepresence will likely increase its use and provide an incentive to improve the technology. During the COVID-19 pandemic, many doctors also began to rely on telepresence to maintain contact with their patients, The National Institutes of Health (NIH) also recommended using telepresence for patient-based teaching, during the pandemic was also a problem for many people, especially the older population, as described in the article at tinyurl.com/ykvadwxb. All these pandemic-enhanced uses of telepresence will likely make the technology more common and potentially reduce its cost due to economies of scale.


TIP

The capabilities of the telepresence device determine its usefulness. The site at tinyurl.com/y7sm2ytr shows that the robotic form comes in all sorts of sizes and shapes to meet just about every need.

Understanding telepresence limitations

The problem with telepresence is that humans can quickly become too comfortable using it. For example, many people criticized a doctor who used telepresence, rather than a personal visit, to deliver devastating news to a family (see tinyurl.com/3azcb7w8). In some cases, personalized human touch and interaction is an essential component of life.

Telepresence also can't replace human presence in some situations requiring senses that these devices can't currently offer. For example, if the task requires the sense of smell, telepresence can't support the need at all. Given how often the

sense of smell becomes an essential part of performing a task, even in a hospital, overreliance on telepresence can be a recipe for disaster.

TIP

The article at tinyurl.com/w8pbvx78 provides some additional insights into when telepresence may simply be a bad idea.

Devising New Surgical Techniques

Robots and AI now routinely participate in surgical procedures. In fact, some surgeries would be nearly impossible without the use of robots and AI. However, the history of using this technology isn't lengthy. The first surgical robot, Arthrobot, made its appearance in 1983. Even so, the use of these life-saving technologies has reduced errors, improved results, decreased healing time, and generally made surgery less expensive over the long run. The following sections describe the use of robots and AI in various aspects of surgery.

Making surgical suggestions

You can view the whole idea of surgical suggestions in many different ways. For example, an AI might analyze all the data about a patient and provide the surgeon with suggestions about the best approaches to take based on that individual patient's record. The surgeon could decide on the approach, but it would take longer and might be subject to errors that the AI won't make. The AI doesn't grow tired or overlook things; it consistently views all the data available in the same way every time.

Unfortunately, even with an AI assistant, surprises still happen during surgery, which is where the next level of suggestion comes into play. The patient receives the benefit of what amounts to a second opinion to handle unforeseen complications during surgery. Mind you, the device isn't actually doing anything more than making already existing research, which was created by other doctors, readily available in response to surgeon requests; no real thinking is involved.

Preparing for surgery also means analyzing all those scans that doctors insist on ordering. Speed is an advantage that AI has over a radiologist. Products such as Enlitic (www.enlitic.com), a deep learning technology, can analyze radiological scans in milliseconds — up to 10,000 times faster than a radiologist. In addition, the system is 50 percent better at classifying tumors and has a lower false-negative rate (0 percent versus 7 percent) than humans.

WORKING IN THIRD WORLD COUNTRIES

Frequently, people perceive that none of the amazing technologies relied on by medical professionals today actually make it to third world countries. Actually, though, some of these technologies, such as products from Caption Health (caption–care.com), are meant specifically for third world countries. Doctors used the resulting technology in Africa to identify signs of rheumatic heart disease (RHD) in Kenyan children. During a visit in September 2016, doctors used the Caption Health equipment to scan 1,200 children in four days and spotted 48 children with RHD or congenital heart disease. Without AI, the equipment couldn't exist; it would never be small enough or easy enough to operate for use in these environments because of a lack of consistent energy sources and economic means.

Assisting a surgeon

Most robotic help for surgeons today assists, rather than replaces, the surgeon. The first robot surgeon, the PUMA system, appeared in 1986. It performed an extremely delicate neurosurgical biopsy, which is a nonlaparoscopic type of surgery. *Laparoscopic* surgery is minimally invasive, with one or more small holes serving to provide access to an organ, such as a gallbladder, for removal or repair. The first robots weren't adept enough to perform this task.

By 2000, the da Vinci Surgical System provided the ability to perform robotic laparoscopic surgery using a 3D optical system. The surgeon directs the robot's movements, but the robot performs the actual surgery. The surgeon watches a high-definition display during the surgery and can see the operation better than being in the room performing the task personally. The System also uses smaller holes than a surgeon can, reducing the risk of infection.

The most important aspect of the da Vinci Surgical System, though, is that the setup augments the surgeon's native capabilities. For example, if the surgeon shakes a bit during part of the process, the System removes the shake — similarly to how antishake features work with a camera. The system also smooths out external vibrations. The system's setup also enables the surgeon to perform extremely fine movements — finer than a human can natively perform, thereby making the surgery far more precise than the surgeon could accomplish alone.

The da Vinci Surgical System is a complex and extremely flexible device. The FDA has approved it for both pediatric and adult surgeries of the following types:

- Urological surgeries
- General laparoscopic surgeries

- General noncardiovascular thoracoscopic surgeries
- Thoracoscopically assisted cardiotomy procedures

The point behind including all this medical jargon is that the da Vinci Surgical System can perform many tasks without involving a surgeon directly. At some point, robot surgeons will become more autonomous, keeping humans even farther away from the patient during surgery. In the future, no one will actually enter the clean room with the patient, thereby reducing the chances of infection to nearly zero. You can read more about the System at `tinyurl.com/4h44vtyy`.

Replacing the surgeon with monitoring

In *Star Wars*, you see robotic surgeons patching up humans all the time. In fact, you might wonder whether any human doctors are available. Theoretically, robots could take over some types of surgery in the future, but the possibility is still a long way off. Robots would need to advance quite a bit from the industrial sort of applications that you find today. The robots of today are hardly autonomous and require human intervention for setups.

However, the art of surgery for robots is making advances. For example, the Smart Tissue Autonomous Robot (STAR) outperformed human surgeons when sewing a pig intestine, as described at `tinyurl.com/aezx65u3`. Doctors supervised STAR during the surgery, but the robot actually performed the task on its own, which is a huge step forward in robotic surgery.

Performing Tasks Using Automation

AI is great at automation. It never deviates from the procedure, never grows tired, and never makes mistakes as long as the initial procedure is correct. Unlike humans, AI never needs a vacation or a break, or even an 8-hour day (not that many in the medical profession have that luxury, either). Consequently, the same AI that interacts with a patient for breakfast will do so for lunch and dinner as well. So, at the outset, AI has some significant advantages if viewed solely on the basis of consistency, accuracy, and longevity (see the earlier sidebar "Bias, sympathy, and empathy" for areas in which AI falls short). The following sections discuss various ways in which AI can help with automation through better access to resources, such as data.

Working with medical records

One major way in which an AI helps in medicine is with medical records. In the past, everyone used paper records to store patient data. Each patient might also have a blackboard that medical personnel use to record information daily during a hospital stay. Various charts contain patient data, and the doctor might also have notes. Storing all these sources of information in so many different places made it hard to keep track of the patient in any significant way. Using an AI, along with a computer database, helps make information accessible, consistent, and reliable. Products such as DeepMind, a part of Google Health (`health.google`) enable personnel to mine the patient's information to see patterns in data that aren't obvious.

Medicine is about a team approach, with many people of varying specialties working together. However, anyone who watches the process for a while soon realizes that the various specialists don't always communicate among themselves sufficiently because they're all quite busy treating patients. Products such as CloudMedX (`cloudmedxhealth.com`) take all the input from all the parties involved and perform risk analysis on it. The result is that the software can help locate potentially problematic areas that could reduce the likelihood of a good patient outcome. In other words, this product does some of the communicating that the various stakeholders would likely do if they weren't submerged in patient care.

Predicting the future

Some truly amazing predictive software based on medical records includes Autonomous Health, which uses algorithms to determine the likelihood of a patient's need for readmission to the hospital after a stay. By performing this task, hospital staff can review reasons for potential readmission and address them before the patient leaves the hospital, making readmission less likely. Along with this strategy, Anju (`www.anjusoftware.com`) helps doctors evaluate various therapies and choose those most likely to result in a positive outcome — again reducing the risk that a patient will require readmission to the hospital.

In some respects, your genetics form a map of what will happen to you in the future. Consequently, knowing about your genetics can increase your understanding of your strengths and weaknesses, helping you to live a better life. Deep Genomics (`www.deepgenomics.com`) is discovering how mutations in your genetics affect you as a person. Mutations need not always produce a negative result; some mutations actually make people better, so knowing about mutations can be a positive experience, too. Check out the video at `tinyurl.com/fjhs638b` for more details.

Making procedures safer

Doctors need lots of data to make good decisions. However, with data being spread out all over the place, doctors who lack the ability to analyze that disparate data quickly often make imperfect decisions. To make procedures safer, a doctor needs not only access to the data but also some means of organizing and analyzing it in a manner reflecting the doctor's specialty. Oncora Medical (`www.oncora.ai`) is a product that collects and organizes medical records for radiation oncologists. As a result, these doctors can deliver the right amount of radiation to just the right locations to obtain a better result with a lower potential for unanticipated side effects.

Doctors also have trouble obtaining necessary information because the machines they use tend to be expensive and huge. An innovator named Jonathan Rothberg decided to change all that by using the Butterfly Network (`www.butterflynetwork.com`). Imagine an iPhone-size device that can perform both an MRI and an ultrasound. The picture on the website is nothing short of amazing.

Creating better medications

Everyone complains about the price of medications today. Yes, medications can do amazing things for people, but they cost so much that some people end up mortgaging homes to obtain them. Part of the problem is that testing takes a lot of time. Performing a tissue analysis to observe the effects of a new drug can take up to a year. Fortunately, products such as Strateos (`strateos.com`) can greatly reduce the time required to obtain the same tissue analysis to as little as one day.

Of course, better still would be for the drug company to have a better idea of which drugs are likely to work and which aren't before investing any money in research. Atomwise (`www.atomwise.com`) uses a huge database of molecular structures to perform analyses on which molecules will answer a particular need. In 2015, researchers used Atomwise to create medications that would make Ebola less likely to infect others. The analysis that would have taken human researchers months or possibly years to perform took Atomwise just one day to complete.

Drug companies also produce a huge number of drugs. The reason for this impressive productivity, besides profitability, is that every person is just a little different. A drug that performs well and produces no side effects on one person might not perform well at all for another person, and could even do harm. Turbine (`turbine.ai/`) enables drug companies to perform drug simulations so that the drug companies can locate the drugs most likely to work with a particular person's body. Turbine's current emphasis is on cancer treatments, but it's easy to see how this same approach could work in many other areas.

Some companies have yet to realize their potential, but they're likely to do so eventually. One such company is Recursion Pharmaceuticals (wwww.recursion.com), which employs automation to explore ways to solve new problems using known drugs, bioactive drugs, and pharmaceuticals that didn't previously make the grade. The company has had some success in helping to solve rare genetic diseases, and it has a goal of curing 100 diseases in the long term (obviously, an extremely high goal to reach).

Combining Robots and Medical Professionals

Semiautonomous robots with limited capabilities are starting to become integrated into society. Japan has used these robots for a while now (see tinyurl.com/5x5u5va8). The robots are also appearing in America in the form of RUDY (see infrobotics.com). In most cases, these robots can perform simple tasks, such as reminding people to take medications and playing simple games, without much in the way of intervention. However, when needed, a doctor or another medical professional can take control of the robot from a remote location and perform more advanced tasks by way of the robot. Using this approach means that the person obtains instant help when necessary, reducing the potential for harm to the patient and keeping costs low.

REMEMBER

These sorts of robots are in their infancy now, but expect to see them improve with time. Although these robots are tools to assist medical personnel and can't actually replace a doctor or nurse for many specialized tasks, they do provide the constant surveillance that patients need, along with a comforting presence. In addition, the robots can reduce the need to hire humans to perform common, repetitive tasks (such as dispensing pills, providing reminders, and assisting with walking) that robots can perform quite well even now.

Considering Disruptions AI Causes for Medical Professionals

As you can see, integrating AI into medical practices is extremely valuable. However, it's not without challenges and disruptions (both positive and negative) for medical professionals themselves. Here are three to consider:

- **Change in clinical roles and responsibilities:** AI's ability to automate diagnostic processes and analyze vast amounts of medical data can shift the traditional roles of medical professionals. Though AI can enhance diagnostic accuracy and treatment plans, it necessitates changing how physicians and other healthcare providers approach their roles, moving toward a more collaborative model with AI systems.
- **Training and adaptation:** Integrating AI into healthcare requires medical professionals to acquire new skills related to AI technologies. This includes understanding how AI tools work, interpreting AI-generated insights, and integrating these into clinical decision-making. The need for ongoing education and training to keep up with rapidly evolving AI technologies can be a significant disruption.
- **Patient-physician relationship:** The introduction of AI into patient care can impact the patient-physician relationship. Though AI can free up time for physicians to focus more on patient interaction by automating administrative tasks, there is a concern that an overreliance on AI could depersonalize care. Ensuring that AI enhances rather than detracts from the human aspects of care is a critical challenge.

IN THIS CHAPTER

- Distinguishing between robots in sci-fi and in reality
- Reasoning about robot ethics
- Finding more applications for robots
- Looking inside how a robot is made

Chapter 13
Developing Robots

People often mistake robotics for AI, but robotics is different from AI. Artificial intelligence aims to find solutions to some difficult problems related to human abilities (such as recognizing objects or understanding speech or text); robotics aims to use machines to perform tasks in the physical world in a partially or completely automated way. It helps to think of AI as the software used to solve problems and to think of robotics as the hardware for making these solutions a reality.

Robotics often utilizes AI techniques, but not all robots require AI to function. Some simple algorithms or just humans remotely control some robots, as with the da Vinci robot discussed in Chapter 12, in the section about assisting a surgeon. In many cases, AI does provide augmentation, but humans are still in control. Besides these examples of complete human control, there are robots that take more or less detailed instructions from humans (such as moving from point A to point B on a map or picking up an object) and rely on AI to execute the orders. Other robots autonomously perform assigned tasks with no human intervention. Integrating AI into a robot makes the robot smarter and more useful in performing tasks, but robots don't always need AI to function properly. Human imagination has made AI and robots overlap as a result of sci-fi films and novels.

This chapter explores how the overlap between AI and robots occurred and distinguishes between the current realities of robots and how the extensive use of AI solutions might transform them. Industrial robots have been used in manufacturing since the 1960s, whereas more advanced, multipurpose robots have emerged

more recently. This chapter also explores how people are employing robots more and more in industrial work, scientific discoveries, medical care, and war. Some AI discoveries are accelerating this process because they solve difficult problems in robots, such as recognizing objects in the world, predicting human behavior, understanding voice commands, speaking correctly, learning to walk upright and, yes, doing backflips, as well as the ability to recover from unexpected disturbances and maintain balance in challenging situations, as you can read in this article on recent robotic milestones: news.mit.edu/2019/mit-mini-cheetah-first-four-legged-robot-to-backflip-0304. Note that the situation has progressed and now robots can even perform parkour (it's French for "the art of movement"): www.youtube.com/watch?v=tF4DML7FIWk.

Defining Robot Roles

Robots are a relatively recent idea. The word comes from the Czech word *robota,* which means "forced labor." The term first appeared in the 1920 play *Rossum's Universal Robots,* written by Czech author Karel Čapek. However, humanity has long dreamed of mechanical beings. Ancient Greeks developed a myth of a bronze mechanical man, Talus, built by the god of metallurgy, Hephaestus, at the request of Zeus, the father of the gods. The Greek myths also contain references to Hephaestus building other automata, apart from Talus. *Automata* are self-operated machines that execute specific and predetermined sequences of tasks (in contrast to robots, which have the flexibility to perform a wide range of tasks). The Greeks actually built water-hydraulic automata that worked the same as an algorithm executed in the physical world. As algorithms, automata incorporate the intelligence of their creator, thus providing the illusion of being self-aware, reasoning machines.


REMEMBER

Differentiating automata from other human-like animations is important. Nowadays we have holograms, which are not automata (although AI can also power them) — they're just light projections with no mechanical parts. As another example of some myths not fitting in as automata, but inspiring robotic thoughts, in Jewish lore the *golem* is a mix of clay that magically comes alive, with no machinery involved (tinyurl.com/4m33pw7x).

You find examples of automata in Europe throughout the ancient Greek civilization, the Middle Ages, the Renaissance, and modern times. Some European automata were complex mechanical designs, but others were complete hoaxes, such as the Mechanical Turk, an 18th century machine that was said to be able to play chess but hid a man inside. Automata weren't exclusive to Europe. In the Middle East, many designs were created by the mathematician and inventor

Al-Jazari (see tinyurl.com/e7yjh557 for details) and in Asia, China and Japan also developed their own versions of automata.

The robots described by Čapek weren't exactly mechanical automata, but rather living beings engineered and assembled as if they were automata. His robots possessed a human-like shape and performed specific roles in society meant to replace human workers. Reminiscent of Mary Shelley's Frankenstein, Čapek's robots were something that people view as *androids* today — bioengineered artificial beings, as described in Philip K. Dick's novel *Do Androids Dream of Electric Sheep?* (the inspiration for the film *Blade Runner*). Yet the name *robot* also describes autonomous mechanical devices not made to amaze and delight, but rather to produce goods and services. In addition, robots became a central idea in sci-fi, in both books and movies, further contributing to a collective imagination of the robot as a human-shaped AI, designed to serve humans — not too dissimilar from Čapek's original idea of a servant. Slowly, the idea transitioned from art to science and technology and became an inspiration for scientists and engineers.


REMEMBER

Čapek created the idea of robots *and* that of a robot apocalypse, like the AI takeover you see in sci-fi movies and that, given AI's recent progress, is feared by notable figures such as Bill Gates, the founder of Microsoft, physicist Stephen Hawking, and the inventor and business entrepreneur Elon Musk. Čapek's robotic slaves rebel against the humans who created them at the end of *Rossum's Universal Robots* by eliminating almost all of humanity. However, other thinkers, such as Anthony Zador and Yann LeCun, are pushing back on these concerns, arguing that intelligence, whether artificial or biological, doesn't necessarily equate to the ability to destroy the planet or enslave humanity. You can read their more optimistic opinions in this 2019 *Scientific American* article at tinyurl.com/4zbjcesu, which is still relevant today.

Overcoming the sci-fi view of robots

The first commercialized robot, the Unimate (tinyurl.com/442x33mw), appeared in 1961. It was simply a robotic arm — a programmable mechanical arm made of metal links and joints — with an end that could grip, spin, or weld manipulated objects according to instructions set by human operators. It was sold to General Motors for use in the production of automobiles. The Unimate had to pick up die castings from the assembly line and weld them together, a physically dangerous task for human workers. To get an idea of the capabilities of such a machine, check out this video: tinyurl.com/jzt5w2hh. The following sections describe the realities of robots today.

Considering robotic laws

Before the appearance of Unimate, and long before the introduction of many other robot arms employed in industry that started working with human workers on assembly lines, people already knew how robots should look, act, and even think. Isaac Asimov, an American writer renowned for his works in science fiction and popular science, produced a series of novels in the 1950s that suggested a completely different concept of robots from those used in industrial settings.

REMEMBER

Asimov coined the term *robotics* and used it in the same sense as people use the term *mechanics.* His powerful imagination still sets the standard for people's expectations of robots. Asimov set robots in an age of space exploration, having them use their positronic brains to help humans perform both ordinary and extraordinary tasks daily. A *positronic brain* is a fictional device that makes robots in Asimov's novels act autonomously and capable of assisting or replacing humans in many tasks. Apart from providing human-like capabilities in understanding and acting (a clear display of a strong AI), the positronic brain works under the three laws of robotics as part of the hardware, controlling the behavior of robots in a moral way:

1. A robot may not injure a human being or, through inaction, allow a human being to come to harm.
2. A robot must obey the orders given it by human beings except where such orders would conflict with the First Law.
3. A robot must protect its own existence as long as such protection does not conflict with the First or Second Laws.

Later the author added a zeroth rule, with higher priority over the others in order to ensure that a robot acted to favor the safety of the many:

0. A robot may not harm humanity, or, by inaction, allow humanity to come to harm.

Central to all of Asimov's stories about robots, the three laws allow robots to work with humans with no risk of rebellion or AI apocalypse. Impossible to bypass or modify, the three laws execute in priority order and appear as mathematical formulations in the positronic brain functions. Unfortunately, the laws have loopholes and ambiguity problems, from which arise the plots of most of his novels. The three laws come from a fictional *Handbook of Robotics*, 56th Edition, 2058 AD and rely on the principles of harmlessness, obedience, and self-survival.

Asimov imagined a universe in which you can reduce the moral world to a few simple principles, with some risks that drive many of his story plots. In reality, Asimov believed that robots are tools to serve humankind and that the three laws could work even in the real world to control their proper use (read this 1981

interview in *Compute!* magazine for details: tinyurl.com/227352ff). Defying Asimov's optimistic view, however, current robots lack the capability to

- Understand the three laws of robotics
- Select actions according to the three laws
- Sense and acknowledge a possible violation of the three laws

You may think that today's robots really aren't smart because they lack these capabilities, and you'd be right. However, the Engineering and Physical Sciences Research Council (EPSRC), which is the UK's main agency for funding research in engineering and the physical sciences, and the Arts and Humanities Research Council (AHRC), promoted revisiting Asimov's laws of robotics in 2010 for use with real robots, given the technology of the time. The result is much different from the original Asimov statements (see tinyurl.com/5cmr7bdr). Recognized at the time as a useful starting point, EPSRC/AHRC principles of robotics sprout a conversation that is ongoing and even more actual in the current landscape of large language models and Generative AI, as described in the article at www.psychologytoday.com/intl/blog/the-digital-self/202310/asimovs-three-laws-of-robotics-applied-to-ai. EPSRC/AHRC principles admit that robots may even kill (for national security reasons) exactly because they are a tool. As with all the other tools, complying with the law and existing morals is up to the human user, not the machine, with the robot perceived as an executor. A human being should always be accountable for the results of a robot's actions.


TIP

The EPSRC/AHRC's principles offer a more realistic point of view on robots and morality, considering the weak AI technology in use now, but they could also provide a partial solution in advanced technology scenarios. Chapter 15 discusses problems related to using self-driving cars, a kind of mobile robot that drives for you. For example, in the exploration of the trolley problem in that chapter, you face possible but unlikely moral problems that challenge the reliance on automated machines when it's time to make certain choices.

Defining actual robot capabilities

Existing robot capabilities are not only still far from the human-like robots found in Asimov's works but also of different categories. The kind of bipedal robot imagined by Asimov is currently uncommon and mostly just under development. Achieving the level of agility and dexterity depicted by Asimov's robots still remains an engineering challenge.

The largest category of robots is the robot arm, such as the previously described Unimate. Robots in this category are also called *manipulators*. You can find them in factories, working as industrial robots, where they assemble and weld at a speed and precision unmatched by human workers. Some manipulators also appear in

hospitals to assist in surgical operations. Manipulators have a limited range of motion because they integrate into their location (they might be able to move a little, but not a lot because they lack motors that would allow movement or they need an electrical hookup), so they require help from specialized technicians to move to a new location. In addition, manipulators used for production tend to be completely automated (in contrast to surgical devices, which are remote-controlled, relying on the surgeon to make medical operation decisions). More than 3.9 million manipulators appeared in factories throughout the world as of 2022, with the Republic of Korea leading the way in robot adoption (1,012 robots per 10,000 employees), followed by Singapore (730 units) and Germany (415 units) according to `ifr.org/ifr-press-releases/news/global-robotics-race-korea-singapore-and-germany-in-the-lead`.

The second largest, and growing, category of robots is that of *mobile robots* — their specialty, contrary to that of manipulators, is to move around by using wheels, rotors, wings, or even legs. The major use of these robots is in industry, as described in "Mobile robotics applications" at Robotnik.eu. Mobile robots are mostly unmanned (no one travels with them) and remotely controlled, but autonomy is increasing, and you can expect to see more independent robots in this category. Two special kinds of mobile robots are flying robots, called *drones* (see Chapter 14), and self-driving cars (discussed in Chapter 15).

The last kind of robot is the *mobile manipulator,* which can move (as do mobile robots) and manipulate (as do robot arms). The pinnacle of this category doesn't just consist of a robot that moves and has a mechanical arm but also imitates human shape and behavior. The *humanoid robot* is a bipedal robot (it moves on two legs) that has a human-like torso and communicates with humans by way of voice and expressions. This kind of robot is what sci-fi dreamed of, but it's not easy to obtain. The COVID-19 pandemic has spawned greater use of humanoid robots like Sophia (see `tinyurl.com/2ve3479k`).

Being humanoid can be hard

Human-like robots are hard to develop, and scientists are still at work on them. A humanoid robot not only requires enhanced AI capabilities to make it autonomous but also needs to move as humans do. The biggest hurdle, though, is persuading humans to accept a machine that looks like humans. The following sections look at various aspects of creating a humanoid robot.

Creating a robot that walks

Consider the problem of having a robot walking on two legs (a *bipedal* robot). This is something that humans learn to do adeptly and without conscious thought, but it's problematic for a robot. Four-legged robots balance easily, and they don't

consume much energy doing so. Humans, however, do consume energy simply by standing up, as well as by balancing and walking. Humanoid robots, like humans, have to continuously balance themselves, and do it in an effective and economical way. Otherwise, the robot needs a large battery pack, which is heavy and cumbersome, making the problem of balance even more difficult.

A video provided by IEEE Spectrum gives you a better idea of just how challenging the simple act of walking can be. The video shows robots involved in the DARPA Robotics Challenge (DRC), a challenge held by the US Defense Advanced Research Projects Agency (DARPA) from 2012 to 2015: `tinyurl.com/xsatxdfp`. The purpose of the DRC is to explore robotic advances that could improve disaster and humanitarian operations in environments that are dangerous to humans. For this reason, you see robots walking on various terrains, opening doors, grasping tools such as an electric drill, or trying to operate a valve wheel. A robot called Atlas, from Boston Dynamics, shows much promise, as initially described in this article: `tinyurl.com/6smshpfk`. The Atlas robot truly is exceptional, but further development is required. The challenge is ongoing, with new features and capabilities added along the way, as described at `techcrunch.com/2023/01/18/boston-dynamics-latest-atlas-video-demos-a-robot-that-run-jump-and-now-grab-and-throw-things`.

REMEMBER

A robot with wheels can move easily on roads, but in certain situations, you need a human-shaped robot to meet specific needs. Most of the world's infrastructures are made for a person to navigate. The passage size and the presence of obstacles such as the presence of doors or stairs makes using variously shaped robots difficult. For instance, during an emergency, a robot may need to enter a nuclear power station and close a valve. The human shape enables the robot to walk around, descend stairs, and turn the valve wheel.

TALK WITH THE ROBOT! THE CHATTY ROBOTS OF FIGURE

We are quite accustomed to the video of the amazing achievements of the robots from Boston Dynamics, a company that dates to 1992 and that has gained fame and reputation as the pioneer of agile robots inspired by humans and animals. Boston Dynamics' most renowned robots are Spot (`www.bostondynamics.com/spot`), a four-legged canine robot, and Atlas (`www.bostondynamics.com/atlas`), a bipedal humanoid robot, which represents the most human-like robot on the market at the moment. However, at the present time, the lion's share of the attention is held by generative AI and large language model (LLM) applications. The new frontier involves integrating the

(continued)

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language capabilities of LMMs with robotics. An example is provided by Figure (`www.figure.ai`), an AI robotics company with investments from Microsoft, OpenAI Startup Fund, NVIDIA, Jeff Bezos (via Bezos Expeditions), Parkway Venture Capital, Intel Capital, and others. Particularly impressive is Figure's video depicting the interaction between a human user and a robotic AI system called Figure One (`www.youtube.com/watch?v=Sq1QZB5baNw`). The user is asking Figure One to describe what it sees in the scene and then perform certain actions, such as picking up an apple and then trash and then putting dishware away in a drying rack.

Overcoming human reluctance: The uncanny valley

Humans have a problem with humanoid robots that look a little too human. In 1970, a professor at the Tokyo Institute of Technology, Masahiro Mori, studied the impact of robots on Japanese society. He coined the term *Bukimi no Tani Genshō*, which translates to "uncanny valley." Mori realized that the more realistic robots look, the greater affinity humans feel toward them. This increase in affinity remains true until the robot reaches a certain degree of realism, at which point we start disliking them strongly (even feeling revulsion). The revulsion increases until the robot reaches the level of realism that makes it a copy of a human being. You can find this progression depicted in Figure 13-1 and described in Mori's original paper at `tinyurl.com/5zxepyux`.

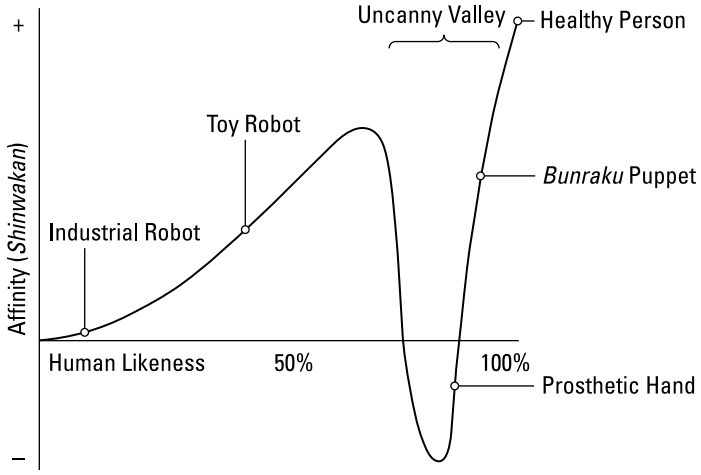

FIGURE 13-1: The uncanny valley.

Various hypotheses have been formulated about the reasons for the revulsion that humans experience when dealing with a robot that is almost, but not completely,

human. The cues that humans use to detect robots are the tone of the robotic voice, the rigidity of movement, and the artificial texture of the robot's skin. Some scientists attribute the uncanny valley to cultural reasons, and others to psychological or biological ones. One experiment with monkeys found that primates might undergo a similar experience when exposed to more or less realistically processed photos of monkeys rendered by 3D computer-generated imagery (CGI) technology (see the story here: `tinyurl.com/c69vbhzt`). Monkeys participating in the experiment displayed a slight aversion to realistic photos, hinting at a common biological reason for the uncanny valley. An explanation could, therefore, relate to a self-protective reaction against beings negatively perceived as unnatural-looking because they're ill or even possibly dead. The research is ongoing, as described in the article at `tinyurl.com/ye9dshs4`.

The interesting point about the uncanny valley is that if we need humanoid robots because we want them to assist humans, we must also consider their level of realism and key aesthetic details in order to achieve a positive emotional response that will allow users to accept robotic help. Some observations show that even robots with little human resemblance generate attachment and create bonds with their users. For instance, many US soldiers report feeling a loss when their small tactical robots for explosive detection and handling are destroyed in action. (You can read an article about this topic in the MIT Technological Review: `tinyurl.com/6chj2m3a`.) At the other extreme, some robots have been canceled because people thought they were too creepy, such as the New York police dog Spot (`tinyurl.com/79dkb8vt`). Even though Spot doesn't look much like a dog, the headless aspect of the robot made people feel uneasy. Perhaps it would have received a better reception if it had had a head of some sort.

Working with robots

Different types of robots have different applications. As humans developed and improved the three classes of robots (manipulator, mobile, and mobile manipular), new fields of application opened to robotics. It's now impossible to enumerate exhaustively all the existing uses for robots, but the following sections touch on some of the most promising and revolutionary uses.

Enhancing economic output

Manipulators, or industrial robots, still account for the largest percentage of operating robots in the world. However, you see them used more in some countries than in others. The article "Robot Race: The World´s Top 10 automated countries" at `IFR.org` is enlightening because robot use has increased even faster than predicted, but where the number of robots has increased (mostly in Asia) is as important as the fact that usage has increased. In fact, factories (as an entity) will use robots to become smarter, a concept dubbed *Industry 4.0*. Thanks to the

widespread use of the Internet, sensors, data, and robots, Industry 4.0 solutions allow easier customization and higher quality of products in less time than they can achieve without robots. No matter what, robots already operate in dangerous environments — and for tasks such as welding, assembling, painting, and packaging, they operate faster, with higher accuracy, and at lower costs than human workers can.

Taking care of you

Since 1983, robots have assisted surgeons in difficult operations by providing precise and accurate cuts that only robotic arms can provide. Apart from offering remote control of operations (keeping the surgeon out of the operating room to create a more sterile environment), an increase in automated operations is steadily opening the possibility of completely automated surgical operations in the near future, as speculated in this article: `tinyurl.com/c2j4cabm`. You might also want to check out the Society of Robotic Surgery (SRS) page at `tinyurl.com/4vwcjrab` to discover more about the human end of this revolution.

Providing services

Robots provide other care services, in both private and public spaces. Many service robots today are specifically targeted at home use, and the most famous indoor robot is the Roomba vacuum cleaner, a robot that vacuums the floor of your house by itself, but there are other service robots to consider as well (as described in the article at `tinyurl.com/6dxnhfbt`). There is also the use of robots for elder care, with an eye toward keeping elderly people in their homes as long as possible.

The definition of a service robot is changing almost daily because of a combination of worldwide events, like the COVID-19 pandemic, the overall aging of the population, and the ability of technology to meet certain needs. The article at `tinyurl.com/2cjzune7` provides some insights into how people view service robots today, but it's guaranteed that the definitions will change in the future.

Venturing into dangerous environments

Robots go where people can't or would be at great risk if they did. Some robots have been sent into space (the NASA Mars rover *Perseverance* is one of the most notable), and more will support future space exploration. (Chapter 18 discusses robots in space.) Many other robots stay on Earth and are employed in underground tasks, such as transporting ore in mines or generating maps of tunnels in caves. Underground robots are even exploring sewer systems, as does Luigi (a name inspired by the brother of a famous plumber in videogames). Luigi is a sewer-trawling robot developed by MIT's Senseable City Lab to investigate public

health in a place where humans can't go unharmed because of high concentrations of chemicals, bacteria, and viruses (see tinyurl.com/da4hwucw).

Robots are even employed where humans will definitely die, such as in nuclear disasters like Three Mile Island, Chernobyl, and Fukushima. These robots remove radioactive materials and make the area safer. Only *radiation-hardened electronic components* allow robots to resist the effects of radiation enough to carry out their job, such as the Little Sunfish, an underwater robot that operated in one of Fukushima's flooded reactors where the meltdown happened (as described in this article at tinyurl.com/yes4duwd).

In addition, warfare or criminal scenes represent life-threatening situations in which robots see frequent use for transporting weapons or defusing bombs. These robots can also investigate packages that could include a lot of harmful items other than bombs. Robot models such as iRobot's PackBot (from the same company that manufactures Rumba, the house cleaner) or QinetiQ North America's Talon handle dangerous explosives by remote control, meaning that an expert in explosives controls their actions at a distance. Some robots can even act in place of soldiers or police in reconnaissance tasks or direct interventions (for instance, police in Dallas used a robot to take out a shooter tinyurl.com/fk85wpsb). Of course, lots of questions are being asked about this practice, as detailed at tinyurl.com/56xk4pzw.

REMEMBER

People expect the military to increasingly use robots in the future. Beyond the ethical considerations of these new weapons, it's a matter of the old guns-versus-butter model), meaning that a nation can exchange economic power for military power. Robots seem a perfect fit for that model, more so than traditional weaponry that needs trained personnel to operate. Using robots means that a country can translate its productive output into an immediately effective army of robots at any time, something that the *Star Wars* prequels demonstrate all too well.

Understanding the role of specialty robots

Specialty robots include drones and self-driving (SD) cars. Drones are controversial because of their usage in warfare, but unmanned aerial vehicles (UAVs) are also used for monitoring, agriculture, and many less-menacing activities, as discussed in Chapter 14.

People have long fantasized about cars that drive themselves. Most car producers have realized that being able to produce and commercialize SD cars could change the actual economic balance in the world. At one point, it seemed as though the world was on the cusp of seeing SD cars. However, for a whole lot of reasons today, SD car technology has stalled. Chapter 15 discusses SD cars, their technology, and their implications in more detail.

Assembling a Basic Robot

An overview of robots isn't complete without discussing how to build one, given the state of the art, and considering how AI can improve its functioning. The following sections discuss robot basics.

Considering the components

A mobile robot's purpose is to act in the world, so it needs arms and end effectors to grip, rotate, and translate objects (modify the orientation outside of rotation). These capabilities are provided by *manipulators*, which are the components designed for manipulation tasks. An *actuator* is one of the mechanisms that compose the manipulators, allowing for a single movement. Thus, a robot arm has different actuators, such as electric motors or hydraulic cylinders, that perform movements like orienting the arm or bending it. Furthermore, in order to accomplish specific operations, at the end of the manipulators, you find an end effector, a device to carry out specific tasks, such as welding or cutting. If moving around is part of the robot's job, moving legs, tracks, or wheels powered by a motor will provide the *locomotion capability*.

Acting in the world requires determining the composition of the world and understanding where the robot resides in the world. *Sensors* provide input that reports what's happening outside the robot. Devices such as cameras, lasers, sonars, and pressure sensors measure the environment and report to the robot what's going on as well as hint at the robot's location. The robot therefore consists mainly of an organized bundle of sensors and effectors. Everything is designed to work together using architecture, which is exactly what makes up a robot. (Sensors and effectors are actually mechanical and electronic parts that you can use as stand-alone components in different applications.)

The common internal architecture is made of parallel processes gathered into layers that specialize in solving one kind of problem. Parallelism is important. As human beings, we perceive a single flow of consciousness and attention; we don't need to think about basic functions such as breathing, heartbeat, and food digestion because these processes go on by themselves in parallel to conscious thought. Often, we can even perform one action, such as walking or driving, while talking or doing something else (although it may prove dangerous in certain situations). The same goes for robots. For instance, in the three-layer architecture, a robot has many processes gathered into three layers, each one characterized by a different response time and complexity of response:

- **Reactive:** Takes immediate data from the sensors, the channels for the robot's perception of the world, and reacts immediately to sudden problems

(for instance, turning immediately after a corner because the robot is going to crash into an unknown wall).

- **Executive:** Processes sensor input data, determines where the robot is in the world (an important function called *localization*), and decides what action to execute given the requirements of the previous layer, the reactive one, and the following one, the deliberative.
- **Deliberative:** Makes plans on how to perform tasks, such as planning how to go from one point to another and deciding what sequence of actions to perform to pick up an object. This layer translates into a series of requirements for the robot that the executive layer carries out.

Another popular architecture is the pipeline architecture, commonly found in SD cars, which simply divides the robot's parallel processes into separate phases such as sensing, perception (which implies understanding what you sense), planning, and control.

Sensing the world

Chapter 15 discusses sensors in detail and presents practical applications to help explain SD cars. Many kinds of sensors exist, with some focusing on the external world and others on the robot itself. For example, a robotic arm needs to know how much its arm extended or whether it reached its extension limit. Furthermore, some sensors are active, and others are passive. Active sensors emit some sort of signal and measure the consequent response. Passive sensors continuously receive signals from the environment, based on light, sound, or other signals emitted by a target. Each sensor provides an electronic input that the robot can immediately use or process to gain a perception.

Associated with *perception* is the process of building a local map of real-world objects and determining the location of the robot in a more general map of the known world. Combining data from all sensors, a process called *sensor fusion*, creates a list of basic facts for the robot to use. Machine learning and deep learning contribute by providing vision algorithms to recognize objects and segment images (as discussed in Chapter 7). It also puts all the data together into a meaningful representation using unsupervised machine learning algorithms. This task, called *low-dimensional embedding*, means translating complex data from all sensors into a simple flat map or other representation. Determining a robot's location based on all this information is called *simultaneous localization and mapping (SLAM)*, and it's just like when you look at a map to understand at a glance where you are in a city.

Controlling a robot

After sensing provides all the needed information, planning provides the robot with a list of the right actions to take to achieve its objectives. Planning can be done programmatically (by using an expert system, for example, as described in Chapter 3) or by using a machine learning algorithm, such as Bayesian networks, as described in Chapter 6. Currently, reinforcement learning, as discussed in Chapter 8, is considered the most promising technology for planning activities when interacting with the external world. In addition, there's a growing interest in, and exploration of, using LLMs to enhance various aspects of robot systems, including planning and control and human-robot interaction, such as illustrated in this article from Google DeepMind: `www.roboticsproceedings.org/rss19/p024.pdf`.

Finally, planning isn't always a matter of smart algorithms because, when it comes to execution, things don't always go as planned. Think about this issue from a human perspective. When you're blindfolded, even if you want to go straight in front of you, you won't unless you have a constant source of corrections. The result is that you start going in circles. In addition, based on your dexterity, your legs might not always perfectly follow instructions. Robots face the same problem. In addition, robots face issues such as delays in the system (technically called *latency*), or they don't execute instructions exactly on time, thus messing things up. However, most often the issue is a problem with the robot's environment, in one of the following ways:

- **Uncertainty:** The robot isn't sure where it is, or it can partially observe the situation but can't figure it out exactly. Because of uncertainty, developers say that the robot operates in a *stochastic environment.*
- **Adversarial situations:** People or moving objects are in the way. In some situations, these objects even become hostile (see an earlier article from Business Insider at `tinyurl.com/r3mkw23y`). An ongoing study in this area is described in the article in iScience at `tinyurl.com/f8zsdwm4`.


REMEMBER

Robots have to operate in environments that are partially unknown, changeable, mostly unpredictable, and in a constant flow, meaning that all actions are chained and the robot has to continuously manage the flow of information and actions in real-time. Being able to adjust to this kind of environment can't be fully predicted or programmed, and such an adjustment requires learning capabilities, which AI algorithms provide more and more often to robots.

IN THIS CHAPTER

- Distinguishing between military and civilian drones
- Discovering the possible uses of drones
- Determining the feats AI might allow drones to achieve
- Acknowledging regulations and limitations of drone operability

Chapter 14
Flying with Drones

Drones are mobile robots that move in the environment by flying around. Initially connected to warfare, drones have become a powerful innovation for leisure, exploration, commercial delivery, and much more. However, military investment still lurks behind developments, with drones being actively used in many current war scenarios. This situation causes concern from many AI experts and public figures who foresee them as possibly unstoppable killing machines when integrated with AI systems and sent to the battlefield.

Nowadays, flying technology is advanced, so drones are more mature than other mobile robots because the key technology that makes them work is well understood. The drones' frontier is to incorporate AI. Moving by flying poses some important limits on what drones can achieve, such as the weight they can carry or the actions they can take when arriving at a destination. However, drones typically don't encounter the same obstacle avoidance challenges that ground-based mobile robots do, making them more versatile in many scenarios.

This chapter discusses the present state of drones: consumer, commercial, and military. It starts from the drone's military origin and present role in warfare. It also explores the roles drones might play in the future. These roles for drones depend partly on integration with AI solutions, which will give them more autonomy and extended capabilities in moving and operating.

Acknowledging the State of the Art

Drones are mobile robots that fly. This type of robot has existed for a long time, especially for military uses (where the technology originated). The official military name for this type of flying machine is unmanned aircraft system (UAS), which includes the unmanned aerial vehicle (UAV) and the associated support systems. More commonly, the public knows such mobile robots as drones because their sound resembles that of the male bee — though you won't find the term in many official papers because officials prefer names like UAS or UAV or UACV (unmanned aerial combat vehicles) or even RPA (remotely piloted aircraft).

In recent years, in many conflicts, drones have first appeared as substitutes for warplanes — smaller, remotely controlled replicas capable to strike strategic and tactical targets accurately. Progressively, however, their usage has become more widespread and pervasive as their price becomes more accessible. Equipped with enough explosives to penetrate a tank's shell, a drone is cheaper than an artillery shell but much more effective in striking a target because it can reach places inaccessible to artillery — for instance, into a building, a shelter, or trenches. In addition, though an artillery shell can miss its target, a drone cannot because it can pursue the target relentlessly. Already a key component on contemporary battlefields, drones are meant to complement, rather than replace, other weapons in order to increase the effectiveness and reach of war operations. Currently operated mostly by humans, there is a significant push to integrate them with AI and make them an even more fearful weapon.

Flying unmanned to missions

Resembling a standard airplane (but generally in smaller form), most military drones are flying wings; that is, they have wings and one or more propellers (or jet engines) and to some extent aren't much different from airplanes that civilians use for travel. Military drones are unmanned and remotely controlled using satellite communications, even from the other side of the Earth. Military drone operators acquire telemetry information and vision as transmitted from the drone they control, and the operators can use that information to operate the machine by issuing specific commands. Some military drones perform surveillance and recognizance tasks, and thus they simply carry cameras and other devices to acquire information. Others are armed with weapons and can carry out deadly attacks on objectives. Some of the deadliest of these aircraft match the capabilities of manned aircraft (see, for instance, the experimental X-62A aircraft at `www.theverge.com/2024/4/18/24133870/us-air-force-ai-dogfight-test-x-62a`) and can travel anywhere on Earth — even to places where a pilot can't easily go.

Military drones have a long history. When exactly they began is a topic for much debate, though the Royal Navy began using drone-like planes for target practice

in the 1930s. The United States used actual drones regularly for targets as early as 1945. Starting in 1971, researchers began to apply hobbyist drones to military purposes. John Stuart Foster, Jr., a nuclear physicist who worked for the US government, had a passion for model airplanes and envisioned the idea of adding weapons to them. That led to the development of two prototypes by the US Defense Advanced Research Projects Agency (DARPA) in 1973. However, above all, it has been the use of similar drones by Israel in Middle Eastern conflicts since the 1980s that spurred interest in and further development of military drones. Interestingly enough, 1973 is the year the military first shot down a drone, using a laser, of all things. The first drone killing occurred in 2001 in Afghanistan. Of course, at the time a human operator was at the other end of the trigger. At the moment, three main types of drones are used in military operations:

- Medium-altitude long-endurance UAVs are capable of extended surveillance and reconnaissance missions, as well as carrying air-to-ground weapons.
- Stealth and advanced combat drones are designed with stealth capabilities and can carry a wider range of weapons, including air-to-air missiles.
- Smaller and specialized drones, which can be used for a variety of missions, from surveillance to precision strikes in a disposable way: The drone detonates upon reaching its target.

Recent efforts by the militaries of the world lean toward supplying drones with AI capabilities and more sensors. (A wide spectrum of sensors is being tested, including optical, thermal, and electromagnetic.) The challenge is twofold. First, scientists are working to increase the autonomy of unmanned devices sent to the battlefield, because the enemy could disturb or jam communications — for instance, by jamming GPS so that drones cannot determine where they are flying. As a second challenge, military experts are also working on how to increase the trust of operators and commanders that will send the AI to fight. Trust is essential to empower the drone with the appropriate role in the fighting.

An example of such efforts is DARPA's Gremlin project, which consists of a range of unmanned reusable drones (see `www.militaryaerospace.com/uncrewed/article/14222917/unmanned-gremlins-air-superiority` for more details). These new drones feature the capabilities for

- Multiple deployments
- Swarm assets
- Surveillance, reconnaissance, and intelligence
- Autonomous attack after target recognition
- Fighting even when communications with headquarters are cut off

REMEMBER

The key reason for employing unmanned drones in the battlefield in the future is their capability to operate in swarms, which require smaller drones, which are thus harder to detect and hit.

People debate whether to give military drones AI capabilities. Some feel that doing so would mean that drones could bring destruction and kill people through their own decision-making process. However, AI capabilities could also enable drones to more easily evade destruction or perform other nondestructive tasks, just as AI helps guide cars today. Presently, military drones with killing capabilities are also controversial because the AI would tend to make the act of war abstract and further dehumanizing, reducing it to images transmitted by drones to their operators and to commands issued remotely. Yes, the operator would still make the decision to kill by unleashing the drone, but the drone would perform the actual act, distancing the operator from responsibility for the act even more than when a pilot drops bombs from a plane.

TIP

Discussions about military drones are essential in this chapter because they interconnect with the development of civilian drones and influence much of the present discussion on this technology through public opinion. Also, giving military drones full autonomy inspires stories about an AI apocalypse that have arisen outside the sci-fi field and become a concern for the public.

Meeting the quadcopter

Many people first heard about consumer and hobbyist quadcopter drones, and then about commercial quadcopter drones or even hexacopters drones (such as the MK30 model employed by Amazon) through the mobile phone revolution. Many military drones aren't of the copter variety today, but you can find more and more employed on the battlefield, such as the Duke University TIKAD sniper drone and many civil drones that have been adapted for the purpose of carrying and releasing explosives. The military copter drones actually started as hobbyist prototypes (see `tinyurl.com/vknd9v7u` for details).

However, mobile phones were integral to making all this work. As mobile phones became smaller, their batteries also became smaller and lighter. Mobile phones also carry miniaturized cameras and wireless connectivity — all features that are needed in a contemporary drone. A few decades ago, small drones had a host of limitations, as described in this list:

- They were radio controlled using large command sets.
- They needed a line of sight (or else you would have flown blind).

- They were fixed-wing small airplanes (with no hovering capability).
- They ran on noisy diesel or oil engines, limiting their range and user-friendliness.

Recently, lightweight lithium-polymer batteries have allowed drones to

- Run on smaller, quieter, and more reliable electric motors
- Be controlled by wireless remote controls
- Rely on video feedback signals from the drones (no more line-of-sight requirement)

Drones also possess GPS, accelerometers, and gyroscopes now — all of which appear as part of consumer mobile phones. These features help control position, level, and orientation, factors that are useful for phone applications but also quite essential for flying drones.

Thanks to all these improvements, drones evolved from being fixed-wing, airplane-like models to a structure similar to helicopters, but using multiple rotors to lift themselves in the air and move in different directions. Using multiple rotors creates an advantage: Contrary to helicopters, drones don't need variable-pitch rotors for orientation. Variable-pitch rotors are more costly and difficult to control. Drones instead use simple, fixed-pitch propellers, which can emulate, as an ensemble, the same functions of variable-pitch rotors. Consequently, you now see multirotor drones: tricopter, quadcopter, hexacopter, and octocopter, respectively having three, four, six, or eight rotors to use. Among the various possible configurations, the quadcopter gained the upper hand and became the most popular drone configuration for commercial and civilian use. Because the quadcopter is based on four rotors (of small size), with each one oriented to a direction, an operator can easily turn and move the drone around by applying a different spin and speed to each rotor, as shown in Figure 14-1.

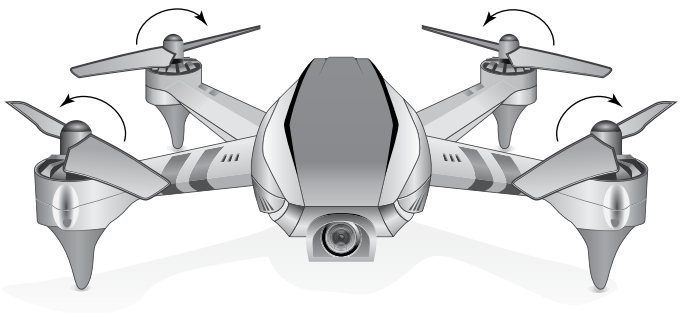

FIGURE 14-1: A quadcopter flies by opportunely spinning its rotors in the right directions.

Defining Uses for Drones

Each kind of drone type has current and futuristic applications, and consequently different opportunities to employ AI. The large and small military drones already have their parallel development in terms of technology, and those drones will likely see more use for surveillance, monitoring, and military action in the field. Experts forecast that military uses will likely extend to personal and commercial drones, which generally use technology different from the military ones. (Some overlap exists, such as Duke University's TIKAD, which actually started life in the hobbyist world.)

Also, nonstate actors, such as terrorist and insurgent groups, have increasingly acquired and weaponized commercial drones for use in military operations. Apart from rogue uses of small but cheap and easily customizable drones by insurgents and terrorist groups, governments are increasingly interested in smaller drones for urban and indoor combat. Indoor places, like corridors or rooms, are where intervention capabilities of aircraft-size *Predator* and *Reaper* military drones are limited (unless you need to take down the entire building). The same goes for scout drones, such as *Ravens* and *Pumas,* because these drones are made for the operations on the open battlefield, not for indoor warfare.

Commercial drones are far from being immediately employed from shop shelves onto the battlefield, though they offer the right platform for the military to develop various technologies using them. An important reason for the military to use commercial drones is that off-the-shelf products are mostly inexpensive compared to standard weaponry, making them both easily disposable and employable in swarms composed of large numbers of them. Easy to hack and modify, they require more protection than their already hardened military counterparts do (their communications and controls could be jammed electronically), and they need the integration of some key software and hardware parts before being effectively deployed in any mission.

Navigating in a closed space requires enhanced abilities to avoid collisions, to get directions without needing a GPS (whose signals aren't easily caught while in a building), and to engage a potential enemy. Moreover, drones would need targeting abilities for reconnaissance (spotting ambushes and threats) and for taking out targets by themselves. Such advanced characteristics aren't found in present commercial technology, and they would require an AI solution developed specifically for the purpose. Military researchers are actively developing the required additions to gain military advantage. Recent developments in nimble deep learning networks installed on a standard mobile phone — such as YOLO (`tinyurl.com/u7hwu88u`), or MobileViT and MobileNet, which are fast and lightweight neural networks for mobile vision tasks — point out how fitting advanced AI into a small drone is achievable, given the present technology advances.

Seeing drones in nonmilitary roles

Commercial drones don't now have a lot to offer in the way of advanced functionality found in military models. A commercial drone designed for the consumer market could possibly take a snapshot of you and your surroundings from an aerial perspective, with some benefit, such as an image stabilizer and a *follow-me* feature (which enables the drone to follow you without your issuing any other specific command). However, commercial drones intended for specific usage in various industries are also becoming more sophisticated. Because commercial drones are equipped with more sensors, AI, and sometimes even robotic arms, they are finding their way into many applications in advanced economies, where efficiency in productivity and automation are becoming paramount.

With such enhanced commercial drones, a few innovative uses will become quite common in the near future:

- Delivering goods in a timely fashion, no matter the traffic, which is being developed by X (Alphabet's incubator), Amazon, and many start-ups
- Performing monitoring for maintenance and project management
- Assessing various kinds of damage for insurance
- Creating field maps and counting herds for farmers
- Assisting search-and-rescue operations
- Providing Internet access in remote, unconnected areas (an idea being developed by Facebook)
- Generating electricity from high-altitude winds
- Carrying people around from one place to another

Having goods delivered by a drone is a feature that grabbed the public's attention early, thanks to promotion by large companies. One of the earliest and most recognized innovators is Amazon, which promises that its service, Amazon Prime Air, will become operative soon. Another well-known company operating drones in the USA and part of Africa is Zipline International, Inc., a logistics company specializing in delivering blood, plasma, vaccines, and other medical products (`time.com/rwanda-drones-zipline`). Google promises a similar service to Amazon's with its Project Wing. Tested primarily in Australia, Project Wing has already accomplished 350,000 deliveries, and it has tested a new, larger delivery drone that can handle packages up to 5 lbs., doubling the capacity of current drones. All these operators are confident that drone deliveries will soon take off as a profitable business. Recently, the Federal Aviation Administration (FAA) has authorized some drone operators to fly "beyond the visual line of sight" (BVLOS), enabling them to extend their deliveries — and that could help to scale up

operations and develop the business more (www.emergingtechbrew.com/stories/2024/01/23/google-wing-delivery-drones). However, industry may still be years away from having a feasible and scalable air delivery system based on drones.

Behind the media hype showing drones successfully delivering small parcels and other items, such as pizza or burritos, at target locations in an experimental manner, the truth is that drones can't fly far or carry all that much weight yet. To put it in perspective, carrying 5 pounds. is equivalent to the weight of a standard bag of sugar or potatoes. The biggest problem is one of regulating the flights of swarms of drones, all of which need to move an item from one point to another. There are obvious issues, such as avoiding obstacles like power lines, birds, buildings, and other drones; facing bad weather; and finding a suitable spot to land near you. The drones would also need to avoid sensitive air space and meet all required regulatory requirements that traditional aircraft meet. AI will be the key to solving many, but not all, of these problems. For now, delivery drones seem to work fine on a small scale for more critical deliveries than having your groceries flown to your home.

REMEMBER

Even though the idea would be to cut intermediaries in the logistics chain in a profitable way, many technical problems and regulatory ambiguities remain to be solved before having a thriving drone delivery business.

Drones can become your eyes, providing vision in situations that are too costly, dangerous, or difficult to see by yourself. Remotely controlled or semiautonomous (using AI solutions for image detection or processing sensor data), drones can monitor, maintain, surveil, or search and rescue because they can view any infrastructure from above and accompany and support on-demand human operators in their activities. For instance, drones have successfully inspected power lines, pipelines, and railway infrastructures, allowing more frequent and less costly monitoring of vital, but not easily accessible, infrastructures. Even insurance companies find them useful for damage assessments and other purposes, such as inspecting the roof of a home before insuring it or after a natural disaster has happened.

Chasing crooks

Police forces and first responders around the world have found drones useful for a variety of activities, from search-and-rescue operations to forest fire detection and localization, and from border patrol missions to crowd monitoring. Drones are already widespread in law enforcement, and police are always finding newer ways to usefully employ them, including finding traffic violators.

Drones used by police are fitted with optical, zoom, and often also thermal cameras; therefore, they excel at surveillance and search from distance. This kind of aerial surveillance has proven to be the key to successfully solving a range of problems that law enforcers may encounter during their service, even though they're extremely invasive. Drones not only keep an eye in the sky on highly frequented locations, as well as enforce surveillance in otherwise critical areas because of crowd and car traffic, but they are also becoming indispensable for apprehending suspected criminals. When chasing suspects, a drone can report the criminal's whereabouts and specify whether they're carrying weapons while going unnoticed because of their low profile and low-noise engines.

Finally, drones see use in many rescue situations, in which a bird's-eye view can help locate people in distress better than a squad on the ground. UAV Coach, a drone community website, reports quite a few interesting stories of people saved by drones. Police are also increasingly using drones for assessments that could otherwise take time and require more personnel onsite. Such tasks range from mapping areas of interest to documenting car accident and crime scenes to mapping damages after a disaster.

Growing better crops

Agriculture is another important area in which drones are revolutionizing work. They can not only monitor crops, report progress, and spot problems but also apply pesticides or fertilizer only where and when needed, as described by MIT Technology Review (`tinyurl.com/t5x6hsz2`). Drones offer images that are more detailed and less costly to obtain than those acquired from an orbital satellite, and they can be employed to

- Analyze soil and map the result using image analysis and 3D laser scanners to make seeding and planting more effective
- Control planting by controlling tractor movements
- Monitor real-time crop growth
- Spray chemicals when and where needed
- Irrigate when and where needed
- Assess crop health using infrared vision, which a farmer can't do

Precision agriculture uses AI capabilities for movement, localization, vision, and detection. Precision agriculture could increase agriculture productivity (healthier crops and more food for everyone) while diminishing costs for intervention (no need to spray pesticides everywhere).

Enhancing environmental monitoring and conservation efforts

Drones are transforming the field of environmental science by facilitating data collection from areas that were previously inaccessible or difficult to monitor. These aerial devices have advanced sensors and imaging technologies that capture detailed photographs, thermal images, and multispectral data. This capability is particularly valuable in tracking environmental changes and managing natural resources effectively.

For example, scientists have employed drones to conduct surveys across the Greenland ice sheet, capturing data that helps them understand ice melt dynamics and its contribution to sea level rise. Drones can also fly over vast areas, collecting temperature data and imagery that reveal the formation of melt ponds and ice movement.

These observations are crucial for predicting future changes in the ice sheet and their global consequences. For more about this topic, see (`insideunmanned systems.com/measuring-global-ice-melt`).

Delivering innovative uses in entertainment

Drones have revolutionized aerial photography by making it more accessible and affordable for the entertainment industry. They enable the capture of footage from angles and locations that would be challenging or impossible to reach with traditional on-ground camera setups. This has opened new creative possibilities for filmmakers and event organizers, allowing them to enhance the visual storytelling and audience experience.


TIP

A primary advantage of using drones in film production is their cost-effectiveness compared to traditional methods, such as helicopters and cranes. Drones reduce production costs and empower filmmakers to capture unique perspectives and angles, leading to the development of new cinematographic techniques.

Drones have been used in live events, such as Sony Pictures' livestreaming a Marvel red carpet event using a drone, making it a first in the industry. For more about the event, see (`tinyurl.com/49pb7e3k`).

Drones offer numerous advantages in photography, such as capturing unique aerial shots and providing cost-effective solutions for filming. However, they do have limitations. One constraint is their payload capacity. Drones can carry only a limited amount of weight, restricting the types and sizes of cameras and equipment they can support. This limitation impacts the quality and variety of shots that can be captured.

REMEMBER

Payload refers to the additional weight a drone can carry beyond its weight. This includes any equipment, cameras, sensors, or other items attached to the drone for various purposes.

Supporting smart cities

Drones are increasingly connected to smart city infrastructure. They provide innovative solutions for factors such as traffic monitoring and public safety. Here are some examples:

- **Real-time traffic analysis:** Drones with high-resolution cameras and AI can monitor traffic flow in real-time. They can detect congestion, accidents, and other incidents and provide immediate data to traffic management systems.
- **Optimizing traffic signals:** Drones can help optimize traffic signal timing to reduce congestion and improve flow by analyzing traffic patterns. This real-time adjustment can lead to efficient traffic flow and shorter commute times.
- **Incident response:** In case of accidents or emergencies, drones can quickly reach the scene, provide live video feeds to emergency responders, and even deliver AEDs (Automated External Defibrillators, used to treat sudden cardiac arrest) before paramedics arrive. This fast response capability can save lives and reduce the impact of traffic disruptions.

Inspecting and maintaining infrastructure

Drones can effectively inspect and maintain infrastructure in county-wide areas. They can help with

- **Bridge and building inspections:** Drones can inspect critical infrastructure such as bridges, buildings, and roads. Equipped with high-resolution cameras and sensors, they can detect structural issues, cracks, and other maintenance needs.
- **Utility monitoring:** Drones can monitor power lines, pipelines, and water systems. They can identify leaks, faults, or other issues, enabling well-timed maintenance and reducing the risk of service disruptions.

Organizing warehouses

Other areas where drones also shine are in logistics and manufacturing operations. Drones operating in enclosed spaces can't rely on GPS geolocation to determine where they are and where they're going. Recent advances in visually based

navigation and other sensors have improved the ability of drones to navigate indoors, rendering them suitable to operate in the larger warehouse spaces necessary for global manufacturing operations and the trading of export goods.

In warehouses, drones seem particularly adept at checking inventories. Checking inventories and counting available parts and goods is a menial activity that usually requires a large amount of time and effort from warehouse workers. It can sometimes turn dangerous when it involves climbing to reach higher shelves. Drones can handle the task perfectly by using barcodes, QR codes, or radio frequency identification (RFID) technology. In addition, drones can engage in intralogistics, which involves moving goods among different parts of the warehouse (though a drone is limited by how much weight it can carry).

Manufacturing is undergoing a technological transformation by using AI solutions in production and organization, resulting in smart factories. In general, the possible use cases for drones increase because of the large number of potential activities they enable:

- Replacing workers in risky operations or in less attractive activities
- Increasing workers' productivity by supporting and speeding up their operations
- Saving costs by replacing more costly technology or methods
- Providing entry to inaccessible or difficult-to-reach locations in the factory

Because of these reasons, market research companies like Gartner and Statista estimate that the number of drones sold for commercial purposes will increase every year and generate more revenue than consumer drones. Commercial drones are better equipped than consumer drones and are thus more expensive, but they're expected to be quite profitable — the commercial drone market is expected to exceed $8.5 billion USD by 2027 (as you can read at `tinyurl.com/4x78rc9b`).

Drones can perform amazing feats in industries where you may have never thought about using drones, ranging from communication to energy. The communications industry intends to move existing infrastructure to the sky using drones. Transportation plans to use drones to transport people, replacing common means of transportation, such as the taxi. Another possibility in the energy sector is to produce electricity up high, where winds are stronger and no one will protest the rotor noise.


TIP

For an extensive list of possible uses of drones in various industries, you can skim a complete list of 128 possible activities in 22 different areas compiled by dronegenuity, a company providing drone services: `tinyurl.com/z72puwm5`. The list is quite large, although not certainly exhaustive because new drone applications are continually emerging.

Powering up drones using AI

With respect to all drone applications — whether consumer, business, or military related — AI is both a game enabler and a game changer. AI allows many applications to become feasible or better executed because of enhanced autonomy and coordination capabilities. *Autonomy* affects how a drone flies, reducing the role of humans issuing drone commands by automatically handling obstacle detection and allowing safe navigation in complicated areas. *Coordination* implies the ability of drones to work together without a central unit to report to and get instructions from, making drones able to exchange information and collaborate in real-time to complete any task.

Taken to its extreme, autonomy may even exclude any human guiding the drone so that the flying machine can determine the route to take and execute specific tasks by itself. (Humans issue only high-level orders.) When not driven by a pilot, drones rely on GPS to establish an optimal destination path, but that's possible only outdoors, and it's not always precise. Indoor usage increases the need for precision in flight, which requires the increased use of other sensor inputs that help the drone understand *proximity surrounds* (the elements of a building, such as a wall protrusion, that could cause it to crash). The cheapest and lightest of these sensors is the camera that most commercial drones have installed as a default device. But having a camera doesn't suffice, because it requires proficiency in processing images using computer vision and deep learning techniques (discussed in this book, for instance, in Chapter 7 when discussing convolutional networks).

Companies expect autonomous execution of tasks for commercial drones, for instance, making them able to deliver a parcel from the warehouse to the customer and handling any trouble along the way. (As with robots, something always goes wrong that the device must solve using AI on the spot.) No one knows who in 2023 took the upper hand in a simulated dogfight between an American X-62A VISTA aircraft piloted by AI and a human operating an F-16 combat jet, as revealed by the United States Air Force's Air Force Research Laboratory (AFRL). However, we do know the results that the researchers at NASA's Jet Propulsion Laboratory in Pasadena, California, have obtained by testing automated drone flight against a high-skilled professional drone pilot (see `tinyurl.com/panpurf9` for details). Interestingly, the human pilot had the upper hand in this test until he became fatigued, at which point the slower, steadier, and less error-prone drones caught up with him. In the future, you can expect the same as what happened with chess and Go games: Automated drones will outrun humans as drone pilots in terms of both flying skills and especially endurance.

Coordination can be taken to extremes as well, permitting hundreds, if not thousands, of drones to fly together. Such capability could make sense for commercial and consumer drones when drones crowd the skies. Using coordination would be beneficial in terms of collision avoidance, information sharing on obstacles, and

traffic analysis in a manner similar to that used by partially or fully automated interconnected cars (see Chapter 15 for a discussion of AI-driven cars).

Rethinking existing drone algorithms is already going on, and some solutions for coordinating drone activities already exist. Most research is, however, proceeding unnoticed because a possible use for drone coordination is military in nature. Drone swarms, targeting multiple objects at once, may be more effective in saturating enemy defenses and carrying out strike actions that are difficult to fend off. The enemy will no longer have a single large drone to aim at, but rather hundreds of small ones flying around. Of course, there are solutions for taking down drone swarms.

REMEMBER

When the entrepreneur Elon Musk, the Apple cofounder Steve Wozniak, the physicist Stephen Hawking, and many other notable public figures and AI researchers raised alarms about recent AI weaponry developments, they didn't think of robots as shown in films like *Terminator* or *I, Robot*, but rather of armed flying drones and other automated weapons. Autonomous weapons could start an arms race and forever change the face of warfare.

Understanding regulatory issues

Drones aren't the first and only crafts to fly over clouds, obviously. Decades of commercial and military fights have crowded the skies, requiring both strict regulation and human monitoring control to guarantee safety. In the United States, the Federal Aviation Administration (FAA) is the organization with the authority to regulate all civil aviation, making decisions about airports and air traffic management. The FAA has issued a series of rules for the UAS, and you can read those regulations at `tinyurl.com/c355drrw`.

The FAA issued a set of rules known as *Part 107* in August 2016. These rules outline the use of commercial drones during daylight hours. The rules come down to these five straightforward rules:

- Fly below 400 feet (120 meters) altitude.
- Fly at speeds less than 100 mph.
- Keep unmanned aircraft in sight at all times.
- The operator must have an appropriate license.
- Never fly near manned aircraft, especially near airports.
- Never fly over groups of people, stadiums, or sporting events.
- Never fly near emergency response efforts.

The FAA will soon issue additional rules for drone flight at night that pertain to when the drone can be out of the line of sight and in urban settings, even though it's currently possible to obtain special waivers from the FAA. The Operations Over People rule (tinyurl.com/4h88ea2j), which became effective in April 2021, allows pilots who meet certain standards to fly at night and to fly over people and moving vehicles without waiver, as long as they meet certain requirements. The purpose of such regulatory systems is to protect the public safety, given that the impact of drones on our lives still isn't clear. These rules also allow innovation and economic growth to be derived from such a technology.

Presently, the lack of AI means that drones may easily lose their connection and behave erratically, sometimes causing damage. Consequently, when signal loss occurs, the video feed also goes off, but there's a chance you're still connected to your drone. The recommended steps include heading toward the last-seen direction to regain control, using another drone for search, utilizing the Return to Home (RTH) button, looking for the drone manually, checking the last known coordinates, and examining the drone's telemetry information on the controller. Even though most drones now have safety measures in case of a lost connection with the controller, such as having them automatically return to the exact point at which they took off, the FAA restricts their usage to staying within the line of sight of their controller unless the pilot meets certain criteria.

Another important safety measure is *geofencing.* Drones using GPS service for localization have software that limits their access to predetermined perimeters described by GPS coordinates, such as airports, military zones, and other areas of national interest. You can see the list of parameters at tfr.faa.gov/tfr2/list.html.

Algorithms and AI are coming to the rescue by preparing a suitable technological setting for the safe usage of a host of drones that deliver goods in cities. NASA's Ames Research Center is working on a system called Unmanned Aircraft System Traffic Management (UTM), which is playing the same air-traffic-control tower role for drones as used for manned airplanes (see tinyurl.com/5595ndfw). However, this system is completely automated; it counts on the drones' capabilities to communicate with each other. UTM will help identify drones in the sky (each one will have an identifier code, just like car license plates) and will set a route and a cruise altitude for each drone, thus avoiding possible collisions, misbehavior, or potential damage for citizens. You can read the current progress of this initiative at tinyurl.com/2xetras4.


REMEMBER

When restrictions aren't enough and rogue drones represent a menace, police and military forces have found a few effective countermeasures: taking down the drone by shotgun; catching the drone by throwing a net; jamming the drone's controls; taking down the drone using laser or microwaves; and even firing guided missiles at the drone.

URBAN AIR MOBILITY (UAM)

The concept of urban air mobility is emerging, with regulatory discussions around passenger-carrying drones, often provided as electric vertical take-off and landing (eVTOLs) vehicles. This transformative approach could revolutionize urban transportation, necessitating new frameworks and infrastructure. eVTOLs are always powered by electric motors, making them a cleaner and quieter alternative to traditional aircraft that rely on combustion engines. They are being developed primarily for use in urban air mobility solutions, aiming to provide a new form of efficient and environmentally friendly transportation.

Remember: The abbreviation eVTOL stands for electric Vertical Takeoff and Landing vehicles. These aircraft are designed to take off, hover, and land vertically, eliminating the need for runways.


TIP

On an international scale, there's a push for regulatory coordination, especially between the United States and the European Union Aviation Safety Agency (EASA). These efforts aim to standardize regulations, promoting international collaboration and operational consistency.

Reviewing Privacy and Data Protection in Drone Operations

As drones become more prevalent in many commercial and recreational sectors, the capabilities of these devices to collect and transmit data can raise privacy and data protection concerns. Drones with cameras, microphones, and other devices can inadvertently or deliberately gather personal information, which can lead to possible privacy violations.

Raising public awareness about drone privacy is important for promoting a culture of responsible drone use. Educational campaigns and initiatives can inform drone operators and the public about privacy rights, legal responsibilities, and respecting others' privacy when operating drones.

Analyzing implications for personal privacy

Drones can capture high-resolution images and videos from private property or public areas where individuals may expect privacy. This capability challenges

existing privacy norms and can lead to conflicts between drone operators and the public. The potentially intrusive nature of drones and the ability to monitor personal conversations requires strict controls to protect individuals' privacy rights.

Handling data collected by drones

Data management is a critical aspect of drone operations, necessitating strict protocols to ensure the security and integrity of the data collected. Operators should establish clear guidelines on data retention, access, and sharing. Compliance with data protection laws — for example, the General Data Protection Regulation (GDPR) in the European Union — requires operators to implement measures to minimize data collection and securely store and process any personal data obtained.


REMEMBER

Transparency in data handling practices includes informing individuals about what data is collected and how you will use it. Specific risks include *data breaches* and *data misuse*. Data breaches involve unauthorized access to sensitive information, a risk that can be mitigated by strong data encryption and access control to the data. Data misuse occurs when data is used for different purposes other than those for which it was initially collected. Clear data usage policies and restrictions can help prevent this risk.

Considering legal considerations and surveillance

The legal landscape for drone surveillance varies by jurisdiction. In many countries, specific laws regulate the use of drones for surveillance purposes, especially in contexts involving monitoring public areas or capturing images where individuals have a reasonable expectation of privacy.


REMEMBER

Legal frameworks often require drone operators to obtain permits or consent before conducting surveillance activities, and strict penalties are levied for noncompliance.

Developing regulatory frameworks and recommendations

Regulatory frameworks can evolve to provide clear guidelines on the acceptable use of drones. Some suggested recommendations for drone operators can include

- Conducting privacy impact assessments before deploying drones for specific tasks

- Limiting drones with surveillance capabilities to areas and scenarios where they are explicitly authorized
- Implementing technical measures, such as geofencing and data anonymization, to protect personal data
- Engaging with stakeholders, including privacy advocates and the public, to develop best practices for drone privacy

TIP

For some ideas about drone privacy, see these suggested best practices (`www.clemsondrone.com/post/drone-privacy-best-practices`).

REMEMBER

Integrating strong privacy and data protection measures will encourage public trust and compliance with legal standards as drone technology advances.

IN THIS CHAPTER

- Seeing the path to self-driving car autonomy
- Imagining the future in a world of self-driving cars
- Understanding the sense-plan-act cycle
- Discovering, using, and combining various sensors

Chapter 15
Utilizing the AI-Driven Car

A self-driving car (SD car) is an *autonomous vehicle* — one that can drive by itself, without human intervention, from a starting point to a destination. Autonomy implies not simply having some tasks automated, such as Automated Parking Assist, but also being able to perform the right steps to achieve objectives independently. An SD car performs all required tasks on its own, with a human potentially there to observe (and do nothing else unless something completely unexpected happens).

Because SD cars have been part of history for more than 100 years (yes, incredible as that might seem), this chapter begins with a short history of SD cars. The remaining sections cover the ways that SD cars will affect mobility and broader society as they eventually become more common, as well as a primer on the various sensors required for an SD car to function.


REMEMBER

For a technology to succeed, it must provide a benefit that people see as necessary and not as easily obtained using other methods. That's why SD cars are exciting — they offer many valuable features, other than just driving, as you can see throughout this chapter.

Examining the Short History of SD Cars

Developing cars that can drive by themselves has long been part of the futuristic vision provided by sci-fi narrative and film since early experiments in the 1920s with radio-operated cars. (You can read more about the long, fascinating history of autonomous cars at qz.com. Just type *We've had driverless cars for almost a hundred years* in the search bar.) The problem with these early vehicles is that they weren't practical; someone had to follow behind them to guide them using a radio controller. Consequently, even though the dream of SD cars has long been cultivated, the present projects have little to share with the past other than the vision of autonomy.

The modern SD cars are deeply entrenched in projects that started in the 1980s. These newer efforts leverage AI to remove the need for radio control found in earlier projects. Many universities and the military (especially the US Army) fund these efforts. At one time, the goal was to win at the DARPA Grand Challenge, which ended in 2007. However, now the military and commercial concerns provide plenty of incentive for engineers and developers to continue moving forward.

The turning point in the challenge was the creation of the autonomous car called Stanley, designed by scientist and entrepreneur Sebastian Thrun and his team. They won the 2005 DARPA Grand Challenge. After the victory, Thrun started the development of SD cars at Google. Today you can see the Stanley on exhibit in the Smithsonian Institution's National Museum of American History.

REMEMBER

The military isn't the only entity pushing for autonomous vehicles. For a long time, the automotive industry suffered from overproduction because it could produce more cars than required by market demand (though the realities of COVID-19 intervened). Market demand can go down or up as a result of all sorts of pressures, such as car longevity. In the 1930s, car longevity averaged 6.75 years, but cars now average 10.8 or more years and allow drivers to drive 250,000 or more miles. Although circumstances changed at least temporarily during the coronavirus pandemic, the decrease in sales led some makers to exit the industry or fuse together and form larger companies. SD cars are the silver bullet for the industry, offering a way to favorably reshape market demand and convince consumers to upgrade. This necessary technology will result in an increase in the production of a large number of new vehicles.

Understanding the Future of Mobility

SD cars aren't a disruptive invention simply because they'll radically change how people perceive cars, but also because their introduction will have a significant impact on society, economics, and urbanization. At present, SD cars are still in the

prototype stage and haven't yet become a commercial reality. Even the limited number of robotaxi cars (driverless taxis), that you can see operating in cities like San Francisco (by Cruise LLC and Waymo LLC) or Guangzhou, China (by Baidu Inc), are essentially testing prototypes.

Though there are continuous advancements in automotive technology toward electric, autonomous, connected, and sleek vehicles, the widespread adoption of fully autonomous cars is expected to take more time. Many people believe that SD car introduction will require at least another decade, and replacing all the existing car stock with SD cars will take significantly longer. However, even if SD cars are still in the future, you can clearly expect great things from them, as described in the following sections.

Climbing the six levels of autonomy

Foretelling the shape of things to come isn't possible, but many people have at least speculated on the characteristics of SD cars. For clarity, the Society of Automotive Engineers (SAE) International (`www.sae.org`), an automotive standardization body, published a classification standard for autonomous cars (see the J3016 standard at `tinyurl.com/56zsbwdp`). Having a standard creates car automation milestones. Here are the five levels of autonomy specified by the SAE standard:

- **Level 0, no automation:** The driver performs all driving tasks. However, the car may provide warnings and momentary assistance such as automatic emergency braking, blind spot warning, and lane departure warning. These functions can be powered by algorithms or even AI.
- **Level 1, driver assistance:** Control is still in the hands of the driver, yet the car can perform simple support activities such as controlling the speed. This level of automation includes adaptive cruise control (when you set your car to move at a certain speed, automatically adjusting to the speed of the vehicle in front of you), stability control, lane centering, and precharged brakes.
- **Level 2, partial automation:** The car can act more often in lieu of the driver, dealing with acceleration, braking, and steering if required. The driver's responsibility is to remain alert and be ready to take control of the car at all times. A partial automation example is the automatic braking that certain car models execute if they spot a potential collision ahead (a pedestrian crossing the road or another car suddenly stopping). Now the car can perform multiple driving tasks simultaneously, such as providing adaptive cruise control and lane centering at the same time. This level has been available on commercial cars since 2013.
- **Level 3, conditional automation:** Most automakers are working on this level as of the writing of this book. *Conditional automation* means that a car can drive

by itself in certain contexts (for instance, only on highways or on unidirectional roads), under speed limits, and under vigilant human control. The automation could prompt the human to resume driving control. One example of this level of automation is recent car models that drive themselves when on a highway and automatically brake when traffic slows because of jams (or gridlock).

- **Level 4, high automation:** The car performs all the driving tasks (steering, throttle, and brake) and monitors any changes in road conditions from departure to destination. This level of automation doesn't require human intervention to operate, but it's accessible only in certain locations and situations. In some cases, pedals and steering wheel may not even be installed, making it impossible for a human driver to take over. Vendors had originally expected to introduce this level of automation around 2020, but a quick read will tell you that they're still a long way from seeing this level as a reality.
- **Level 5, full automation:** The car can drive from departure to destination with no human intervention, with a level of ability comparable or superior to a human driver. Level-5 automated cars won't have a steering wheel. This level of automation is expected five or more years after Level 4 cars become a reality.

Even when SD cars achieve Level-5 autonomy, you won't see them roaming every road. Such cars are still far in the future, and difficulties might lie ahead. The "Overcoming Uncertainty of Perceptions" section, later in this chapter, discusses some obstacles an AI will encounter when driving a car. The SD car won't happen overnight; it'll probably come about by way of a progressive mutation, starting with the gradual introduction of more and more automatic car models. Humans will keep holding the wheel for a long time. What you can expect to see is an AI that assists in both ordinary driving and dangerous conditions to make the driving experience safer. Even when vendors commercialize SD cars, replacing actual stock may take years. The process of revolutionizing road use in urban settings with SD cars may take 30 years.

WARNING

This section contains a lot of expectations about the introduction of SD cars, but all sorts of things could happen to speed or slow the adoption of SD cars. For example, the insurance industry is suspicious of SD cars because its leaders are afraid that its motor insurance products will be dismissed in the future as the risk of having a car accident becomes rarer. (The McKinsey consulting firm predicts that SD cars will reduce accidents by 90 percent.) Lobbying by the insurance industry could slow the acceptance of SD cars. Also, consumers might put up some resistance because of lack of openness to the new technology (some consumers look for gradual product improvements, not for radical change). On the other hand, people who have suffered the loss of a loved one to an accident are likely to support anything that will reduce traffic accidents. They might be equally successful in speeding the acceptance of SD cars. Consequently, given the vast number of ways in which social pressures change history, predicting a precise date for the full introduction in our everyday lives of SD cars isn't possible.

Rethinking the role of cars in our lives

Mobility is inextricably tied to civilization. It's not just the transportation of people and goods, but also ideas flowing around, to and from distant places. When cars first hit the roads, few people believed that the cars would soon replace horses and carriages. Yet, cars have many advantages over horses: They're more practical to keep, offer faster speeds, and run longer distances. Cars also require more control and attention by humans, because horses are aware of the road and react when obstacles or possible collisions arise, but humans accept this requirement for obtaining greater mobility.

Car use molds both the urban fabric and economic life. Cars allow people to commute long distances from home to work each day (making suburban real estate development possible). Businesses easily send goods farther distances; cars create new businesses and jobs; and factory workers in the car industry have long since become the main actors in a new redistribution of riches. The car is the first true mass-market product, made by workers for other workers. When the car business flourishes, so do the communities that support it; when it perishes, catastrophe can ensue. Trains and airplanes are bound to predetermined journeys, whereas cars are not. Cars have opened and freed mobility on a large scale, revolutionizing, more than other long-range means of transportation, the daily life of humans. As Henry Ford, the founder of the Ford Motor Company, stated, "[C]ars freed common people from the limitations of their geography."

As when cars first appeared, civilization is on the brink of a new revolution brought about by SD cars. When vendors introduce autonomous driving Level 5 and SD cars become mainstream, you can expect significant new emphasis on how humans design cities and suburbs, on economics, and on everyone's lifestyle. There are obvious and less obvious ways that SD cars will change life. The most obvious and often noted ways are described in this list:

- **Fewer accidents:** Fewer accidents will occur, because AI will respect road rules and conditions; it's a smarter driver than humans are. In addition, AI won't get tired (which contributes to about 2.4 percent of fatal accidents), distracted (responsible for 8 to 9 percent of fatal accidents) or drunk (accounting for more than 30 percent of fatal accidents). These factors contribute to over 40 percent of accidents involving human drivers. Accident reduction will deeply affect the way vendors build cars, which are now more secure than in the past because of structural passive protections. In the future, given their absolute safety, SD cars could be lighter because of fewer protections than now. They may even be mostly constructed of plastic or carbon fiber and thus reduce weight and increase efficiency. As a result, cars will consume fewer resources than they do today. In addition, the lowered accident rate will mean reduced insurance costs, creating a major impact on the insurance industry, which deals with the economics of accidents.

- **Fewer jobs involving driving:** Many driving jobs will disappear or require fewer workers. That will bring about cheaper transportation labor costs, thus making the transportation of goods and people even more accessible than now. It will also raise problems in finding new jobs for people. (In the United States alone, several million people are estimated to work in transportation.)
- **More time:** SD cars will help humans obtain more of the most precious aspects of life, such as time. SD cars won't help people go farther, but it will help them put the time they would have spent driving to use in other ways (because the AI will be driving). Moreover, even if traffic increases (because of smaller transportation costs and other factors), traffic will become smoother, with little or no traffic congestion. In addition, the transportation capacity of existing roads will increase. It may sound like a paradox, but this is the power of an AI when humans remain out of the picture.


TIP

There are always opposing points of view when it comes to technology, and it's important to maintain an open mind when hearing them. For example, rather than reduce traffic congestion, some people say that SD cars will actually increase traffic congestion because more people will opt to drive rather than carpool, take a train, or rely on a bus. In addition, given the nature of people, you might see weird behavior, like having a car continue driving in circles around a block while the owner dines at a restaurant when parking spaces are limited.

Apart from these immediate effects are the subtle implications that no one can determine immediately but that can appear evident after reflection. Thinking of the future isn't an easy exercise, because it's not simply a matter of cause and effect. Even looking into more remote orders of effects could prove ineffective when the context changes from the expected.

For instance, Benedict Evans tries to point out a few of these less obvious implications in his blog post "Cars and second order consequences" at `www.ben-evans.com`. This insightful article looks deeper into the consequences of the introduction of both electric cars and Level 5 autonomy for SD cars on the market. As one example, SD cars could make the dystopian Panopticon a reality. The *Panopticon* is the institutional building theorized by the English philosopher Jeremy Bentham at the end of the 18th century, where everyone is under surveillance without knowing when they're being watched, creating a sense of constant control. When SD cars roam the streets in large numbers, car cameras will appear everywhere, watching and possibly reporting everything they happen to witness. Your car may spy on you and others when you least expect it.

Of course, a future Panopticon may never happen because the legal system could force SD cars not to communicate the images they capture. These and other unexpected scenarios may or may not be capable of happening, depending on various circumstances. Most likely, as experts agree, a car enabled with autonomous driving capabilities could engage in four different scenarios, each one redefining how humans use or even own a car:

- **Autonomous driving on long journeys on highways:** When drivers can voluntarily allow the AI to do the driving and take them to their destination, the driver can rest or devote attention to other activities. This is a Level 3, or even higher, autonomy scenario, and many consider it a possible introductory scenario for autonomous cars. However, given the high speeds on highways, others consider that giving up control to an AI isn't completely risk-free because other cars, guided by humans, could cause a crash. People have to consider consequences such as the current inattentive driving laws found in most locations. The question is one of whether the legal system would see a driver using an AI as inattentive.
- **Acting as a chauffeur for parking:** In this scenario, the AI intervenes when the passengers have left the car, saving them the hassle of finding parking. The SD car offers a time-saving service to its occupants because it opens the possibility of both parking lot optimization (the SD car will know where best to park) and car sharing. (After you leave the car, someone else can use it; later, you hail another car left nearby in the parking lot.) Given the limitations of autonomous driving used only for car fetching, this scenario involves a transition from Level 3 to Level 4 autonomy.
- **Acting as a chauffeur for any journey, except those locations where SD cars remain illegal:** This advanced scenario allows the AI to drive in any areas except ones that aren't permitted for safety reasons (such as new road infrastructures that aren't mapped by the mapping system used by the car). This scenario takes SD cars to near maturity (autonomy Level 4).
- **Playing on-demand taxi driver:** This is an extension of scenario 2, when the SD cars are mature enough to drive by themselves all the time (Level 5 autonomy), with or without passengers, providing a transportation service to anyone requiring it. Such a scenario will fully utilize cars (in this era, cars are parked 95 percent of the time; see "Today's cars are parked 95% of the time" at `Fortune.com`) and revolutionize the idea of owning a car because you won't need one of your own.

Taking a step back from unmet expectations

Up to now, vendors have made quite a few announcements that raised expectations and made many hope for the upcoming introduction of autonomous vehicles on the road:

- In 2016, Elon Musk, Tesla's CEO, announced that "by the end of 2017, one of Tesla's cars will be able to drive from New York to Los Angeles without the driver having to do anything" (which you can read about at `tinyurl.com/2368ccj4`).

- Apart from Tesla, many automakers, such as General Motors, have made bold statements (tinyurl.com/yf74m3h3). Audi (tinyurl.com/netjs52d) and Nissan (tinyurl.com/3uvz2xbc) have also made announcements.
- In 2016, Business Insider Intelligence forecasted 10 million autonomous vehicles on roads by 2020, and it wasn't the only business intelligence service to forward such ambitious targets (see tinyurl.com/k8jn9xsk).

Yet in spite of such intense hype about SD cars between 2016 and 2017, current cars haven't changed that much in terms of automation. Recently, accidents, crashes, protests, product recalls, and low earnings are making SD carmakers struggle. At this point, you may even wonder whether the technology will be commercialized anytime soon, with new car models or aftermarket kits capable of transforming your old car into a self-driving one. Actually, the technology behind SD cars did improve in recent years, and security issues didn't limit such development all that much. Yet everyone working on the technology will now tell you that things appear much trickier and more difficult than they looked back in those 2016–2017 years, and they postpone the introduction of SD cars to the end of the 2020 decade (or possibly beyond).

SD cars are being introduced today in limited areas of the United States such as Austin, Phoenix, Las Vegas, and San Francisco. These vehicles have limited scope, such as the cars from Waymo. Waymo is an Alphabet company, heir of the Google Self-Driving Car Project, previously led by Sebastian Thrun, and it has opened its fully driverless service to residents in a few metropolitan areas. Access to this technology by the general public seems delayed, and it will probably first occur in particular areas and sectors, involving large fleets of cars such as taxis, shuttles, and truck transportation. The problems with SD cars reside in two areas:

- **Perception** is necessary for the car to determine where it is, and it relies on various technologies discussed by the end of the chapter. The problem with these technologies is that the more reliable they are, the more expensive, and the more maintenance and care they require.
- **Prediction** helps to elaborate on the perceptions and to provide the car with an idea of what will happen, which is the key to making good decisions on the road and avoiding collisions and other accidents. For instance, such skill is learned when the SD car is engaged in traffic and has to navigate across lanes of oncoming traffic or when, at a crossing, it must perform an unprotected left turn. Determining the behavior of other cars in the surroundings and negotiating your way through the traffic is critical. Unfortunately, what is natural for a human car driver, relying on experience and social cues between drivers, doesn't seem to come easily for a SD car.

SD CARS AND THE TROLLEY PROBLEM

Some say that insurance liability and the trolley problem will seriously hinder SD car use. The insurance problem involves the question of who takes the blame when something goes wrong. Automakers such as Audi, Volvo, and Mercedes-Benz — as well as Google, which is developing its own SD cars — have already pledged to accept liability if their vehicles cause an accident, a fact that should overcome the resistance by the traditional insurance industry, which is wary of the potential impact of self-driving cars on its core business.

The *trolley problem* is a moral challenge introduced by the British philosopher Philippa Foot in 1967 (but it's an ancient dilemma). In this problem, a runaway trolley is about to kill a number of people that are on the track, but you can save them by diverting the trolley to another track, where unfortunately another person will be killed in their place. Of course, you need to choose which track to use, knowing that someone is going to die. Quite a few variants of the trolley problem exist, and the Massachusetts Institute of Technology (MIT) website at `www.moralmachine.net` even proposes alternative situations more suited to those that an SD car may experience.

The point is that when someone's life is at risk, the skills of even the most advanced AI driving systems may not prevent fatalities from occurring. Such scenarios often involve choices between the safety of the car's occupants and pedestrians. Human drivers resolve such extreme situations by making split-second decisions based on instinct and cultural factors, with some prioritizing self-preservation and others opting for altruism. Carmakers might consider that a trolley-problem type of catastrophic situation is already so rare — and SD cars will make it even rarer — and that self-protection is something so innate in us that most SD car buyers will agree on this choice, which is something Mercedes-Benz, the world's oldest carmaker, has already considered (see `tinyurl.com/kfybmkes`).

Believed to be the most challenging prediction task, predictions involving other cars are solved at present by forcing an overly cautious behavior on SD cars. Scientists are working on reinforcement learning solutions and imitation learning to solve these issues.

Getting into a Self-Driving Car

Creating an SD car, contrary to what people imagine, doesn't consist of putting a robot in the front seat and letting it drive the car. Humans perform myriad tasks to drive a car that a bipedal robot may not perform with the same level of success.

Therefore, automation must be integrated directly into the vehicle. This involves connecting many systems to each other and having them work harmoniously together to define a proper and safe driving environment. Some efforts are underway to obtain an end-to-end solution rather than rely on separate AI solutions for each need. The problem of developing an SD car requires solving many single problems and having the individual solutions work effectively together. For example, recognizing traffic signs and changing lanes require separate systems.


REMEMBER

End-to-end solution is something you often hear when discussing deep learning's role in AI. This term means that a single solution will provide an answer to an entire problem rather than some aspect of a problem. Given the power of learning from examples, many problems don't require separate solutions, which are essentially a combination of many minor problems, with each one solved by a different AI solution. Deep learning can solve the problem as a whole by solving examples and providing a unique solution that encompasses all the problems that required separate AI solutions in the past.

NVIDIA, the deep learning GPU producer, is working on end-to-end solutions. Check out the videos at `www.nvidia.com/en-us/self-driving-cars/drive-videos`, which show the effectiveness of some of the solutions that NVIDIA engineers have developed for SD cars. Yet, as is true for any deep learning application, the goodness of the solution depends heavily on the exhaustiveness and number of examples used. To have an SD car function as an end-to-end deep learning solution requires a dataset that teaches the car to drive in an enormous number of contexts and situations, which aren't available yet but could be in the future.


TECHNICAL STUFF

Nevertheless, hope exists that end-to-end solutions will simplify the structure of SD cars. The article at `tinyurl.com/kuar48td` explains how the deep learning process works. You may also want to read the original NVIDIA paper on how end-to-end learning helps steer a car, at `tinyurl.com/3enk2f82`.

Putting all the tech together

Under the hood of an SD car are systems working together according to the robotic paradigm of sensing, planning, and acting. Everything starts at the sensing level, with many different sensors telling the car different pieces of information:

- The GPS system tells where the car is in the world (with the help of a mapping technology), which translates into latitude, longitude, and altitude coordinates.
- The radar, ultrasound, and lidar devices spot objects in the vicinity and provide data about their location and movements in terms of changing coordinates in space.

- The cameras inform the car about its surroundings by providing image snapshots in digital format.


TIP

Many specialized sensors appear in an SD car. The "Overcoming Uncertainty of Perceptions" section, later in this chapter, describes them at length and discloses how the system combines their output. The system must combine and process the sensor data before the perceptions necessary for a car to operate become useful. Combining sensor data therefore defines different perspectives of the world around the car.

Localization is knowing where the car is in the world, a task mainly done by processing the data from the GPS device. GPS is a space-based satellite navigation system originally created for military purposes. When used for civilian purposes, it has some inaccuracy embedded (so that only authorized personnel can use it to its full precision). The same inaccuracies also appear in other systems, such as GLONASS (the Russian navigation system), GALILEO (or GNSS, the European system), or the BeiDou (or BDS, the Chinese system). Consequently, no matter which satellite constellation you use, the car can tell that it's on a certain road, but it can miss the lane it's using (or even end up pointing out a parallel road). Hence, the system processes the GPS data with lidar sensor data to determine the exact position based on the details of the surroundings.

The *detection system* determines what is around the car. This system requires many subsystems, with each one carrying out a specific purpose by using a unique mix of sensor data and processing analysis:

- Lane detection is achieved by processing camera images using image data analysis or deep learning specialized networks for *image segmentation,* in which an image is partitioned into separated areas labeled by type (that is, road, cars, and pedestrians).
- Traffic signs and traffic lights detection and classification are achieved by processing images from cameras using deep learning networks.
- Object tracking is obtained by the combined data from radar, lidar, ultrasound, and cameras that help locate external objects and track their movements in terms of direction, speed, and acceleration.
- Lidar data is mainly used for detecting free space on the road such as unobstructed lanes or parking areas.

Letting AI into the scene

After the sensing phase, which involves helping the SD car determine where it is and what's going on around it, the planning phase begins. AI fully enters the

scene at this point. Planning for an SD car boils down to solving these specific planning tasks:

- **Path planning:** Determines the path that the car should take. Because you're in the car to go somewhere specific (well, that's not always true, but it's an assumption that holds true most of the time), you want to reach your destination in the fastest and safest way. In some cases, you also must consider the cost. Advanced routing algorithms, leveraging machine learning and real-time data, guide the SD car along the most suitable path, considering factors like traffic conditions, road closures, and user preferences.
- **Environment prediction:** Helps the car to project itself into the future because it takes time to perceive a situation, decide on a maneuver, and complete it. During the time necessary for the maneuver to take place, other cars could decide to change their position or initiate their own maneuvers, too. When driving, you also try to determine what other drivers intend to do to avoid possible collisions. An SD car does the same thing using machine learning prediction to estimate in real-time what will happen next, take the future into account, and allow smooth navigation and collision avoidance.
- **Behavior planning:** Provides the car's core intelligence. It incorporates the practices necessary to stay on the road successfully: lane keeping; lane changing; merging or entering into a road; keeping distance; handling traffic lights, stop signs, and yield signs; avoiding obstacles; and much more. All these tasks are performed using AI, such as an expert system that incorporates many drivers' expertise, or a probabilistic model, such as a Bayesian network, or even a specific machine learning model.
- **Trajectory prediction:** Determines how the car will carry out the required tasks, given that, usually, more than one way exists to achieve a goal. The SD car utilizes advanced machine learning models to decide when to change lanes, without harsh accelerations or decelerations, by moving in an acceptable, safe, and pleasant way, without getting too near other cars.

The benefits of using AI are undeniable. The use of deep learning algorithms has enhanced the perception, decision-making, and control capabilities of self-driving cars. Reinforcement learning and deep neural networks play a growing role in modeling human-like reasoning for anticipating movements of objects and vehicles nearby.

Understanding that it's not just AI

At the time of writing, self-driving cars operate based on a sophisticated framework involving path planning, environment prediction, behavior planning, and

trajectory prediction. It may sound a bit complicated, but it's just four systems acting, one after the other, from start to end at destination. Each system contains subsystems that solve a single driving problem, as shown in Figure 15-1.

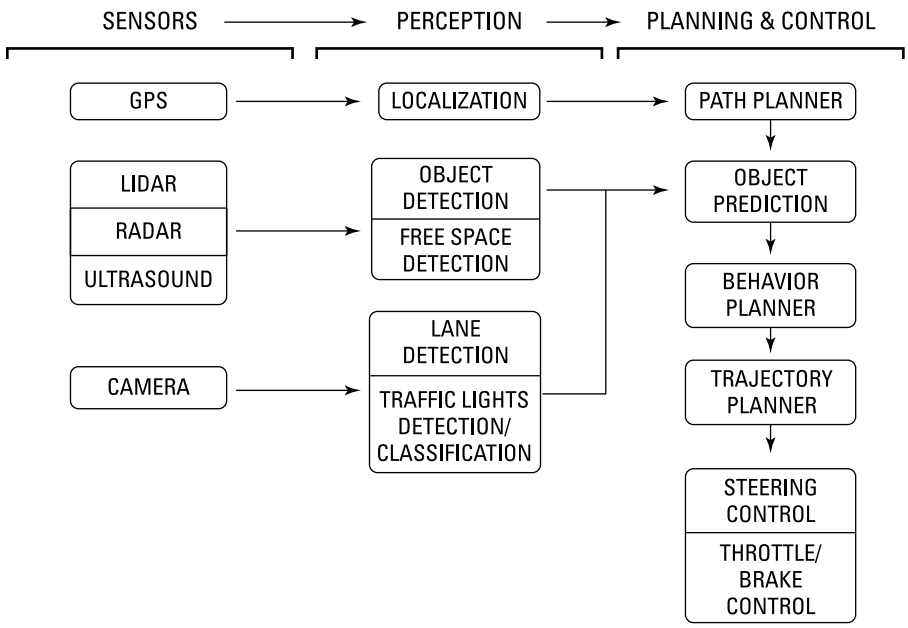

FIGURE 15-1: An overall, schematic view of the systems working in an SD car.

After sensing and planning, it's time for the SD car to act. Acting doesn't involve much AI because it relies on more traditional algorithms and controllers. Sensing, planning, and acting are all part of a cycle that repeats until the car reaches its destination and stops after parking. Acting involves the core actions of acceleration, braking, and steering. The instructions are determined during the planning phase, and the car simply smoothly executes the actions with controller system aid, such as the Proportional-Integral-Derivative (PID) controller or Model Predictive Control (MPC), which are algorithms that check whether prescribed actions execute correctly and, if not, immediately ensure suitable countermeasures.

For now, this framework is the state of the art. SD cars will likely continue as a bundle of software and hardware systems housing different functions and operations, with some powered by AI and others utilizing various technologies. In addition, safety remains a paramount priority in the advancement of autonomous vehicles, and the systems will provide redundant functionality, such as using multiple sensors to track the same external object or relying on multiple perception processing systems to ensure that you're in the right lane. Redundancy helps to ensure zero errors and therefore reduce fatalities.

Overcoming Uncertainty of Perceptions

Steven Pinker, professor in the department of psychology at Harvard University, says in his book *The Language Instinct: How the Mind Creates Language* that "in robotics, the easy problems are hard and the hard problems are easy." In fact, an AI playing chess against a master of the game is incredibly successful; however, more mundane activities, such as picking up an object from the table, avoiding a collision with a pedestrian, recognizing a face, or properly answering a question over the phone can prove quite hard for an AI.


REMEMBER

The *Moravec paradox* says that what is easy for humans is hard for AI (and vice versa), as explained in the 1980s by the robotics and cognitive scientists Hans Moravec, Rodney Brooks, and Marvin Minsky. Humans have had a long time to develop skills such as walking, running, picking up an object, talking, and seeing; these skills developed through evolution and natural selection over millions of years. To survive in this world, humans do what all living beings have done since life has existed on earth — they develop skills that enhance their ability to interact with the world as a whole based on species goals.

In terms of mobility, cars have some advantages over robots, which have to make their way in buildings and on outside terrain. Cars operate on roads created specifically for them (usually, well-mapped ones), and cars already have working mechanical solutions for moving on road surfaces. Hence, actuators aren't the greatest problem for SD cars. Planning and sensing are what pose serious hurdles. Planning is at a higher level (what AI generally excels in). When it comes to general planning, SD cars can already rely on GPS navigators, a type of AI specialized in providing directions. Additionally, path planning algorithms, which utilize heuristics and AI solutions, are employed to determine trajectories, make decisions based on constraints such as traffic laws or passenger comfort, and navigate routes efficiently. However, sensing is the true bottleneck for SD cars because, without it, no planning and actuation are possible. Drivers sense the road all the time to keep the car in its lane, to watch out for obstacles, and to respect the required rules.


REMEMBER

Sensing hardware is updated continuously at this stage of the evolution of SD cars to find more reliable, accurate, and less costly solutions. On the other hand, both processing sensor data and using it effectively rely on robust algorithms, such as the Kalman filter (see `tinyurl.com/2ken4zjx`), which have already been around a few decades.

Introducing the car's senses

Sensors are the key components for perceiving the environment, and an SD car can sense in two directions, internal and external:

- **Proprioceptive sensors:** Responsible for sensing vehicle states, such as systems status (engine, transmission, braking, and steering) and the vehicle's position in the world by using GPS localization, rotation of the wheels, the speed of the vehicle, and its acceleration. Recently, manufacturers incorporated more sophisticated systems for monitoring the vehicle's internal state, including real-time diagnostics of critical components like engine, transmission, braking, and steering systems. Moreover, advancements in inertial measurement units (IMUs) provide precise positioning and orientation data (`www.mdpi.com/2306–5729/6/7/72`).
- **Exteroceptive sensors:** Responsible for sensing the surrounding environment by using sensors such as camera, lidar, radar, and ultrasonic sensors. Recent advances have made them more compact, reliable, cost-effective, and capable of higher resolution, range, and reliability.

Both proprioceptive and exteroceptive sensors contribute to SD car autonomy. GPS localization, in particular, provides a guess (possibly viewed as a rough estimate) to the SD car's location, which is useful at a high level for planning directions and actions aimed at getting the SD car to its destination successfully. GPS helps an SD car in the same way it helps any human driver: by providing the right directions. In recent SD car prototypes, AI algorithms and machine learning models play a crucial role in processing all such sensor data efficiently. Deep learning neural networks are used for object detection, classification, and decision-making based on sensor inputs. Another key aspect in regard to sensors to keep in mind is that they're costly and that designing more cost-effective solutions without compromising performance will definitely help cause a wider adoption of autonomous driving technology.

The exteroceptive sensors (shown in Figure 15-2) help the car specifically in driving. They replace or enhance human senses in a given situation. Each sensor offers a different perspective of the environment; each suffers specific limitations; and each excels at different capabilities.

Limitations come in a number of forms. As you explore what sensors do for an SD car, you must consider cost, sensitivity to light, sensitivity to weather, noisy recording (which means that sensitivity of the sensor changes, affecting accuracy), range, and resolution. On the other hand, capabilities involve the ability to accurately track the velocity, position, height, and distance of objects, as well as the skill to detect what those objects are and how to classify them. Engineers designing SD cars are striving and succeeding in providing sensors designed to be more robust against environmental challenges such as adverse weather (rain, fog, snow) and varying light conditions.

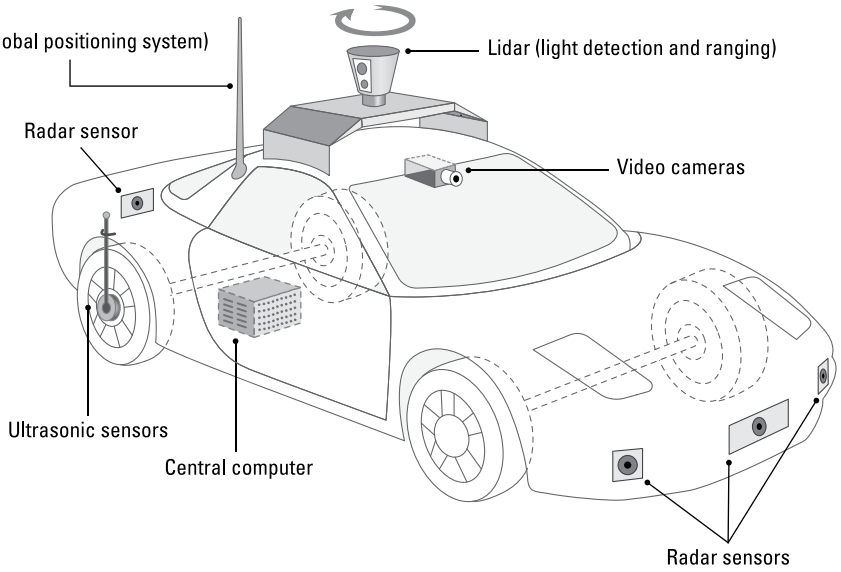

FIGURE 15-2: A schematic representation of exteroceptive sensors in an SD car.

Camera

Cameras are passive, vision-based sensors. They can provide mono or stereo vision. Given their low cost, you can place plenty of them on the front windshield, as well as on the front grilles, the side mirrors, the rear door, and the rear windshield. Commonly, stereo vision cameras mimic human perception and retrieve information on the road and from nearby vehicles, whereas mono vision cameras are usually specialized in detecting traffic signs and traffic lights. The data they capture is processed by algorithms for image processing or by deep learning neural networks to provide detection and classification information (for instance, spotting a red light or a speed-limit sign). Cameras can have high resolution (they can spot small details) but are still sensitive to light and weather conditions (night, fog, or snow). However, recent technological advances have greatly improved the vision performance of cameras. As drivers ourselves, we rely heavily on vision while driving. Based on the same principle, some autonomous car manufacturers favor vision as a solution for their vehicles over other sensors.

Lidar (LIght Detection And Ranging)

Lidar uses infrared beams (about 900 nanometer wavelength, invisible to human eyes) to estimate the distance between the sensor and the hit object. They use a rotating swivel to project the beam around and then return estimations in the form of a cloud of collision points, which helps estimate shapes and distances. Depending on price (with higher generally meaning better), lidar can have higher resolution than radar. However, lidar is frailer and easier to get dirty than radar because it's exposed outside the car. Despite its aesthetically unappealing

appearance on the roof of a car, lidar is a critical component in how a SD car perceives the world.

Radar (RAdio Detection And Ranging)

Based on radio waves that hit a target and bounce back and whose time of flight defines distance and speed, radar can be located in the front and rear bumpers as well as on the sides of the car. Vendors have used it for years in cars to provide adaptive cruise control, blind-spot warning, collision warning, and avoidance. In contrast to other sensors that need multiple successive measurements, radar can detect an object's speed after a single ping because of the Doppler effect (see `tinyurl.com/4a567s23`). Radar comes in short-range and long-range versions, and can both create a blueprint of surroundings and be used for localization purposes. Radar is least affected by weather conditions when compared to other types of detection, especially in rain or fog. It has 150 degrees of sight and 1–250 meters of range. Its main weaknesses are the lack of resolution (radar doesn't provide much detail) and the inability to detect static objects properly. In addition, you need different types of radars to handle detections at different distances. Typically, there is a long-range radar for obstacles up to 250 meters away, a medium-range radar operating up to 60 meters and a short-range radar for monitoring the surroundings up to 30 meters.

Ultrasonic sensors

Ultrasonic sensors are similar to radar but use high-frequency sounds (ultrasounds, inaudible by humans, but audible by certain animals) instead of microwaves. The main weakness of ultrasonic sensors (used by manufacturers instead of the frailer and more costly lidars) is their short range.

Putting together what you perceive

When it comes to sensing what is around an SD car, you can rely on a host of different measurements, depending on the sensors installed on the car. Yet each sensor has different resolution, range, and noise sensitivity, resulting in different measures for the same situation. In other words, none of them is perfect, and their sensory weaknesses sometimes hinder proper detection. Sonar and radar signals might be absorbed; lidar's rays might pass through transparent solids. In addition, it's possible to fool cameras with reflections or bad light, as described by this article at MIT Technology `Review.com`, at `tinyurl.com/yfudnv9c`.

SD cars are here to improve our mobility, which means preserving our lives and those of others. An SD car can't be permitted to fail to detect a pedestrian who suddenly appears in front of it. For safety reasons, vendors focus much effort on sensor fusion, which combines data from different sensors to obtain a unified

measurement that's better than any single measurement. Sensor fusion is most commonly the result of using Kalman filter variants (such as the Extended Kalman Filter or the even more complex Unscented Kalman Filter). Although AI has shown promising advancements in the field of sensor fusion and filtering, particularly when integrated with Kalman filters, traditional Kalman filters remain the favored choice for fusing inputs from the myriad of sensors onboard.

A Kalman filter algorithm works by filtering multiple and different measurements taken over time into a single sequence of measurements that provide a real estimate (the previous measurements were inexact manifestations). It has been devised by Rudolf E. Kálmán, a Hungarian electrical engineer and an inventor who immigrated to the United States during World War II. Because of his invention — which found many applications in guidance, navigation, and vehicle control, from cars to aircraft to spacecraft — Kálmán received the National Medal of Science in 2009 from US President Barack Obama. A Kalman filter operates by first taking all the measurements of a detected object and processing them (the state prediction phase) to estimate the current object position. Then, as new measurements flow in, it uses the new results it obtains and updates the previous ones to obtain a more reliable estimate of the position and velocity of the object (the measurement update phase), as shown in Figure 15-3.

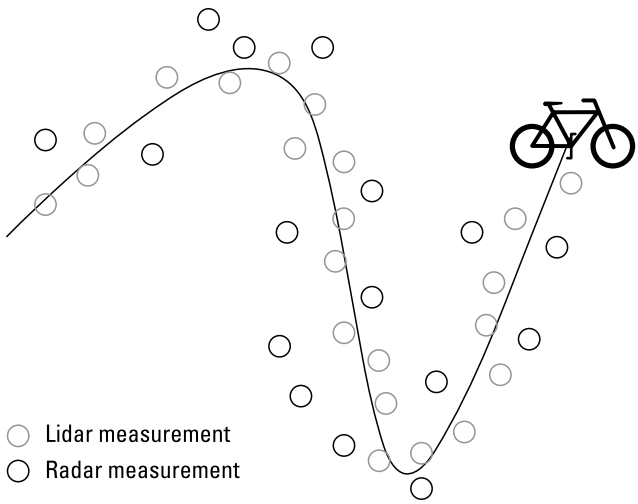

FIGURE 15-3: A Kalman filter estimates the trajectory of a bike by fusing radar and lidar data.

In this way, an SD car can feed the algorithm the sensor measurements and use them to obtain a resulting estimate of the surrounding objects. The estimate combines all the strengths of each sensor and avoids their weaknesses. This is possible because the filter works using a more sophisticated version of probabilities and Bayes' theorem, which are described in Chapter 6.

5 Getting Philosophical About AI

IN THIS PART . . .

Determine when an AI application won't work.

Create new human occupations.

Consider the use of AI in space.

IN THIS CHAPTER

- Defining AI usage scenarios
- Understanding what happens when AI fails
- Developing solutions to nonexistent problems

Chapter 16

Understanding the Nonstarter Application – Why We Still Need Humans

Previous chapters in this book explore what AI is and what it isn't, along with which problems it can solve well and which problems are seemingly out of range. Even with all this information, you can easily recognize a potential application that will never see the light of day because AI simply can't address that particular need, also known as *nonstarter* applications.

As part of this chapter, you discover the effects of attempting to create nonstarter applications. The most worrisome of those effects is the *AI winter*, which occurs whenever the promises of AI proponents exceed their capability to deliver, resulting in a loss of funding from entrepreneurs.

AI can also fall into the trap of developing solutions to problems that don't really exist. Yes, the wonders of the solution do look quite fancy, but unless the solution addresses a true need, no one will buy it. Technologies thrive only when they

address needs that users are willing to spend money to obtain. This chapter finishes with a look at solutions to problems that don't exist.

Using AI Where It Won't Work

Table 1-1 (in Chapter 1) lists the eight kinds of intelligence. A fully functional society embraces all eight kinds of intelligence, and different people excel in different kinds of intelligence. When you combine the efforts of all those people, you can address all eight kinds of intelligence in a manner that satisfies society's needs.

REMEMBER

You'll quickly note from Table 1-1 that AI doesn't address two kinds of intelligence at all, and provides only modest capability with three more. AI only excels at AI when it comes to math, logic, and kinesthetic intelligence, limiting its ability to solve many kinds of problems that a fully functional society needs to address. The following sections describe situations in which AI simply can't work, because it's a technology — not a person.

Defining the limits of AI

When talking to Alexa (a cloud-based voice assistant from Amazon that lets you give it verbal instructions.), you might forget that you're talking with a machine. The machine has no idea what you're saying, fails to understand you as a person, and has no real desire to interact with you; it only acts as defined by the algorithms created for it and the data you provide. Even so, the results are amazing. It's easy to anthropomorphize (attribute human qualities to) the AI without realizing it and then see it as an extension of a human-like entity. However, an AI lacks the essential characteristics described in the following sections.

Creativity

You can find an endless variety of articles, sites, music, art, and writings and all sorts of supposedly creative output from an AI. The problem with AI is that it can't *create* anything. When you think about creativity, think about patterns of thought. For example, Beethoven had a distinct way of thinking about music. You can recognize a classic Beethoven piece even if you're unfamiliar with all his works, because the music has a specific pattern to it, formed by the manner in which Beethoven thought.

An AI can create a new Beethoven piece by viewing his thought process mathematically, which the AI does by learning from Beethoven music examples. The resulting basis for creating a new Beethoven piece is mathematical in nature. In

fact, because of the mathematics of patterns, you can even hear an AI play Beethoven in the style of the Beatles, as well as other music genres. (If you want to listen, head to TechCrunch.com and search for *Hear AI Play Beethoven Like the Beatles.*)


REMEMBER

The problem with equating creativity to math is that math isn't creative. To be creative means to develop a new pattern of thought — one that no one has ever seen. Creativity isn't just the act of thinking outside the box — it's the act of defining a new box.

Creativity also implies developing a different perspective, which is essentially defining a different sort of dataset (if you insist on the mathematical point of view). An AI is limited to the data you provide. It can't create its own data; it can create only *variations* of existing data — the data from which it learned. To teach an AI something new, something different, something amazing, a human must decide to provide the appropriate data orientation.

Imagination

To *create* is to define something real, whether it's music, art, writing, or any other activity that results in something that others can see, hear, touch, or interact with in other ways. *Imagination* is the abstraction of creation, and is therefore even further outside the range of AI capability than creativity. Someone can imagine things that aren't real and can never be real. Imagination is the mind wandering across fields of endeavor, playing with what might be — if the rules didn't get in the way. True creativity is often the result of a successful imagination.

From a purely human perspective, everyone can imagine something. Imagination sets us human apart from everything else and often places us in situations that aren't real at all. AI, on the other hand, must exist within the confines of reality. Consequently, it's unlikely that anyone will ever develop an AI with imagination. Imagination requires not only creative intelligence but also intrapersonal intelligence, and an AI possesses neither form of intelligence.


TIP

Imagination, like many human traits, is emotional. AI lacks emotion. In fact, when viewing what an AI can do versus what a human can do, it often pays to ask the simple question of whether the task requires emotion.

Original ideas

To imagine something, you create something real from what was imagined; and then to use that real-world example of something that never existed in the past is to develop an idea. To successfully create an idea, a human needs creative, intrapersonal, and interpersonal intelligence.

REMEMBER

Creating something new is useful if you want to define one-off versions of something or entertain yourself. However, to make it into an idea, you must share it with others in a manner that allows them to see it as well.

Data deficiencies

Chapter 2 tells you about data issues that an AI must overcome to perform the tasks it's designed to do. The only problem is that an AI typically can't recognize mistruths in data with any ease unless there's an accompanying wealth of sample data that lacks these mistruths, which might be harder to come by than you think. A human can picture the mistruth in a manner that the AI can't because the AI is stuck in reality.

REMEMBER

Mistruths are added into data in so many ways that listing them all isn't even possible. Humans often add these mistruths without thinking about it. In fact, avoiding mistruths can be impossible, caused as they are by perspective, bias, and frame of reference at times. Because an AI can't identify all the mistruths, the data used to make decisions will always have some level of deficiency. Whether that deficiency affects the AI's capability to produce useful output depends on the kind and level of deficiency, along with the capabilities of the algorithms.

The oddest sort of data deficiency to consider, however, is when a human actually wants a mistruth as output. This situation occurs more often than most people think, and the only way to overcome this particular human issue is through the subtle communication provided by interpersonal intelligence that an AI lacks. For example, someone buys a new set of clothes. They look hideous — to you, at least, (and clothing can be amazingly subjective). However, if you're smart, you'll say that the clothes look amazing. The person isn't looking for your unbiased opinion — the person is looking for your support and approval. The question then becomes not one of "How do these clothes look?" — which is what the AI would hear — but one of "Do you approve of me?" or "Will you support my decision to buy these clothes?" You can partially overcome the problem by suggesting accessories that complement the clothes or by using other means, such as subtly persuading the person to see that they might not even wear the clothes publicly.

There is also the issue of speaking a hurtful truth, which an AI will never be able to handle because an AI lacks emotion. A *hurtful truth* is one in which the recipient gains nothing useful, but instead receives information that causes harm — whether it's emotional, physical, or intellectual. For example, a child may not know that one parent was unfaithful to the other. Because both parents have passed away, the information is no longer pertinent, and it would be best to allow the child to believe that their parents' marriage was a happy one. However, someone comes along and ensures that the child's memories are damaged by discussing the unfaithfulness in detail. The child doesn't gain anything but most definitely

suffers hurt feelings. An AI can cause the same degree of hurt by reviewing family information in ways the child would never consider. After discovering the unfaithfulness by examining police reports, hotel records, store receipts, and other sources, the AI tells the child about the unfaithfulness, again causing hurt by presenting the truth.

WARNING

However, in the case of the AI, the truth is presented because of a lack of emotional intelligence (empathy); the AI is unable to understand the child's need to remain in a blissful state about the parent's fidelity.

WARNING

Unfortunately, even when a dataset contains enough correct and truthful information for an AI to produce a usable result, the result can prove more hurtful than helpful.

Applying AI incorrectly

The limits of AI define the realm of possibility for applying AI correctly. However, even within this realm, you can obtain unexpected or unhelpful output. For example, you might provide an AI with various inputs and then ask for a probability of certain events occurring based on those inputs. When sufficient data is available, the AI can produce a result that matches the mathematical basis of the input data. However, the AI can't produce new data, create solutions based on that data, imagine new ways of working with that data, or provide ideas for implementing a solution. All these activities reside within the human realm. All you should expect is a probability prediction.

REMEMBER

Many of the results of AI are based on probability or statistics. Unfortunately, neither of these mathematical methods applies to individuals; these methods work only with groups. In fact, using statistics creates myriad problems for just about any purpose other than concrete output, such as driving a car. The article "The Problems with Statistics" at `http://public.wsu.edu` discusses the problems with using statistics. When your AI application affects individuals, you must be prepared for the unexpected, including a complete failure to achieve any of the goals you had set out to achieve.

Another issue is whether the dataset contains any sort of opinion, which is far more prevalent than you might think. An opinion differs from a fact in that the fact is completely provable, and everyone (or at least everyone with an open mind) agrees that a fact is truthful. Opinions occur when you lack sufficient scientific facts to back up the data. In addition, opinions occur whenever emotion is involved. Even when faced with conclusive proof to the contrary, some humans would rather rely on opinion than on fact. The opinion makes us feel comfortable; the fact doesn't. AI nearly always fails when opinion is involved. Even with the best algorithm available, someone will be dissatisfied with the output.

Entering a world of unrealistic expectations

Earlier, this chapter discusses how expecting an AI to perform certain tasks or applying AI in less-than-concrete situations causes problems. Unfortunately, humans don't seem to comprehend that the sorts of tasks that many of us think an AI can perform will never come about. These unrealistic expectations have many sources, including

- **Media:** Books, movies, and other forms of media all seek to obtain an emotional response from us. However, that emotional response is the very source of unrealistic expectations. We imagine that an AI can do something, but it truly can't do those things in the real world.
- **Anthropomorphization:** Along with the emotions that media generates, humans also tend to form attachments to many of the objects in their daily lives. For example, people often name their cars, talk to them, and wonder whether they're feeling bad when they break down. An AI can't feel, can't understand, can't communicate (really), and can't do anything other than crunch numbers — lots and lots of numbers. When the expectation is that the AI will suddenly develop feelings and act human, the result is doomed to failure.
- **Undefined problem:** An AI can solve a defined problem but not an undefined one. You can present a human with a set of potential inputs and expect a human to create a matching question based on extrapolation. Say that a series of tests keeps failing for the most part, but some test subjects do achieve the desired goal. An AI might try to improve test results through interpolation by locating new test subjects with characteristics that match those who did well. However, a human might improve the test results through extrapolation by questioning why some test subjects succeeded and then finding the cause, whether the cause is based on test subject characteristics or not (perhaps environmental conditions have changed or the test subject simply has a different attitude). For an AI to solve any problem, however, a human must be able to express that problem in a manner that the AI understands. Undefined problems, those that represent something outside human experience, simply aren't solvable using an AI.
- **Deficient technology:** In many places in this book, you find that a problem wasn't solvable at a certain time because of a lack of technology. It isn't realistic to ask an AI to solve a problem when the technology is insufficient. For example, the lack of sensors and processing power would have made creating a self-driving car in the 1960s impossible, yet advances in technology have made such an endeavor possible today.

Considering the Effects of AI Winters

AI winters occur when scientists and others make promises about the benefits of AI that don't come to fruition within an expected time frame, causing funding for AI to dry up and research to continue at only a glacial pace. (Scare tactics employed by those who have no idea how AI works have likely had an effect on AI winters as well.) Since 1956, the world has seen two AI winters (more on this later in the section). As of this writing, in 2024, the current level of investment in AI is positive, with a history of growth and a strong focus from major tech companies. Though there are concerns about potential adverse effects, the investment community's overall sentiment is optimism about the future of AI and its role in driving economic growth and innovation. The following sections discuss the causes, effects, and results of AI winter in more detail.

Defining the causes of the AI winter

As we mention earlier, an AI winter occurs when funding for AI dwindles. The use of the word *winter* is appropriate because, like a tree in winter, AI didn't stop growing altogether. When you view the rings of a tree, you see that the tree does continue to grow in winter — just not very fast. Likewise, during the AI winters from 1974 to 1980 and again from 1987 to 1993, AI did continue to grow, but at a glacial pace.

The cause of an AI winter can easily be summarized as resulting from outlandish promises that are impossible to keep. At the outset of the efforts at Dartmouth College in 1956, the soon-to-be leaders of AI research predicted that developing a computer as intelligent as a human would take no more than a generation. Sixty-plus years later, computers still aren't nearly as smart as humans. In fact, if you've read previous chapters, you know that computers are unlikely to ever be as smart as humans, at least not in every kind of intelligence (and by now have exceeded human capability only in a scant few kinds and only in limited situations).

REMEMBER

Part of the problem with overpromising capabilities is that early proponents of AI believed that all human thought could be formalized as algorithms. In fact, this idea goes back to the Chinese, Indian, and Greek philosophers. However, as shown in Table 1-1 (see Chapter 1), only certain components of human intelligence are formalized. In fact, the best possible outcome is that human mathematical and logical reasoning could be mechanized. Even so, in the 1920s and 1930s, David Hilbert challenged mathematicians to prove that all mathematical reasoning can be formalized. The answer to this challenge came from Gödel's incompleteness proof, Turing's machine, and Church's Lambda calculus. Two outcomes emerged: Formalizing *all* mathematical reasoning isn't possible; and in the areas in which formalization is possible, you can also mechanize the reasoning, which is the basis of AI.

Another part of the problem with overpromising is excessive optimism. During the early years of AI, computers solved algebra word problems, proved theorems in geometry, and learned to speak English. The first two outputs are reasonable when you consider that the computer is simply parsing input and putting it into a form that the computer can manipulate. The problem lies with the third of these outputs. The computer wasn't truly speaking English; instead, it was converting textual data into digital patterns that were in turn converted to analog and output as something that seemed like speech but wasn't. The computer didn't understand anything about English, or any other language, for that matter. Yes, the scientists did indeed hear English, but the computer simply saw 0s and 1s in a specific pattern that the computer didn't see as language.

WARNING

Even the researchers were often fooled into thinking that the computer was doing more than it really was. For example, Joseph Weizenbaum's ELIZA at psych.fullerton.edu appeared to hear input and then respond in an intelligent manner. Unfortunately, the responses were canned, and the application wasn't hearing, understanding, or saying anything. Yet ELIZA was the first chatterbot and did represent a step forward, albeit an incredibly small one. The hype was simply significantly greater than the actual technology — a problem that AI faces today. People feel disappointed when they see that the hype isn't real, so scientists and promoters continue to set themselves up for failure by displaying glitz rather than real technology. The first AI winter was brought on by predictions such as these:

- **Herbert (H. A.) Simon:** "Within ten years, a digital computer will be the world's chess champion" (1958) and "[M]achines will be capable, within twenty years, of doing any work a man can do." (1965)
- **Allen Newell:** "Within ten years, a digital computer will discover and prove an important new mathematical theorem." (1958)
- **Marvin Minsky:** "[W]ithin a generation . . . the problem of creating 'artificial intelligence' will substantially be solved" (1967) and "In from three to eight years, we will have a machine with the general intelligence of an average human being." (1970)

Oddly enough, a computer became chess champion in 1997, though not within ten years (see "How 22 Years of AI Superiority Changed Chess" at `towardsdatascience.com`), but the other predictions still aren't true. In viewing these outlandish claims today, you can easily see why governments withdrew funding.

The second AI winter came about as a result of the same issues that created the first AI winter — overpromising, overexcitement, and excessive optimism. In this case, the boom started with the expert system (see "Leveraging expert systems" in Chapter 3 for more details on expert systems), a kind of AI program that solves problems using logical rules. In addition, the Japanese entered the fray with their

Fifth Generation Computer Systems project, a computer system that offered massively parallel processing. The idea was to create a computer that could perform many tasks in parallel, similar to the human brain. Finally, John Hopfield and David Rumelhart resurrected connectionism, a strategy that models mental processes as interconnected networks of simple units.

The end came about as sort of an economic bubble. The expert systems proved brittle, even when run on specialized computer systems. The specialized computer systems ended up as economic sinkholes that newer, common computer systems could easily replace at a significantly reduced cost. In fact, the Japanese Fifth Generation Computer Systems project was also a fatality of this economic bubble. It proved extremely expensive to build and maintain.

Rebuilding expectations with new goals

An AI winter does not necessarily prove devastating. Quite the contrary: Such times can be viewed as opportunities to stand back and think about the various issues that cropped up during the rush to develop an amazing product. Two major areas of thought benefitted during the first AI winter (along with minor benefits to other areas of thought):

- **Logical programming:** This area of thought involves presenting a set of sentences in logical form (executed as an application) that expresses facts and rules about a particular problem domain. Examples of programming languages that use this particular paradigm are Answer Set Programming (ASP), Datalog, and Prolog. This is a form of rule-based programming, which is the underlying technology used for expert systems.
- **Common-sense reasoning:** This area of thought uses a method of simulating the human ability to predict the outcome of an event sequence based on the properties, purpose, intentions, and behavior of a particular object. Common-sense reasoning is an essential component in AI because it affects a wide variety of disciplines, including computer vision, robotic manipulation, taxonomic reasoning, action and change, temporal reasoning, and qualitative reasoning.

The second AI winter brought additional changes that have served to bring AI into the focus it has today:

- **Using common hardware:** At one point, expert systems and other uses of AI relied on specialized hardware. The reason is that common hardware didn't provide the necessary computing power or memory. However, these custom systems proved expensive to maintain, difficult to program, and extremely brittle when faced with unusual situations. Common hardware is general

purpose in nature and is less prone to the issues of having a solution that's attempting to find a problem (see the later section "Creating Solutions in Search of a Problem" for details).


TECHNICAL STUFF

Common hardware indicates hardware that you can buy anywhere and that other groups use. For example, machine learning benefits greatly from the inclusion of a graphics processing unit (GPU) in the host system. However, gaming and other graphics-intensive tasks also rely on these devices, so the hardware is theoretically common, but not every system has one.

- **Recognizing a need to learn:** Expert systems and other early forms of AI required special programming to meet each need, thereby making them extremely inflexible. It became evident that computers would need to be able to learn from the environment, sensors, and data provided.
- **Creating a flexible environment:** The systems that did perform useful work between the first and second AI winters did so in a rigid manner. When the inputs didn't quite match expectations, these systems were likely to produce grotesque errors in the output. It became obvious that any new systems would need to know how to react to real-world data, which is full of errors, incomplete, and often formatted incorrectly.
- **Relying on new strategies:** Imagine that you work for the government and have promised all sorts of amazing feats based on AI, except that none of them seem to materialize. That's the problem with the second AI winter: Some governments tried various ways of making the promises of AI a reality. When the current strategies obviously weren't working, these same governments started looking for other ways to advance computing, some of which have produced interesting results, such as advances in robotics.

The point is that AI winters aren't necessarily bad for AI. In fact, these occasions to step back and view the progress (or lack thereof) of current strategies are important. Taking advantage of these thoughtful moments is hard when you're rushing headlong into the next hopeful achievement.


REMEMBER

When considering AI winters and the resulting renewal of AI with updated ideas and objectives, an adage known as Amara's law, coined by the American scientist and futurist Roy Charles Amara, is worth remembering: "We tend to overestimate the effect of a technology in the short run and underestimate the effect in the long run." After all the hype and disillusionment, the time always comes when people can't perceive the long-term impact of a new technology clearly and understand the revolutions it brings about with it. As a technology, AI is here to stay and will change our world for better and worse, no matter how many winters it still has to face.

Creating Solutions in Search of a Problem

Two people are looking at a mass of wires, wheels, metal bits, and odd, assorted items that appear to be junk. The first person asks the second, "What does it do?" The second answers, "What doesn't it do?" Yet the invention that apparently does everything ends up doing nothing at all. The media is rife with examples of the solution looking for a problem. We humans laugh because everyone has already encountered the solution that's in search of a problem. These solutions end up as so much junk, even when they do work, because they fail to answer a pressing need. The following sections discuss in more detail the AI solution in search of a problem.

Defining a gizmo

When it comes to AI, the world is full of gizmos. Some of those gizmos are truly useful, but many aren't, and a few fall between these two extremes. For example, Alexa comes with many useful features, but it also comes with a hoard of gizmos that will leave you scratching your head when you try to use them.

Here are some pros and cons:

It can:

- Call people hands free.
- Integrate with many third-party apps making it very useful to your specific needs.
- Create and add items to a shopping list hands free.

It can't:

- Ensure your privacy. You sign away your privacy rights when you sign up, and the device is always listening.

  Always understand your commands and you may need to repeat them.

  Easily switch between languages.

An *AI gizmo* is any application that seems on first glance to do something interesting, but ultimately proves unable to perform truly useful tasks. In this list of common aspects to look for when identifying a gizmo, the first letter of each

bullet in the list spells the acronym CREEP, as a reminder not to create "creepy" AI applications:

- **Cost effective:** Before anyone decides to buy into an AI application, it must prove to cost the same or less than existing solutions. Everyone is looking for a deal. Paying more for a similar benefit simply won't attract attention.
- **Reproducible:** The results from using an AI application must be reproducible, even when the circumstances of performing the task change. In contrast to procedural solutions to a problem, people expect an AI to adapt — to learn from doing, which means that the bar is set higher on providing reproducible results.
- **Efficient:** When an AI solution suddenly consumes huge amounts of resources of any sort, users look elsewhere. Businesses, especially, have become extremely focused on performing tasks with the fewest possible resources.
- **Effective:** Simply providing a practical benefit that's cost-effective and efficient isn't enough; an AI must also provide a solution that fully addresses a need. Effective solutions enable someone to allow the automation to perform the task without having to continually recheck the results or prop up the automation.
- **Practical:** A useful application must provide a practical benefit. The benefit must be something that the end user requires, such as access to a road map or reminders to take medication.

Avoiding the infomercial

Bedazzling potential users of your AI application is a sure sign that the application will fail. Oddly enough, the applications that succeed with the greatest ease are those whose purpose and intent are obvious from the outset. A voice recognition application is obvious: You talk, and the computer does something useful in exchange. You don't need to sell anyone on the idea that voice recognition software is useful. This book is filled with a number of these truly useful applications, none of which requires the infomercial approach of the hard sell. If people start asking what something does, it's time to rethink the project.

Understanding when humans do it better

This chapter is all about keeping humans in the loop while making use of AI. Some sections describe tasks that we humans perform better than AI, when an AI can accomplish them at all. Anything that requires the use of imagination or creativity, the discernment of truth, the handling of opinion, or the creation of an idea is best left to humans. Oddly enough, the limits of AI leave lots of places for humans to go, many of which aren't even possible today because humans are overly engaged in repetitive, boring tasks that an AI can easily do.

CONSIDERING THE INDUSTRIAL REVOLUTION

The human/AI collaboration won't happen all at one time. In addition, the new kinds of work that humans will be able to perform won't appear on the scene immediately. However, the vision of humans just sitting around waiting to be serviced by a machine is farfetched and, obviously, untenable. Humans will continue to perform various tasks. Of course, the same claims about machines taking over were made during all major human upheavals in the past; the industrial revolution is one of the more recent and more violent of those upheavals. Humans will always do certain things better than an AI, and you can be certain that we'll continue to make a place for ourselves in society. We just need to hope that this upheaval is less violent than the industrial revolution was.

Look for a future in which AI acts as an assistant to humans. In fact, you'll see this use of AI more and more as time goes on. The best AI applications will be those that look to assist rather than replace, humans. Yes, robots will replace humans in hazardous conditions, but humans will need to make decisions on how to avoid making those situations worse, which means having a human at a safe location to direct the robot. It's a hand-in-hand collaboration between technology and humans.

Looking for the simple solution

The KISS principle is the best idea to keep in mind when it comes to developing AI applications. The basic idea is to ensure that any solution is the simplest you can make it. All sorts of principles exist for the use of simple solutions. However, of these, Occam's razor (that the simplest answer is usually the right answer) is probably the most well-known.

Why is KISS important? The easiest answer is that complexity leads to failure: The more parts something has, the more likely it is to fail. This principle has its roots in mathematics and is easy to prove.


REMEMBER

When it comes to applications, however, other principles come into play. For most people, an application is a means to an end. People are interested in the end and don't much care about the application. If the application were to disappear from view, the user would be quite happy because then just the end result is in view. Simple applications are easy to use — they tend to disappear from view and require no complex instructions. In fact, the best applications are obvious. When your AI solution has to rely on all sorts of complex interactions, consider whether it's time to go back to the drawing board and come up with something better.

IN THIS CHAPTER

- Getting paid in space
- Building cities in new locations
- Enhancing human capabilities
- Fixing our planet

Chapter 17
Engaging in Human Endeavors

When people view news about robots and other automation created by advances in technology, such as AI, they tend to see the negative more than the positive. The problem is that most of these articles are quite definite when it comes to job losses, but nebulous, at best, when speaking of job creation. While some experts say that AI may take more jobs in the future, the overall impact will depend on factors like technology, the economy, and society. The main challenge will be helping workers adapt to these changes.

The overall goal of this chapter is to clear away the hype, disinformation, and outright fearmongering with some better news.

This chapter looks at interesting new human occupations that incorporate AI. But first, don't assume that your job is on the line. (See Chapter 17 for just a few examples of AI-safe occupations.) Unless you're involved in work that is mind-numbingly simple and extremely repetitive, an AI isn't likely to replace you. Quite the contrary: You may find that an AI *augments* you, enabling you to derive more enjoyment from your occupation. Even so, after reading this chapter, you may just decide to get a little more education and some job training in some truly new and amazing occupation.

REMEMBER

Some of the jobs noted in this chapter are a bit on the dangerous side, too. AI will also add a host of mundane applications to the list that you'll perform in an office or perhaps even in your home. These are the more interesting entries on the list, and you shouldn't stop looking for that new job if an AI does manage to grab yours. The point is that humans have been in this place multiple times in our history — the most disruptive of which was the industrial revolution — and we've managed to continue to find things to do. If you get nothing else from this chapter, be aware that all the fearmongering in the world is just that: someone trying to make you afraid so that you'll believe something that isn't true.

Keeping Human Beings Popular

The headline for an online advertisement in the future reads, "Get the New and Improved Human for Your Business!" It's one of those advertising gimmicks that many people find annoying. For one thing, something is either new or it's improved, but it isn't both. For another, aren't humans simply humans? However, the headline does have merit. Humans are constantly evolving, constantly adapting to change. We're the most amazing of species because we're always doing the unexpected in order to survive. Part of the reason for writing this chapter is to ensure that people think about the future — that is, where we're headed as a species, because we're certainly going to evolve as AI generally invades every aspect of our lives.

Children (and many adults) love video games! For many people, video games are only so much wasted time, yet they have a profound effect on children (or anyone else playing them), as described at `www.raisesmartkid.com/3-to-6-years-old/4-articles/34-the-good-and-bad-effects-of-video-games`. In fact, playing games permanently changes the brain, as described at `interestingengineering.com/playing-video-games-can-actually-change-the-brain`. Video games are just one of many aspects of life that AI changes, so the human of tomorrow is unlikely to be mentally the same as the human of today. This likelihood leads to the idea that humans will remain popular and that AI won't take over the world.

When you extend the effects of brain changes due to game playing, it's not too difficult to assume that brain changes also occur for other uses of technology, especially technology that creates a brain-computer interface (BCI), as described at `hbr.org/2020/09/are-you-ready-for-tech-that-connects-to-your-brain`. Currently, BCI enables people to do things like move limbs or overcome spinal cord injuries, but there's nothing preventing a BCI from letting humans interact directly with an AI in ways we can't even imagine yet. Far from being replaced by AI, humans are evolving to work with AI to perform amazing feats that were never possible in the past.

Living and Working in Space

The media has filled people's heads with this idea that we'll somehow do things like explore the universe or fight major battles in space with aliens who have come to take over the planet. The problem is that most people wouldn't know how to do either of those things. Yet you can get a job with SpaceX today that involves some sort of space-oriented task (see `www.spacex.com/careers/index.html`). The list of potential job opportunities is huge, and many of them are internships so that you can get your feet wet before diving deeply into a career. Of course, you might expect the jobs to be quite technical, but look down the list and you see a bit of everything — including a barista, at the time of this writing. The fact is that space-based careers will include everything that other careers include; you just have the opportunity to eventually work your way up into something more interesting.

TIP

Companies like SpaceX are also involved in providing their own educational opportunities and interacting with universities on the outside. Space represents a relatively new venture for humans, so everyone is starting at about the same level, in that everyone is learning something new. One of the most thrilling parts of entering a new area of human endeavor is that we haven't done the things we're doing now, so there's a learning curve. You might find yourself in a position to make a significant contribution to the human race, but only if you're willing to take on the challenge of discovering and taking the risks associated with doing something different.

Today, the opportunities to live and work in space are limited, but the opportunities will improve over time. Chapter 18 discusses all sorts of things that humans will do in space eventually, such as mining or performing research. Yes, we'll eventually found cities in space after visiting other planets. Mars could become the next Earth. Many people have described Mars as potentially habitable (see `www.planetary.org/articles/can-we-make-mars-earth-like-through-terraforming` as an example) with the caveat that we'll have to re-create the Mars magnetosphere.

Some of the ideas that people are discussing about life in space today don't seem feasible, but they're quite serious about those ideas and, theoretically, they're possible. For example, after the Mars magnetosphere is restored, it should be possible to terraform the planet to make it quite habitable. Some of these changes would happen automatically; others would require intervention from us. Imagine what being part of a terraforming team might be like. To make endeavors like this work, though, humans will rely heavily on AIs, which can actually see things that humans can't and react in ways that humans can't even imagine today. Humans and AIs will work together to reshape places like Mars to meet human needs. More important, these efforts will require huge numbers of people here on Earth, on the moon, in space, and on Mars. Coordination will be essential.

Creating Cities in Hostile Environments

As of this writing, Earth is host to more than 8 billion people, and that number will increase. Today the Earth will add about 120,000 people. In 2030, the Earth will have about 8.5 billion people. In short, a lot of people inhabit Earth today, and there will be more of us tomorrow. Eventually, we'll need to find other places to live. If nothing else, we'll need more places to grow food. However, people also want to maintain some of the world's wild places and set aside land for other purposes, too. Fortunately, AI can help us locate suitable places to build, discover ways to make the building process work, and maintain a suitable environment after a new place is available for use.

As AI and humans become more capable, some of the more hostile places to build become more accessible. Theoretically, we might eventually build habitats in a volcano, but there are certainly a few locations more ideal than that to build before then. The following sections look at just a few of the more interesting places that humans might eventually use as locations for cities. These new locations all provide advantages that humans have never had — opportunities for us to expand our knowledge and ability to live in even more hostile places in the future.

Building cities in the ocean

There are multiple ways to build cities in the ocean. However, the two most popular ideas are building floating cities and building cities that sit on the ocean floor. In fact, a floating city is in the planning stages right now (`www.architecturaldigest.com/story/surprising-facts-worlds-first-floating-city`). The goals for floating cities are many, but here are the more attainable:

- Protection from rising sea levels
- Opportunities to try new agricultural methods
- Growth of new fish-management techniques
- Creation of new kinds of government

People who live on the oceans in floating cities are *seasteading* (sort of like homesteading, except on the ocean). The initial cities will exist in relatively protected areas. Building on the open ocean is definitely feasible (oil platforms already rely on various kinds of AI to keep them stable and perform other tasks) but expensive.

Underwater cities are also quite feasible, and a number of underwater research labs already exist (interestingengineering.com/7-things-you-should-know-about-the-future-of-underwater-cities). None of these research labs is in truly deep water, but even at 60 feet deep, they're pretty far down. According to a number of sources, the technology exists to build larger cities, further down, but they'd require better monitoring. That's where AI will likely come into play. The AI could monitor the underwater city from the surface and provide the safety features that such a city would require. Monitoring from the surface lets the AI use reliable and easier-to-maintain technologies like satellites, drones, and communication networks.


REMEMBER

Cities in the ocean might not look anything like cities on land. For example, some architects want to build an underwater city near Tokyo that will look like a giant spiral (constructionglobal.com/construction-projects/underwater-construction-concept-could-harness-seabed-energy-resources). This spiral could house as many as 5,000 people. This particular city would sit at 16,400 feet below the surface and rely on advanced technologies to provide features like power. It would be a full-fledged city, with labs, restaurants, and schools, for example.

No matter how people eventually move to the ocean, the move will require extensive use of AI. Some of this AI is already in the development stage (https://link.springer.com/article/10.1007/s43154-022-00088-3) as companies develop underwater autonomous vehicles. As you can imagine, robots like these will be part of any underwater city development because they will perform various kinds of maintenance that would be outright impossible for humans to perform.

SUBMERSIBLE TRAGEDY

On June 22, 2023, the submersible *Titan,* operated by OceanGate, went missing during a descent to visit the *Titanic* wreckage site. The vessel, carrying five passengers, suffered a catastrophic implosion, leading to the loss of all aboard. (See the full story at www.cnn.com/2023/06/28/americas/titan-submersible-debris-st-johns/index.html.)

Although this accident did not involve AI, it's a reminder of the risks associated with deep-sea and underwater exploration. It highlights the critical need for stringent safety measures and rigorous testing of submersibles intended for these missions.

Creating space-based habitats

A *space habitat* differs from other forms of space station in that a space habitat is a permanent settlement. The reason to build a space habitat is to provide long-term accommodations for humans. The assumption is that a space habitat will provide a *closed-loop* environment, one in which people can exist without resupply indefinitely (or nearly so). Consequently, a space habitat would need air and water recycling, a method of growing food, and the means to perform other tasks. Although all space stations require an AI to monitor and tune conditions, the AI for a space habitat would be an order of magnitude (or greater) more complex.

Chapter 18 offers some discussion of space-based habitats in the "Taking your first space vacation" section of the chapter. Of course, short visits will be the first way in which people interact with space. A space vacation would certainly be interesting! However, a near-Earth vacation is different from a long-term habitat in deep space. NASA has already commissioned six companies to start looking into the requirements for creating habitats in deep space and as of 2024 testing is underway (`www.nasa.gov/feature/nasa-begins-testing-habitation-prototypes`).

For some organizations, space-based habitats aren't so much a means for enhancing exploration as for protecting civilization. At this moment, if a giant asteroid impacts Earth, most of humanity will perish. People on the International Space Station (ISS) might survive, though — at least, if the asteroid didn't hit it as well. However, the ISS isn't a long-term survival strategy for humans, and the number of people on the ISS at any given time is limited. So, people like members of the Lifeboat Foundation (`lifeboat.com/ex/spacehabitats`) are looking into space habitats as a means for ensuring humanity's survival. Their first attempt at a space habitat is Ark I, which is designed for 1,000 permanent residents and up to 500 guests. Theoretically, the technology can work, but it will require a great deal of planning.

Another use for space habitats is as a *generational ship,* a kind of vessel to explore interstellar space using technologies we have available today (`scienceline.org/2021/02/novel-science-talkin-bout-my-generation-ship/`). People would live on this ship as it traveled to the stars. They'd have children in space in order to make long voyages feasible. The idea of generational ships isn't new. They have appeared in both movies and books for years. The problem with a generational ship is that the ship would require a consistent number of people who are willing to work in each of the various trades needed to keep the ship moving. Even so, growing up knowing that you have an essential job waiting for you would be an interesting change from what humans have to deal with today.

HABITATS VERSUS TERRAFORMING

Significant use of AI will occur no matter how we decide to live and work in space. The way we create the AI will differ depending on where we go and when. People now have the idea that we could be living on Mars in a relatively short period. However, when reviewing sites such as phys.org/news/2017-03-future-space-colonization-terraforming-habitats.html, it becomes obvious that terraforming Mars will take a very long time indeed. Just to warm the planet (after we build the technology required to re-create the Mars magnetosphere) will take about a hundred years. Consequently, we really don't have a choice between habitats and terraforming — habitats will come first, and we'll likely use them extensively to make any plans we have for Mars work. Even so, the AI for both projects will be different, and seeing the sorts of problems that the AI will help address should be interesting.

Rather than build space habitat components on Earth and then move them into space, the current strategy is to mine the materials needed from asteroids and use space factories to produce the space habitats. The solar system's main asteroid belt is currently estimated to contain enough material to build habitats containing the same area as 3,000 Earths. That's a lot of human beings in space.

Constructing moon-based resources

At times, people have talked of military bases on the moon, but the Outer Space Treaty, signed by 60 nations as a way to keep politics out of space (www.cfr.org/report/outer-space-treaty), has largely put an end to that idea. Moon-based structures and the services they provide will more likely answer exploration, mining, and factory needs at first, followed by complete cities. Even though these projects will likely rely on robots, they will still require humans to perform a wide range of tasks, including robot repair and robot management. Building bases on the moon will also require a host of new occupations that you won't likely see as part of space habitats or in scenarios that deal exclusively with working in space. For example, someone will have to deal with the aftermath of moonquakes (see www.nasa.gov/press-release/goddard/2019/moonquakes for details).

Using existing moon features to build housing is also a possibility. The recent discovery of moon structures suitable to colonization uses would make building bases on the moon easier. For example, you can read about a huge cave that's suitable for colonization at time.com/4990676/moon-cave-base-lunar-colony-exploration. In this case, Japan discovered what appears to be a lava tube that would protect colonists from a variety of environmental threats.

Making Humans More Efficient

An AI can make a human more efficient in lots of different ways. Most of the chapters in this book have some sort of example of a human relying on an AI to do things more efficiently. One of the more interesting chapters, though, is Chapter 12, which points out how an AI will help with medical needs in various ways. All these uses of an AI assume that a human remains in charge but uses the AI to become better at performing a task. For example, the da Vinci surgical system doesn't replace the surgeon; it simply makes the surgeon able to perform the task with greater ease and less potential for errors. A new occupation that goes along with this effort is a trainer who shows professionals how to use new tools that include an AI.

REMEMBER

In the future, you should plan to see consultants whose only job is to find new ways to incorporate AIs into business processes to help people become more efficient. To some extent, this profession already exists, but the need will increase at some point when generic, configurable AIs become common. For many businesses, the key to profitability will hinge on finding the right AI to augment human workers so that workers can complete tasks without error and as quickly as possible.

When dealing with human efficiency, you should think about areas in which an AI can excel. For example, AI does perform searches exceptionally well, so you might train a human to rely on an AI to perform search-related tasks while the human does something creative. Here are some ways in which you may see humans using an AI to become more efficient in the future:

- **Hiring:** A person hiring people for an organization now may not know all the candidate's true credentials and history. An AI can research candidates before an interview so that the hiring person has more information to use during the interview. In addition, because the AI would use the same search methodology for every candidate, the organization can ensure that each candidate is treated both consistently and equally.
- **Scheduling:** Today, a business is constantly at risk because someone didn't think about the need to schedule a task. In fact, people might not have had time to even think about the need for the task in the first place. Secretaries and assistants used to manage schedules, but in the new, flattened hierarchies, these assistants have all but disappeared and individual employees perform their own scheduling tasks. Thus, overworked employees often miss opportunities to help a business excel because they're too busy managing a schedule. Coupling an AI with a human frees the human from performing the

scheduling. Instead, the human can look ahead and see what will need to be scheduled. It's a matter of focus: By focusing the human where the human can excel, the business gets more out of the human. The AI makes possible this focus on human excellence.

- **Locating hidden information:** More than ever, businesses now get blindsided by the competition because of hidden information. Information overload and ever-growing science, technology, business, and societal complexity are at the root of the problem. Perhaps a new way to package goods exists that reduces costs significantly, or the structure of a business changes as a result of internal politics. Knowing what's available and what's going on at all times is the only way that businesses can truly succeed, but the job simply isn't feasible. If a human were to take the time required to become all-knowing about everything that a particular job requires, no time would remain to actually do the job.

  AIs, however, are exceptional at finding things. By incorporating machine learning into the mix, a human can train an AI to look for precisely the right issues and requirements to keep a business running efficiently without wasting quite so much time in manual searches.

- **Adaptive help:** Anyone using products today will have to admit that having to remember how to perform a certain task is incredibly frustrating at times, especially when rediscovering how to perform the task requires using application help. You can already see how an AI becomes an adaptive aid when it comes to typing certain kinds of information into forms. However, an AI can go much further. By using machine learning techniques to discover patterns of use, an AI can provide adaptive help that would help users advance past hard-to-remember parts of an application. Because every user is different, an application that's hardwired to provide adaptive help would never work. Using machine learning enables people to customize the Help system to fit each individual user.

- **Adaptive learning:** Today you can take an adaptive exam that tailors itself to ask questions about perceived weak areas in your knowledge. The adaptive exam either discovers that you really do know enough or asks enough questions to identify where you need more training. Eventually, applications will be able to sense how you use them and then provide automated training to make you better. For example, the application may discover that you could perform a task using five fewer clicks, so it could show you how to perform the task using this approach. By continually training people to use the most efficient approach when interacting with computers or performing other tasks, the person becomes more efficient but the need for the human in that particular role remains.

Fixing Problems on a Planetary Scale

Regardless of whether you believe in global warming, think that pollution is a problem, or are concerned about overpopulation, the fact is that we have only one planet Earth, and it has problems. The weather is most definitely growing stranger; large areas are no longer useful because of pollution; and some areas of the world have, frankly, too many people. An out-of-control storm or forest fire doesn't care what you think; the result is always the same: destruction of areas where humans live. The act of trying to cram too many people into too little space usually results in disease, crime, and other problems. The issues are real, and AI can help solve them by helping knowledgeable people look for the right patterns. The following sections discuss planetary problems from the perspective of using an AI to see, understand, and potentially fix them. We're not stating or implying any political or other kind of message.

Contemplating how the world works

Sensors monitor every aspect of the planet today. In fact, so much information exists that it's amazing that anyone can collect all of it in one place, much less do anything with it. In addition, because of the interactions among various Earth environments, you can't truly know which facts have a causal effect on some other part of the environment. For example, it's hard to know precisely how much wind patterns affect sea warming, which in turn affects currents that potentially produce storms. If humans actually understood all these various interactions, the weather report would be more accurate. Unfortunately, the weather report is usually sort of right — if you squint just right and hold your mouth a certain way. The fact that we accept this level of performance from the people who predict the weather testifies to our awareness of the difficulty of the task.

Over the years, weather prediction has become much more reliable. Part of the reason for this increase in reliability is all those sensors out there. The weather service has also created better weather models and amassed a much larger store of data to use for predictions. However, the overriding reason that the weather report is more accurate is the use of AI to handle the number crunching and look for identifiable patterns in the resulting data (see `emerj.com/ai-sector-overviews/ai-for-weather-forecasting` for details).

The weather is actually one of the better-understood Earth processes. Consider the difficulty in forecasting earthquakes. The use of machine learning has made it more likely that scientists will know when an earthquake will happen (`www.wired.co.uk/article/ai-predicting-earthquakes`), but only time will tell whether the new information is truly useful. At one time, people thought that the weather could affect earthquakes, but this isn't the case. On the other hand, earthquakes

may affect the weather by changing the environmental conditions. Also, earthquakes and weather can combine to make a situation even worse (science.nasa.gov/earth/climate-change/can-climate-affect-earthquakes-or-are-the-connections-shaky).

Even more difficult to predict are volcanic eruptions. At least NASA can now detect and obtain images of volcanic eruptions with great accuracy. Volcanic eruptions often cause earthquakes, so knowing about one helps to predict the other. Of course, volcanoes also affect the weather.

The natural events that this section has covered comprise just the tip of the iceberg. If you're forming the idea that Earth is so complex that no lone person could ever understand it, you're right. That's why we need to create and train AIs to help humans do a better job of understanding how the world works. By creating this sort of knowledge, avoiding catastrophic events in the future may be possible, along with reducing the effects of certain manmade ills.

WARNING

No matter what you've read, no current strategy exists to prevent bad weather, earthquakes, or volcanoes. The best that humans can hope to achieve today is to predict these events and then act to reduce their impact. However, even the ability to reduce the impact of natural events is a major step forward. Before AI, humans were at the mercy of whatever event occurred because prediction was impossible before it was too late to truly act in a proactive manner to reduce the effects of the natural disaster.

Likewise, even though preventing all manmade disasters might seem possible, it often isn't. No amount of planning will keep accidents from happening. This said, most human-made events are controllable and potentially preventable with the correct insights, which can be provided via the pattern matching an AI can provide.

Locating potential sources of problems

With all the eyes in the sky today, you'd think that satellite data could provide an absolute source of data for predicting problems on Earth. However, this viewpoint has a number of problems:

- The Earth is huge, so detecting a particular event means scouring millions of pictures every second of every day.
- The pictures must appear at the correct resolution to accurately find an event.
- Using the proper light filter is essential because some events become visible only in the right light.
- Weather can prevent the acquisition of certain types of images.

Even with all these problems, scientists and others use AI to scan the pictures taken each day, looking for potential problems (https://www.interactive.satellitetoday.com/via/november-2023/how-ai-and-ml-are-supercharging-earth-observation). However, the AI can show possible problem areas and perform analysis only when the images appear in the correct form. A human still has to determine whether the problem is real and needs to be addressed. For example, a major storm in the middle of the Pacific Ocean and away from the transportation routes or any landmass probably won't be considered a high-priority problem. The same storm over the top of a landmass is a cause for concern. Of course, when it comes to storms, detecting the storm before it becomes an issue is always better than trying to do something about it later.


TIP

Besides scanning images for potential problems, AI can enhance images. The article at www.jdsupra.com/legalnews/artificial-intelligence-and-satellite-72364 talks about how AI can increase the resolution and usability of images taken from space. By enhancing the images, the AI can make better determinations of specific kinds of events based on the event pattern (such as carbon tracking). Of course, if the AI has never seen a particular pattern, it still can't make any sort of prediction. Humans will always need to double-check the AI and ensure that an event truly is what the AI purports it to be.

Defining potential solutions

The solution to planetary problems depends on the problem. For example, with a storm, earthquake, or volcanic eruption, preventing the event isn't even a consideration. The best that humans can hope to achieve today is to get the area of the event evacuated and provide people with another place to go. However, by knowing as much about the event as possible as far in advance as possible, people can act proactively rather than react to the event after chaos breaks out.

Other events don't necessarily require an evacuation. For example, with current technology and a bit of luck, people can reduce the effects of forest fires. In fact, some fire professionals are now using AI to predict forest fires before they occur (www.nytimes.com/2021/07/15/us/wildfires-artificial-intelligence.html#). Using AI to enable people to see the problem and then create a solution for it based on historical data is feasible because humans have recorded a great deal of information about these events in the past.

Using historical data to work through planetary problems is essential. Having just one potential solution is usually a bad idea. The best plans for solving a problem include several solutions, and an AI can help rank the potential solutions based on historical results. Of course, here again, a human may see something in the

solutions that makes one option preferable to another. For example, a particular solution may not work because the resources aren't available or the people involved don't have the proper training.

Seeing the effects of the solutions

Tracking the results of a particular solution means recording data in real-time, analyzing it as quickly as possible, and then displaying the effects in a way that humans understand. An AI can gather data, analyze it, and provide several presentations of that data far faster than any human can do it. Humans are still setting the criteria for performing all these tasks and making the final decisions; the AI simply acts as a tool to enable the human to act in a reasonable amount of time.


TIP

In the future, some people might specialize in interacting with AIs to make them work with data better. Getting the right results often means knowing what question to ask and how to ask it. People today often get poor results from an AI because they aren't familiar enough with how the AI works to ask reasonable questions of it.

Humans who assume that AIs think in a human-like manner are doomed to fail at getting good results from the AI. Unfortunately, that's what our society promotes today. The Siri and Alexa commercials make them appear to be human, but they aren't, of course. In an emergency, even with an AI accessible to the humans who are dealing with the event, the humans must know how to ask appropriate questions and in what way to ask them to get the required results. You can't see the effect of a solution if you don't know what to expect from the AI.

Trying again

The Earth is a complicated place. Various factors interact with other factors in ways that no one can anticipate. Consequently, the solution you created may not actually solve a problem. In fact, if you read the news often, you find that many solutions solve *nothing*. Trial-and-error help people understand what does and doesn't work. However, by using an AI to recognize patterns of failure — those solutions that didn't work, and why — you can reduce the number of solutions you need to try to find one that works. In addition, an AI can look for similar scenarios for solutions that have worked in the past, sometimes saving time and effort in trying to find new solutions to try. AI isn't a magic wand you can wave to create a solution that works the first time you try it. The reason that humans will always remain in the picture is that only humans can see the results for what they are.

The AIs you use in creating solutions will eventually run out of ideas, at which point the AI becomes basically useless. That's because an AI isn't creative. The patterns an AI works with already exist. However, those patterns may not address a current need (one that you can see today but haven't creatively thought out), which means that you need new patterns. Humans are adept at creating new patterns to apply to problems. Consequently, trying again becomes essential as a means to create new patterns that an AI can then access and use to help a human remember something that worked in the past. In short, humans are an essential part of the problem-solving loop.

IN THIS CHAPTER

- Investigating the universe
- Building off-world mines
- Looking for new places to explore
- Developing structures in space

Chapter 18
Seeing AI in Space

We humans have been observing the heavens since time immemorial. People love gazing at the stars and thinking about them, which is why many cultures have thought about actually seeing what the stars look like. As we have become capable of space travel, the universe, as a whole, has taken on new meaning, as described in this chapter. AI enables people to see the universe more clearly and handle the task of reaching it in new and more efficient ways. AI plays both actual and potential roles in space missions and exploration. Some potential contributions of AI are so futuristic that we can only imagine and envision them at the moment.

This chapter covers both present space projects and those projects that may be possible in the future, and we show you how AI is an enabling tool in the new space race propelling humanity toward new cosmic aspirations.

Integrating AI into Space Operations

Currently, AI's role in space missions is primarily played through the utilization of machine learning and deep learning algorithms by scientists and engineers at space control centers on Earth. However, AI has recently started being used in on-site applications, such as the Terrain-Relative Navigation, which helped the Perseverance rover land and allowed Ingenuity to fly autonomously on Mars (see `science.nasa.gov/mission/mars-2020-perseverance`). AI is also involved in an

increasing number of projects aimed at embedding it directly into satellites, spacecraft, space stations, and other space rovers.

Most results have been provided up to now by algorithms that guide the behavior of large satellite constellations and from those that analyze the vast volumes of data transmitted from space. Additionally, onboard most advanced satellites, AI algorithms can process data autonomously and send only the analyzed information back to Earth, reducing the need for large transmissions of raw data.

REMEMBER

Large satellite constellations are groups of satellites that work together to provide global or nearly global coverage for observation, communication, or navigational purposes (such as the global position system, or GPS). They're made up of many satellites spread out in different orbital paths that are always at risk of colliding, if not controlled and adjusted properly from ground control centers. Apart from GPS, notable examples of these constellations for communication are Starlink (`www.starlink.com`) and OneWeb (`oneweb.net`).

The challenge with using satellite constellations is that they require continuous maintenance to prevent collisions among the satellites within the constellation or with other space objects. This maintenance consists of two parts: keeping the satellites in orbit around the Earth and monitoring communication coverage between each other. Traditionally, these complicated operations have been carried out by engineers on ground operation sites. They performed calculations and transmitted instructions to satellites, but now this task is increasingly automated by AI algorithms, without much human input.

Seeing clearly with the help of algorithms

Additionally, another task AI is contributing to lightening the data load is data processing. AI algorithms, often in the form of machine learning or deep learning algorithms, excel at detecting patterns and handling complex information from multiple sensor inputs or of multiple types — for instance, images and numeric measurements. Consequently, satellites could process a significant amount of data onsite and transmit only the extracted information back to Earth. Moreover, they could also autonomously make decisions based on the data they collect, lessening the burden on humans.

Acting autonomously is becoming more necessary because of the growing limitations of *telemetry,* which is the process of collecting and transmitting data remotely. The challenge arises from the exploding data volumes and the restricted number of ground sites capable of receiving such vast amounts of data from space. Historically, telemetry has been vital in space exploration, enabling scientists and engineers to monitor the status and performance of spacecraft, satellites, and other space assets in real time. Satellites are generating larger volumes of data

because their numbers are increasing, and the sensors they employ have become more advanced and sophisticated in catching more information.

Let's take, for instance, monitoring satellites, that can inspect Earth's surface for information about climate, pollution, and human activities. AI contributes in these ways:

- More and more AI applications deal with Earth observation and environmental monitoring: AI algorithms process satellite imagery and sensor data to monitor Earth's environment, track changes over time, and identify phenomena such as deforestation, methane emissions, urban expansion, and natural disasters.
- AI can also help provide autonomy in filtering and processing information. Previously, satellites indiscriminately gathered all the data and sent it back to the ground, no matter whether it was usable. The situation is changing, though. For instance, in September 2020, the European Space Agency (ESA) launched two cube-shaped satellites and started the phi-sat-1 project (`www.esa.int/Applications/Observing_the_Earth/Ph-sat`), whose purpose was to demonstrate the possible application of artificial intelligence in Earth observation, filtering out imperfectly taken images (because of cloud or other technical problems) and ensuring that only high-quality data are transmitted back to Earth.


TECHNICAL STUFF

AI can contribute much beyond filtering bad images taken by satellites. Imagine having to calculate the blurring effect of the Earth's atmosphere based on the light from an object like a laser thousands of times a second. The only way to make such a huge number of calculations and then move the mirror's actuators in just the right way is to use AI, a technology that is quite adept at performing the sort of math required to make adaptive optics possible. The article about ADONIS, an AI powered instrument for telescopes, at `tinyurl.com/r2a7bwsb` provides just one example of the use of AI in adaptive optics. The pages at `tinyurl.com/3bchhr2a`, about the sky exploration for new habitable planets, and `tinyurl.com/5hwhj53b`, about how to adapt telescopes to atmospheric turbulence, provide additional resources for discovering how neural networks are successfully used in adaptive optic systems.

To provide even better optics, future telescopes will feature 3D correction of blurring effects using multiconjugate adaptive optics (MCAO) (`tinyurl.com/k96suruf` and `tinyurl.com/bwmfh6bn`). This new technology will correct the narrow field of view suffered by current telescopes but will require even greater (and more precise) control of multiple actuator levels through multiple mirrors. Telescopes such as the Giant Magellan Telescope, the Thirty-Meter Telescope, and the European Extremely Large Telescope (see `tinyurl.com/yjfrzx59`) will rely on this technology to make their $1 billion-plus investment price worth the effort. (Efforts are ongoing with MAVIS, the MCAO-Assisted Visible Imager and Spectrograph, described at `tinyurl.com/245ap3nr`.)

Finding new frontiers to challenge

Present AI applications in space sound quite practical and are aimed at easing the work of scientists and engineers back on Earth, especially when large amounts of data are involved. However, there are many more AI-powered projects in preparation for the future, including:

- **Mission planning and operations:** AI helps simplify and partially automate mission planning processes, optimize trajectories, and schedule activities for spacecraft, reducing human intervention and improving efficiency at all levels. A clear example is the Aspen project from NASA: It will help translate and adapt human objectives expressed in complex words and ideas into the often limited software interface of spacecraft (`ai.jpl.nasa.gov/public/projects/aspen`). Another frontier is represented by large language models (LLMs) used to create a more human-friendly interface. Again, the focus is on rendering the commands of spacecraft and satellites accessible to operators.
- **Autonomous navigation:** AI enables spacecraft to navigate autonomously, making real-time decisions to avoid obstacles, adjust trajectories, and maintain proper orientation, especially in remote or hazardous environments. Space rovers will become increasingly autonomous in their operations of exploration and research. Already, the Mars 2020 mission had a special schedule system onboard that helped the rover automatically adjust to any changes while exploring Mars and schedule the proper activities, given the situation (`ai.jpl.nasa.gov/public/projects/m2020-scheduler`).
- **Communication and data transmission:** AI enhances communication systems by optimizing data transmission protocols, managing bandwidth allocation, and predicting signal disruptions, which ensures efficient and reliable communication between spacecraft and ground stations.
- **Robotic exploration and sample analysis:** AI enables robotic systems to perform complex tasks autonomously, such as exploring planetary surfaces, collecting samples, and conducting scientific analyses, without constant human supervision.
- **Spacecraft health monitoring and maintenance:** AI systems monitor the health and status of spacecraft systems, detect anomalies, diagnose faults, and recommend corrective actions, contributing to the reliability and longevity of space missions.

Unveiling new scientific discoveries

Ultimately, the research that humans perform in learning more about space, the local solar system, the galaxy, and the universe must pay some dividends.

Otherwise, no one will want to continue funding it. The AI winters previously discussed are examples of what happens to a technology, no matter how promising, when it fails to deliver on expectations. Consequently, given the long history of space exploration, people must be deriving some benefit. In most cases, these benefits are in the form of new scientific discoveries and new principles — an increase in the understanding of how things work. By applying what was learned from space exploration and travel, people can make life here on Earth better. In addition, space-based technologies often find their way into products that people use daily.

Some of the frontiers in space that AI is helping to challenge are related to scientific discovery and exploration: AI assists in scientific discovery by analyzing astronomical data to identify exoplanets, study celestial objects, detect gravitational waves, and explore fundamental questions about the universe's structure and evolution. Finding objects in space used to rely on telescopes. However, NASA and other organizations increasingly rely on other approaches, such as using AI, as described at `tinyurl.com/u44vey2p`. In this case, machine learning made it possible to locate an eighth planet around Kepler 90, and this type of achievement has been possible because NASA teamed up with Google to train advanced AI algorithms capable of searching for signs of exoplanets that are passing in front of their parent stars.

Another helpful point that AI is contributing to is data analysis and interpretation. AI algorithms analyze large amounts of data collected by spacecraft — such as images, spectra, and sensor readings — to identify patterns, anomalies, and scientifically significant features, aiding in the interpretation of space observations. Humans have stared at the universe for a long time and still have no real idea of precisely what the universe is, except to know that we live in it. Of course, the observations continue, but the essence of the universe is still largely unknown. Scientists are increasingly using AI to carefully plot the motions of various parts of the universe to try to discover just how the universe works (see `tinyurl.com/mrtdbv5x`).

Also, today we have data about space coming from everywhere. This data is helping us create new scientific principles about things we can't even see, such as *dark matter* (an area of space with mass but no visible presence) and *dark energy* (an unknown and unidentified form of energy that counteracts the effects of gravitation between bodies in space). By understanding these invisible entities using technologies like the dark emulator (`tinyurl.com/pvf7pyy7`), we build new knowledge about how forces work on our own planet. Researchers are so buried in data, however, that they must use AI just to make sense of a small part of it (see `tinyurl.com/yvuxk8fu`). The point is that the future of space travel, and our use of technologies created for space research, depend on making use of all the data we're collecting, which requires AI at this point.

Performing Space Mining

Space mining has received more than a little attention in the media, and in the scientific community as well. Movies such as *Alien* provide a glimpse into what a future mining ship might look like. (With luck, space mining won't involve hostile aliens.) People and organizations have a number of reasons to want to exploit space mining, such as to save the earth from further ecological damage. Of course, we have to consider the financial aspect as well (tinyurl.com/244w6s7d), and films such as *Don't Look Up* have warned us how greed for resources from outer space may have consequences. Meanwhile, countries of all sizes are getting involved in space mining with NASA (see www.upi.com/Science_News/2022/03/07/NASA-lunar-mining-Artemis/7281646426839) and Chinese private and state-owned aerospace companies (this article unveils the Chinese road map for space mining: technology.inquirer.net/127699/chinas-space-mining-roadmap), leading the way to starting mining on the moon. Some detractors think the idea will never take solid form (tinyurl.com/2df2krsk). AI is certainly part of this space-mining blueprint because AI will provide invaluable help in the solar system and asteroid exploration and mining:

- **Efficient data analysis for material detection:** AI algorithms can quickly analyze large amounts of data collected by autonomous drones to identify valuable materials in space settings.
- **Smart navigation:** AI can help drones navigate complex environments and avoid obstacles, such as when safely maneuvering around moving asteroids.
- **Robotic mining:** AI-powered robots can perform mining tasks with precision and safety, reducing the need for human intervention in hazardous environments.
- **Centralized control:** AI systems can manage and coordinate robot and drone activities for material identification and mining from a centralized station, improving overall efficiency.
- **Risk mitigation:** AI algorithms can assess risks, predict potential hazards, and optimize mining strategies to ensure safer and more cost-effective operations.

With all this in mind, the following sections take a deeper look at space mining, exploration and colonization, considering the possible role of AI in these potential future activities.

Harvesting water

Water covers about 71 percent of Earth. In fact, Earth has so much water that we humans often find it difficult to keep it out of places where we don't want it.

However, Earth is an exception to the rule. Space doesn't have an abundance of water. Of course, you might wonder why you'd even need water in space, other than of the sort needed to keep astronauts hydrated and potentially to keep plants irrigated. The fact is that water can be transformed into rocket fuel. Separating H_2O into its constituent components produces hydrogen and oxygen, which are both components of rocket fuel (see `climate.nasa.gov/news/788/nasa-exploring-space-applications-of-hydrogen-and-fuel-cell` for details on how NASA plans to derive storage and use hydrogen in space). Consequently, comets — those big, icy, dusty bodies in the sky — might end up being refueling stations at some point.

USING DRONES AND ROBOTS FOR MINING

You can't determine what an asteroid contains until you get close enough to examine it. In addition, the number of asteroids that require exploration before finding anything worthwhile is significant — far more than human pilots could ever explore. Also, getting close to any object that might rotate in an odd way and exhibit strange characteristics involves dangers. For all these reasons, most asteroid exploration for mining purposes occurs by using autonomous drones of various sorts. These drones travel from asteroid to asteroid, looking for needed materials. When a drone finds a needed material, it alerts a centralized station with precise location information and other asteroid characteristics.

At this point, a robot is dispatched to do something with the asteroid. Most people feel that mining will occur in place, but actually, mining in place would prove both dangerous and costly. Another idea is to move the asteroid to a safer location, such as in orbit around the moon, to perform the required mining. The point is that robots would do the moving, and possibly other robots would perform the mining. Humans might be involved in robot repair and will likely be involved in monitoring both drone and robot activities. Think about it as safer, less polluting, and more interesting mining than could happen here on Earth.

Recently there have been interesting developments in space debris removal. A company in China recently sent a space-mining robot into near-Earth orbit to clean up the mess there (`tinyurl.com/3r8u3hpv`), and there are other missions and projects going on from JAXA, the Japan Aerospace Exploration Agency (`tinyurl.com/mtz7fyfs`), the Aerospace Corporation (`tinyurl.com/yvyxdsnh`) and Airbus (`tinyurl.com/3hhefs77`). These might seem like small steps, but scientists will surely gain essential information to advance toward the larger goal of space mining.

Obtaining rare earths and other metals

Mining has always been dirty, but some mining is much dirtier than other mining, and rare earths fall into that category. Rare earth mining is so dirty (see tinyurl.com/mnbh7ayy and tinyurl.com/zue7deyk) that all the rare earth mines in the United States were closed until the US government saw a need to reopen the Mountain Pass rare earth mine as a strategic reserve for the military because of a Chinese chokehold on rare earths (tinyurl.com/4asedrzj). One of the worst parts of rare earth mining is that it irradiates the surrounding areas with thorium radiation.

The cellphone you carry, the tablet you use, the car you drive, the television you watch, and the solar panel and windmill that provide electricity to your house all rely on extremely hazardous materials in the form of rare earths (see tinyurl.com/yt6hak4s for just a few examples). Most people aren't even aware that these materials aren't sustainable because of the way we use them (tinyurl.com/9df6xu25). Given the track record of these minerals, they represent the best reason to mine minerals off the planet so that the toxins don't affect us. In fact, mining should be only the first step; all manufacturing should move off the planet as well (yes, the potential for pollution is that great).

REMEMBER

AI is essential to efforts to find better sources of rare earths that won't pollute our planet into oblivion. One of the interesting oddities of rare earths is that the moon has a significant supply of them (see tinyurl.com/c67pkc68), and mining could start there as early as the next decade. In fact, many politicians now see mining the moon for rare earths as a strategic need (see tinyurl.com/7j9hxczz). The problem is that efforts to discover precisely what the moon is made of haven't been altogether successful so far, and it's important to know what to expect. The Moon Mineralogy Mapper (tinyurl.com/yw8ns87p) is just one of many efforts to discover the composition of the moon. (An upcoming project, Trailblazer, tinyurl.com/2xsr55jf, will look for water, which you may recall can be an important source of fuel.) The probes, robots, data analysis, and all the required planning will require the use of AI because the issues are more complicated than you might think.

Finding new elements

The periodic table, which contains a list of all available elements, has received a number of updates over the years. In fact, four new elements appeared in the table in 2016 (see tinyurl.com/2ab23chb). However, finding those four new elements required the work of a minimum of a hundred scientists using advanced AI (see tinyurl.com/337etd7z), because the elements typically last a fraction of a second in a lab environment. Interestingly enough, space could provide an environment in which these new elements exist naturally, rather than a fraction of a second, as they do on Earth, because the protons in the nucleus repel each other.

REMEMBER

As this story shows, we're still finding new elements to add to the periodic table, and space will almost certainly provide even more. Supernovas and other space phenomena can help replicate elements that scientists create by using particle accelerators or reactors. In fact, particle physicists have used AI in their work since the 1980s (see tinyurl.com/26phwpku).

Combining the elements provides new materials. AI is also directly responsible for helping chemists find new ways to combine elements into interesting new crystals (see tinyurl.com/z6jutf9s). In one case, scientists discovered 2 million new kinds of crystals using just four elements, but those discoveries relied on the use of AI. Just imagine what will happen in the future as scientists start opening the door to AI and deep learning (which will be able to determine whether the resulting crystals are actually useful).

Enhancing communication

Any undertaking in space that's as complex as mining requires the use of advanced communications. Even if the probes and robots used for mining include deep learning capability to handle most of the minor, and some of the major, incidents that will occur during the mining process, humans will still need to solve problems that the AI can't. Waiting for hours only to discover that a problem exists, and then spending yet more hours trying to determine the source of the problem, will spell disaster for space-based mining. Current manual communication techniques require an upgrade that, odd as it might seem, also includes AI (see tinyurl.com/rp7anumz).

REMEMBER

Cognitive radio relies on AI to make decisions automatically about the need to improve radio efficiency in various ways (see tinyurl.com/3xcffd3p). The human operator need not worry about precisely how the signal travels from one place to another; it simply does so in the most efficient manner possible. In many cases, cognitive radio relies on unused or underused spectrum to achieve its goal, but it can rely on other methods as well. In other words, the current methods to control probes such as those listed at tinyurl.com/5dmvkewz just won't work in the future when it's necessary to do more, in less time, with less spectrum (because of the increased communication load).

Exploring New Places

Space is vast. Humans are unlikely to ever explore it all. Anyone who tells you that all the frontiers are gone has obviously not looked up at the sky. Even sci-fi authors seem to think that the universe will continue to hold places for humans to

explore. Of course, if multiverse theory is true (tinyurl.com/4thxmsyf), the number of places to explore may be infinite. The problem isn't even one of finding somewhere to go; rather, it's one of figuring out which place to visit first. The following sections help you understand the role of AI in moving people from planet Earth to other planets and then to the stars.

Starting with the probe

Humans have already started putting probes out everywhere to explore our surroundings in space. In fact, using probes is older than many people think. As early as 1916, Dr. Robert H. Goddard, an American rocket pioneer, calculated that a rocket could be sent to the moon with an explosive payload that could be seen from Earth. However, it was E. Burgess and C. A. Cross who gave the world the term *probe* as part of a paper they wrote entitled *The Martian Probe* in 1952. Most people consider a space probe to be a vehicle designed to escape Earth and explore some other location. The first probe to make a soft landing on the moon was *Luna 9* in 1966.

Probes today aren't just trying to reach the Moon and nearby planets. When probes arrive at the location, they perform complex tasks by using rovers and drones and then radio the results of those tasks back to scientists on Earth. For example, NASA designed the Mars Curiosity rover to determine whether Mars has ever hosted microbial life. (The search for life continues with the Perseverance rover: tinyurl.com/3j6kuv85.) To perform this task, rovers have complex computer systems that can perform many tasks on their own, and Perseverance has a complex set of goals to achieve (mars.nasa.gov/mars2020/mission/science/goals). Of course, the highlight of current Mars visitors is Ingenuity, which is the first helicopter on the planet (mars.nasa.gov/technology/helicopter).

It doesn't take much to imagine the vast amount of information generated by individual probes such as Curiosity. Just analyzing the Curiosity data requires the same big data analytics used by organizations such as Netflix and Goldman Sachs (see tinyurl.com/4ac7k7ft on NASA and big data). The difference is that the data stream comes from Mars, not from local users, so any data analysis must consider the length of time required to actually obtain the information. In fact, the time delay between Earth and Mars is as much as 24 minutes (and when the two planets are in conjunction for a couple of weeks every few years, no communication is possible). With this in mind, Curiosity and other probes must think for themselves (tinyurl.com/rffj8j29) even when it comes to performing certain kinds of analysis.

CONSIDERING EXISTING COLONIZATION TARGETS

Depending on which article you read, scientists are already considering likely places for humans to colonize sometime in the future. Colonization will become essential for numerous reasons, but the burgeoning population of planet Earth figures highly in the math. Of course, the potential factories and mining operations on other planets are also part of the consideration. Plus, having another place to live does improve our chances, should another killer asteroid strike Earth. With these thoughts in mind, the commonly considered colonization targets (your list may differ) are the moon, Mars, Europa (a moon of Jupiter), Enceladus (one of Saturn's moons), Ceres (a dwarf planet and the largest object in the asteroid belt between Mars and Jupiter), and Titan (the largest moon of Saturn).

All these potential candidates come with special requirements that AI can help solve. For example, colonizing the moon requires the use of domes. In addition, colonists must have a source of water — enough water to split into oxygen for breathing and hydrogen to use as a heat source and fuel. So, probes will provide some information, but modeling the colonization environment will require time and a great deal of processing power here on Earth before humans can move to some other location.

After data arrives back on Earth, scientists store and then analyze it. The process, even with the help of AI, will take years. Obviously, reaching the stars will take patience and even more computing power than humans currently possess. With the universe such a messy place, the use of probes is essential — though the probes may need more autonomy just to find the right places to search.

Relying on robotic missions

Humans aren't likely to ever actually visit a planet directly as a means of learning more about it, sci-fi books and movies notwithstanding. It makes more sense to send robots to planets to discover whether sending humans there is even worth the time because robots are less expensive and easier to deploy. Humans have actually sent robots to a number of planets and moons in the solar system already, but Mars seems to be a favorite target for a number of reasons:

- A robotic mission can leave for Mars every 26 months.
- Mars is in the solar system's habitable zone, so it makes a likely target for colonization.

- There seem to be a significant amount of extractable water on Mars, mostly in the form of ice and water vapor.
- Many scientists believe that life once existed on Mars.

The human love affair with Mars started in October 1960, when the Soviet Union launched *Marsnik 1* and *Marsnik 2*. Unfortunately, neither probe even made it into Earth's orbit, much less to Mars. The United States tried next, with the *Mariner 3* spacecraft in 1964 and the *Mariner 4* spacecraft in 1965. The *Mariner 4* fly-by succeeded by sending 12 photos of the red planet back to Earth. Since that time, humans have sent myriad probes to Mars and a host of robots as well, and the robots are starting to reveal the secrets of Mars. (The success rate for trips to Mars, however, is less than 50 percent, according to `tinyurl.com/2djdb6um`.) Besides probes designed to perform fly-bys and observe Mars from space, robots land on Mars in these three forms:

- **Lander:** A robotic device designed to sit in one place and perform relatively complex tasks
- **Rover:** A robotic device that moves from one location to another — increasing the amount of ground covered
- **Flyer:** A robotic device that is able to fly from one location to another — covering large amounts of ground relatively fast and from an aerial vantage point

You can find a list of the landers and rovers sent to Mars since 1971 at `tinyurl.com/5h9y7jzs` and `tinyurl.com/423ataen`. Even though most landers and rovers come from the United States, China, or the former Soviet Union (which actually wasn't successful), at least one rover is from England (Japan has one planned for the near future). As the techniques required for a successful landing become better known, you can expect to see other countries participate in the race to Mars, with some attempting manned missions and others using rovers and other remotely controlled instruments.


REMEMBER

As landers and rovers become more capable, the need for AI increases. For example, *Perseverance* has a relatively complex AI that helps it choose new targets for exploration autonomously, as described at `tinyurl.com/3yyzyjdx`. Don't get the idea, though, that this AI is replacing the scientists on Earth. The scientists still determine the properties of the rocks that the AI will search for when used. In addition, a scientist can override the AI and choose a different target. The AI is there to assist, not replace, the scientist and provides an example of how people and AI will work together in the future.

Adding the human element

Humans want to visit places beyond Earth. Of course, the only place we've visited is the moon. The first such visit occurred on July 20, 1969, with the *Apollo 11* mission. Since then, people have landed on the moon six times, ending with the *Apollo 17* flight on December 7, 1972. The European Union, China, Japan, India, and Russia all have future plans for moon landings, some aiming at manned missions and others focusing only on robotic explorations. A Chinese-manned moon landing is scheduled to occur by 2030 (read about the plan at `tinyurl.com/y57282mp`). NASA plans to land on the moon in the near future, with Artemis III scheduled for 2026 to land astronauts near the lunar South Pole for the first time (see `tinyurl.com/5n75nty9` for more information).

NASA does have plans for Mars. An actual human visit to Mars will likely have to wait until the 2030s. As you might imagine, data science, AI, machine learning, and deep learning will figure prominently in any effort to reach Mars. Because of the distance and environment, people will require a lot of support to make a Mars landing feasible. In addition, returning from Mars will be considerably harder than returning from the moon. Even the lift-off will be harder, due to the presence of a carbon dioxide atmosphere, which creates drag on a launching spacecraft, and Mars' gravity, which is greater than the moon's.

WARNING

In 1968, Arthur C. Clarke released the book *2001: A Space Odyssey.* The book must have struck a chord, because it spawned a movie directed by Stanley Kubrick and a television series, not to mention three additional books. In *2001: A Space Odyssey,* you find the Heuristically programmed ALgorithmic (HAL) 9000 computer that ends up running amok because of a conflict in its mission parameters. Some have claimed that HAL is simply the name IBM with the letters shifted by one position, but Clarke always stated that this was just a coincidence. The main purpose of the computer was to help the space travelers complete their mission, but the implied purpose was to also keep the space travelers from going nuts from loneliness. Whatever hopes you have of seeing a HAL-like computer on any space flight are likely doomed to failure. For one thing, any AI programmed for space is unlikely to purposely keep the crew in the dark about the mission parameters. Space flights will use an AI, no doubt about it, but it will be of a more practical and mundane construction than the HAL 9000. Sticking with film references, AI in space will likely resemble more TARS and CASE, the robots featured in Interstellar, a 2014 science fiction film directed by Christopher Nolan.

Building Structures in Space

Just visiting space won't be enough at some point. The reality of space travel is that everything is located so far from everything else that visitors need waypoints between destinations. Even with waypoints, space travel will require serious

effort. However, the waypoints are important even today. Imagine that people actually do start mining the moon. Having a warehouse in near-Earth orbit will be a requirement because of the immense cost of m transporting mining equipment and other resources from the Earth's surface. Of course, the reverse trip also has to happen, to move the mined resources and finished products from space to Earth. People also want to take vacations in space, and scientists already rely on various structures to continue their investigations. The following sections discuss the use of various structures in different ways to help humanity move from planet Earth to the stars.

Taking your first space vacation

Companies have promised space vacations for some time now. Orbital Technologies made one of the first of these promises in 2011, which had an original expected date of 2016 (see `tinyurl.com/rhxujxpc` for details). The date has slipped a little to 2027. Even though you can't take a space vacation yet, the video at `tinyurl.com/mrrhave7` tells you about the technology required to make such a vacation possible. Most of the concepts found in these sites are feasible, at least to some extent, but aren't really around today. What you're seeing is *vaporware* (a promised product that doesn't exist yet but is probable enough to attract attention), but it's interesting, anyway.


TIP

Blue Origin, the company founded by Jeff Bezos, actually does have a functional rocket and quarters (`tinyurl.com/7ry9fej6`). The rocket has made a number of trips to date with no passengers and at least one with Jeff Bezos aboard. This trip didn't take people all the way into space, but rather into a near-Earth orbit of 100 kilometers. Companies such as Blue Origin (`www.blueorigin.com`) and SpaceX (`www.spacex.com`) have the best chance now of making a space vacation a reality. In fact, in 2022 Elon Musk even mentioned about the possible costs for a travel to Mars (read `tinyurl.com/4yy3pxt6`) although he also noted that such travel opportunity would probably occur in a distant future.

Whatever the future holds, people will eventually end up in space for various reasons, including vacations. You should count on a cost as astronomical as your distance from Earth. Space travel won't be cheap for the foreseeable future. In any case, companies are working on space vacations now, though you can't take one yet.

Industrializing space

Making space travel pay comes in several forms. Humans already enjoy considerable benefits from technologies developed for space flight and adopted for civilian

use here on Earth. (Just one of many articles emphasizing the importance of space to life here on Earth is at tinyurl.com/zr2nmapn.) However, even with the technology transfers, space is still quite expensive, and a better payback could occur by adapting what we know in other ways, such as by creating space factories.

In fact, we may find that space factories provide the only way to produce certain materials and products (see tinyurl.com/87d2pt5t as an example). Having a zero-gravity environment affects how materials react and combine, which means that some of what's impossible here on Earth suddenly becomes quite possible in space. In addition, some processes are easily performed only in space, such as making a completely round ball bearing (tinyurl.com/bhapjsb).

Using space for storage

People will eventually store some items in space, and that makes sense. As space travel becomes more prevalent and humans begin industrializing space; the need to store items such as fuel and mined materials will increase. Because people won't know where mined materials will see use (space factories will require materials, too), keeping the materials in space until a need for them occurs on Earth will be less expensive than storing them on Earth. The Orbit Fab space gas station (tinyurl.com/24hcypny) has already been launched. We may need it as part of our quest to visit Mars.

Although no current plans exist for the storage of hazardous materials in space, the future could also see humans storing such waste there, where it can't pollute the planet. Of course, the question comes to mind of why hazardous waste would be stored rather than incinerated in the sun or simply thrown into outer space. For that matter, logical minds might question the need to even continue producing hazardous waste. As long as we humans exist, however, we'll continue to produce hazardous waste. Storing such waste in space would give us a chance to find some means of recycling it into a useful product while keeping it out of the way.

6 The Part of Tens

IN THIS PART . . .

Discover how AI (mostly) helps society.

Recognize why AI must fail in certain situations.

IN THIS CHAPTER

- Working with humans
- Solving industrial problems
- Developing new technologies
- Performing tasks in space

Chapter 19
Ten Substantial Contributions of AI to Society

A technology is useful only as long as it makes some sort of substantial contribution to society. Moreover, the contribution must come with a strong financial incentive, or else investors won't contribute to it. Although the government may contribute to a technology that it sees as useful for military or other purposes, long-term technological health relies on investor support. Consequently, this chapter focuses on AI components that are useful now — because they're making a substantial contribution to society now.

REMEMBER

Though discussion is valuable in assessing any technology, investors aren't interested in words — investors are interested in *results.* This chapter is about results that demonstrate that AI has become integrated into society in a manner significant enough to make another AI winter (see Chapter 16) truly unlikely. Of course, getting rid of the hype so that people can authentically understand what AI can do for them would be a plus at this point.

Considering Human-Specific Interactions

People drive the sales of products. In addition, people decide what to talk about most, which creates buzz, which in turn creates sales. Although you probably won't read about the technologies discussed in the following sections, the level at which they affect people is amazing. In the first case, an active human foot, people will actually be able to walk using prosthetics with nearly the same ease as they walk with a natural foot. Even though the group needing this product is relatively small, the effects can be widely known. The second and third cases have the potential for affecting millions, perhaps billions, of people. They're mundane offerings, but often the mundane is what becomes expected, which again drives sales. In all three cases, the technologies won't work without AI, which means that stopping AI research, development, and sales is likely to be met with resistance by the people using the technologies.

Devising the active human foot

Prosthetics are big-time moneymakers. They cost a fortune to make and are vital for anyone missing a limb. Many prosthetics rely on passive technology, which means they provide no feedback and don't automatically adjust their functionality to accommodate personal needs. All that has changed in recent years as scientists such as Hugh Herr have created active prosthetics that can simulate the actions of biological limbs and automatically adjust to the person using them (see "MIT's Hugh Herr reveals joys [and challenges] of commercializing bionic limbs" at `tinyurl.com/28s8exry`). Even though Hugh Herr grabbed major headlines, you can now find active technology in all sorts of prosthetics, including knees, arms, and hands.

REMEMBER

You may wonder about the potential value of using active over passive prosthetics. Medical suppliers are already doing the research (see some results in the report "Advanced prosthetics and exoskeletons market size to reach USD 5.43 billion in 2028 growing at a CAGR of 10.2%, says Emergen Research" at `www.biospace.com`).

It turns out that microprocessor-based prosthetics relying on an AI to ensure that the device interacts properly with the user are a huge win. Not only do people who use active technology prosthetics live longer, but these prosthetics have also reduced direct and indirect medical costs. For example, a person using an active technology prosthetic is less likely to fall. Even though the initial cost of an active technology prosthetic is higher, the costs over time are much smaller.

Performing constant monitoring

Chapter 12 discusses a host of monitoring devices used by medicine to ensure that people receive their medications at the right time and in the correct dosage. In addition, medical monitoring can help patients receive care faster after a major incident and even predict when a patient will have a major incident, such as a heart attack. Most of these devices, especially those that are predictive in nature, rely on an AI of some sort to perform the work.

Studies are hard to come by, but the study results found in "Clinical and economic impact of HeartLogic compared with standard care in heart failure patients" (found at `onlinelibrary.wiley.com`) show that remote monitoring of heart patients saves considerable medical costs (besides helping the patient live a happier, longer life). In fact, the use of remote monitoring, even for healthy people, has a significant positive impact on medical costs (see "Benefits of remote patient monitoring" at `tinyurl.com/5486ydcp`). The impact of the savings is so high that remote monitoring is changing how medicine works.

Administering medications

Sick people who forget to take their medications cost the medical establishment huge amounts of money. By combining technologies such as *near field communication,* or NFC, with apps that rely on an AI, you can track how and when people take their medications. In addition, the AI can help people remember when to take medications, which ones to take, and how much to use. When coupled with monitoring, even people with special monitoring needs can obtain the correct dose of their medications.

Developing Industrial Solutions

People drive a ton of small sales. However, when you think about an individual's spending power, it pales in comparison to the amount that just one organization can spend. The difference lies in the quantity. However, investors look at both kinds of sales because both generate money — lots of it. Industrial solutions, which affect organizations, tend to be expensive, yet industry uses them to increase productivity, efficiency, and, most of all, income. It's all about the bottom line. The following sections discuss how AI affects the bottom line of organizations that use the supplied solutions.

Using AI with 3D printing

Three-dimensional (3D) printing began as a toy technology that produced some interesting, but not particularly valuable, results. However, that was before NASA used 3D printing on the International Space Station (ISS) to produce tools (see "International Space Station's 3D printer" at www.nasa.gov). Many people believe that the ISS should have loaded up all the tools it needs when it left Earth. Unfortunately, tools get lost or broken. In addition, the ISS simply lacks storage space for absolutely every required tool. Three-dimensional printing can also create spare parts, and the ISS certainly can't carry a full complement of spare parts. Three-dimensional printers work the same in microgravity as they do on Earth (check out the Space Station Research Explorer page at www.nasa.gov), so 3D printing is a technology that scientists can use in precisely the same manner in both places.

Meanwhile, industry uses 3D printing to meet all sorts of demands. Adding an AI to the mix lets the device create an output, see what it has created, and learn from its mistakes. This means that industry will be able to create robots that correct their own mistakes — at least to an extent, which will reduce mistakes and increase profits.

Advancing robot technologies

This book contains a wealth of information on how robots are being used, from in the home to medicine to industry. The book also talks about robots in cars, in space, and underwater. If you're getting the idea that robots are a significant driving force behind AI, you're right. Robots are becoming a reliable, accessible, and known technology with a visible presence and a track record of success, which is why many organizations are investing in even more advanced robots.

Many existing traditional businesses now rely on robots, which many people may not realize. For example, the oil industry relies heavily on robots to search for new oil sources, perform maintenance, and inspect pipes. In some cases, robots also make repairs in places that humans can't easily access, such as in pipes. Using AI enables engineers to reduce overall risk, which means that oil will also have a potentially smaller environmental impact because of fewer spills.


TIP

The reduced price of oil is part of what has driven the oil industry to adopt AI (see "AI in Oil and Gas Market - Growth, Trends, COVID-19 Impact, and Forecasts [2022–2027]" at tinyurl.com/3k35r54z). Because the oil industry is highly risk-averse, its use of AI makes a good test case for seeing how other businesses will adopt AI. By reviewing articles about the oil industry, you realize that the oil industry waited for successes in the healthcare, finance, and manufacturing

industries before making investments of its own. You can expect to see an uptick in AI adoption as successes in other industries grow.

This book covers all sorts of robotic solutions — some mobile, some not. Part 4 of this book covers robots in general, flying robots (which is what drones truly are, when you think about it), and self-driving (SD) cars. Generally, robots can make a profit when they perform a specific kind of task, such as vacuuming the floor (the Roomba) or assembling various parts to create your car. Likewise, drones are now moneymakers for defense contractors and will eventually become profitable for a significant number of civilian uses as well. These include like photography/videography, delivery, search and rescue, agriculture surveillance, and wildlife monitoring.

Creating New Technology Environments

Everyone generally looks for new products to buy, which means that businesses need to come up with new products to sell. AI helps people look for patterns in all sorts of areas. Patterns often show the presence of something new, such as a new element or a new process for creating a product. In the realm of product development, AI's purpose is to help discover the new product (as opposed to focusing on selling an existing product). By reducing the time required to find a new product to sell, AI helps businesses improve profits and reduces the cost of research associated with finding new products. The following sections discuss these issues in more detail.

Developing rare new resources

As you can see throughout this book, an AI is especially adept at seeing patterns, and patterns can indicate all sorts of factors, including new mineral elements. New elements mean new products, which translate into product sales. An organization that can come up with a new material has a significant advantage over the competition. Many of these inventions rely on a new process or material that AI can help find with significant ease.

Seeing what can't be seen

Human vision doesn't see the broad spectrum of light that actually exists in nature. And even with augmentation, humans struggle to think at a very small scale or a very large scale. Biases prevent humans from seeing the unexpected. Sometimes a random pattern actually has structure, but humans can't see it. An

AI can see what humans can't see and then act on it. For example, when looking for stresses in metal, an AI can see the potential for fatigue and act on it. The cost savings can be monumental when dealing with precision metal surfaces, which are scanned using a waveguide sensor (explained in "Intelligent detection of cracks in metallic surfaces using a waveguide sensor loaded with metamaterial elements" at pubmed.ncbi.nlm.nih.gov/25988871).

Working with AI in Space

Chapter 18 takes you on a tour of what AI can potentially do in space. Even though plans for performing these tasks are on the drawing board, most of them are government-sponsored, which means they provide an opportunity that may not necessarily result in a profit. You also find some business-related research projects in Chapter 18. In this case, the business is looking to make a profit — but may not be making one today.

The following sections look at space in another way and point to what's happening today. AI is now enabling businesses to earn money working in space, which gives businesses an incentive to continue investing in both AI and space-related projects.

Delivering goods to space stations

Perhaps the greatest AI commercial success story in space so far is the resupply of the ISS by companies such as SpaceX and Orbital ATK (see "Commercial resupply services overview" at www.nasa.gov/commercial-resupply-services-overview).

The organizations make money with each trip, of course, but NASA benefits as well. In fact, the United States as a whole has enjoyed these benefits from the venture:

- Reduced cost of delivering materials instead of using vehicles from other countries to resupply the ISS
- Increased use of US-based facilities such as the Kennedy Space Center, amortized the cost of these facilities over several missions
- Added launch centers for future space flights
- More available payload capacity for satellites and other items

SpaceX and Orbital ATK interact with lots of other businesses. Consequently, even though only two companies might appear to benefit from this arrangement, many others benefit as subsidiary partners. The use of AI makes all this possible, and it's happening at this moment. Companies are earning money from space today, not waiting until tomorrow, as you might believe from news reports. That the earnings come from what is essentially a mundane delivery service makes no difference.


REMEMBER

Space deliveries are essentially a new concept. Many Internet-based businesses ran at a deficit for years before becoming profitable. Space-based businesses will take time to ramp up to the same financial impact that earth-based businesses of the same sort now enjoy.

Mining extraplanetary resources

Space mining is undergoing the equivalent of an AI winter. However, the problem that space mining is supposed to fix remains: Earth still has limited resources that are growing more limited by the day. Consequently, people are still looking for ways to make space mining work because the potential for making a profit is huge. One current idea is to mine the moon using a number of intriguing techniques, such as ablative arc mining (explained in "Ablative arc mining for in-situ resource utilization" at `www.nasa.gov/general/ablative-arc-mining-for-in-situ-resource-utilization`). The point is that AI will most definitely be part of any space-mining endeavor (see "Artificial intelligence and space mining: the gateway to infinite riches" at `tinyurl.com/3fzxjufd`).

Exploring other planets

It seems likely that humans will eventually explore and even colonize other planets, with Mars the likely first candidate. Specifically, Elon Musk has stated his long-term goal of enabling Mars colonization. After people reach other worlds, including the moon, many business leaders think that the only way to make money will be via the sale of intellectual property or, possibly, the creation of materials that only that particular world will support.


WARNING

Unfortunately, although some people are making money on space exploration today, we humans likely won't see any actual profit from space exploration for a while. Still, some companies are making a profit today by providing the various tools needed to design the trip. Research does fund the economy. However, the world is also in a buyer-beware environment filled with scam artists. For example, 78,000 people signed up for a trip to Mars (see "78,000 people apply for one-way trip to Mars" at `time.com`), but the company eventually went bankrupt (see "The company that promised a one-way ticket to Mars is bankrupt" at `www.theverge.com`).

IN THIS CHAPTER

- Comprehending the world
- Developing new ideas
- Understanding the human condition

Chapter 20

Ten Ways in Which AI Has Failed

Any comprehensive book on AI must consider the ways in which AI has failed to meet expectations. This book discusses this issue, in part, in other chapters, giving the historical view of the AI winters. However, even with those discussions, you might not grasp that AI hasn't just failed to meet expectations set by overly enthusiastic proponents — it has also failed to meet specific needs and basic requirements. This chapter is about the failures that will keep AI from excelling and performing the tasks we humans need it to carry out to fully achieve the successes described in other chapters. AI is an evolving technology that is partially successful at best.

REMEMBER

One of the essential issues surrounding AI today is that people anthropomorphize it and try to turn it into something it isn't such as a human. An AI accepts cleaned data as input, analyzes it, finds the patterns, and provides a requested output. An AI doesn't understand anything, it can't create or discover anything new, and it has no intrapersonal knowledge, so it can't empathize with anyone about anything. The critical piece of information to take from this chapter is that an AI behaves as designed by a human programmer, and what you often take for intelligence is only a mix of clever programming and vast amounts of data analyzed in a specific manner.

Understanding

The ability to comprehend is innate to humans — and is completely foreign to AIs. Looking at an apple, a human responds to more than just a series of properties associated with a picture of an object. Humans understand apples via the use of senses, such as color, taste, and feel. We understand that the apple is edible and provides specific nutrients. We have feelings about apples; perhaps we like them and believe that they're the supreme fruit. And, we realize that we associate memories with objects, such as the delicious apple pies that Grandma used to bake. The AI sees an object that has properties associated with it — values that the AI doesn't understand, but only manipulates. The following sections describe how this failure to understand causes AI as a whole to fail to meet expectations.

Interpreting, not analyzing

As stated many times throughout this book, an AI uses algorithms to manipulate incoming data and produce an output. The emphasis is on performing an analysis of the data. However, a human controls the direction of that analysis and must then interpret the results. For example, an AI can perform an analysis of an x-ray showing a potential cancer tumor. The resulting output may emphasize a portion of the x-ray containing a tumor so that the doctor can see it. The doctor might be unable to see the tumor otherwise, so the AI undoubtedly provides an important service. Even so, a doctor must still review the result and determine whether the x-ray does indeed show cancer. AI is easily fooled at times when even a small artifact appears in the wrong place. Consequently, even though the AI is incredibly helpful in giving the doctor the ability to see something that isn't apparent to the human eye, the AI also isn't trustworthy enough to make any sort of important decision.

JUST HOW MANY SENSES ARE THERE?

Many people have been taught in school that we humans possess 5 senses, but scientists now specify that we have a minimum of 9, and most agree that we have 21. These additions, such as color, are usually subsets of existing senses, such as sight. That's right: Color is now considered to be an addition to the sight sense, along with strange-sounding sense names like *proprioception,* which is the ability to feel the space around us. Senses have become so important because scientists are also starting to realize that it's nearly impossible to create good deep learning models or useful robots that deal with environmental issues without a good understanding of how we sense things. The five senses that we started with just aren't sufficient to describe how we carry out tasks like eating in darkened restaurants and climbing stairs without looking at them.

CONSIDERING HUMAN BEHAVIOR

Even understanding a behavior isn't enough to replicate or simulate the behavior. A formal mathematical understanding of the behavior must occur to make it accessible to an AI. Given that so many human behaviors aren't understood at all, it's unlikely that anyone will create a formal mathematical model for them anytime soon. Without such models, an AI can't think in a human-like manner or achieve anything approaching sentience.

Interpretation also implies the ability to see beyond the data. It's not the ability to create new data, but rather to understand that the data may indicate something other than what is apparent. For example, humans can often tell that data is fake or falsified, even though the data itself presents no evidence to indicate these problems. An AI accepts the data as both real and true, whereas a human knows that it's neither real nor true. Formalizing precisely how humans achieve this goal is currently impossible because humans don't actually understand it.

Going beyond pure numbers

Despite any appearance otherwise, an AI works only with numbers. An AI can't understand words, for example, which means that when you talk to it, the AI is simply performing pattern matching after converting your speech to numeric form. The substance of what you say is gone. Even if the AI were able to understand words, it couldn't do so because the words are gone after the tokenization process is complete (see Chapter 4 for more about tokenizing). The failure of AIs to understand something as basic as words means that an AI's translation from one language to another will always lack that certain something needed to translate the feeling behind the words, as well as the words themselves. Words express feelings, and an AI can't do that. The same conversion process occurs with every sense that humans possess. A computer translates sight, sound, smell, taste, and touch into numeric representations and then performs pattern matching to create a dataset that simulates the real-world experience.

Further complicating matters, humans often experience things differently from each other. For example, each person experiences color uniquely. For an AI, every computer sees color in precisely the same way, which means that an AI can't experience colors uniquely. In addition, because of the conversion, an AI doesn't actually experience color.

Considering consequences

An AI can analyze data, but it can't make moral or ethical judgments. If you ask an AI to make a choice, it will always choose the option with the highest probability of success unless you provide some sort of randomizing function as well. The AI will make this choice regardless of the outcome. The "SD cars and the trolley problem" sidebar in Chapter 15 expresses this problem quite clearly: When faced with a choice between allowing either the occupants of a car or pedestrians to die when such a choice is necessary, the AI must have human instructions available to it to make the decision. The AI is incapable of considering consequences and is therefore ineligible to be part of the decision-making process.

WARNING

In many situations, misjudging the ability of an AI to perform a task is merely inconvenient. In some cases, you may have to perform the task a second or third time manually because the AI isn't up to the task. However, when it comes to consequences, you might face legal problems in addition to the moral and ethical problems if you trust an AI to perform a task that is unsuited to it. For example, allowing a self-driving (SD) car to drive by itself in a place that doesn't provide the infrastructure required for safe SD car use is likely illegal, and you'll face legal problems in addition to damage and medical charges that the SD car can cause. In short, know what the legal requirements are before you trust an AI to do anything involving potential consequences.

Discovering

An AI can interpolate existing knowledge, but it can't extrapolate existing knowledge to create new knowledge. When an AI encounters a new situation, it usually tries to resolve it as an existing piece of knowledge rather than accept that it's something new. In fact, an AI has no method for creating anything new, or for seeing a situation as unique. These are human expressions that help us discover new products, work with them, devise methods for interacting with them, and create new methods for using them to perform new tasks or augment existing tasks. The following sections describe how an AI's inability to make discoveries prevents it from fulfilling the expectations that humans have of it.

Devising new data from old

One of the more common tasks that people perform is *extrapolation* of data; for example, given A, what is B? Humans use existing knowledge to create new knowledge of a different sort. By knowing one piece of knowledge, a human can make a leap to a new piece of knowledge, outside the domain of the original

knowledge, with a high probability of success. Humans make these leaps so often that they become second nature and intuitive in the extreme. Even children can make such predictions with a high rate of success.


REMEMBER

The best that an AI will ever do is to *interpolate* data; for example, given A and B, is C somewhere in between? The capability to successfully interpolate data means that an AI can extend a pattern, but it can't create new data. However, sometimes developers can mislead people into thinking that the data is new by using clever programming techniques. The presence of C looks new when it truly isn't. The lack of new data can produce conditions that make the AI seem to solve a problem, but it doesn't. The problem requires a new solution, not the interpolation of existing solutions.

Seeing beyond the patterns

Currently, an AI can see patterns in data when they aren't apparent to humans. The capability to see these patterns is what makes AI so valuable. Data manipulation and analysis is time consuming, complex, and repetitive, but an AI can perform the task with aplomb. However, the data patterns are simply an output and not necessarily a solution. Humans rely on their five primary senses and empathy, creativity, and intuition to see beyond the patterns to a potential solution that resides outside what the data would lead one to believe. Chapter 16 discusses this aspect of the human condition in more detail.


TIP

A basic way to understand the human ability to see beyond patterns is to look at the sky. On a cloudy day, people can see patterns in the clouds, but an AI sees clouds and only clouds. In addition, two people may see different images in the same set of clouds. The creative view of patterns in the cloud may have one person seeing a sheep and another a fountain. The same holds true for stars and other kinds of patterns. The AI presents the pattern as output, but it doesn't understand the pattern; moreover, it lacks the creativity to do anything with the pattern, other than report that the pattern exists.

Implementing new senses

As humans have become more knowledgeable, they have also become aware of variances in human senses that don't actually translate well to an AI, because replicating these senses in hardware isn't truly possible now. For example, the ability to use multiple senses to manage a single input, known as *synesthesia,* is beyond an AI.

Describing synesthesia effectively is well beyond most humans' reach. Before they can create an AI that can mimic some of the truly amazing effects of synesthesia, humans must first fully describe it and then create sensors that will convert the experience into numbers an AI can analyze. However, even then, the AI will see only the effects of the synesthesia, not the emotional impact. Consequently, an AI will never fully experience or understand synesthesia.

Empathizing

Computers don't feel anything. That's not necessarily a negative characteristic, but this chapter views it as one. Without the ability to feel, a computer can't see things from the perspective of a human. It doesn't comprehend being happy or sad, so it can't react to these emotions unless a program creates a method for it to analyze facial expressions and other indicators and then act appropriately. Even so, such a reaction is a canned response and one that's prone to error. Think about how many decisions you make based on emotional need rather than on outright fact. The following sections discuss how the lack of empathy on the part of an AI keeps it from interacting with humans appropriately in many cases.

Walking in someone's shoes

The idea of *walking in someone else's shoes* means to view a situation from another person's perspective and feel similar to how the other person feels. No one truly feels precisely the same as someone else, but by feeling empathy, people can get close. This form of empathy requires strong intrapersonal intelligence as a starting point, which an AI will never have unless it develops a sense of self. In addition, the AI would need to be able to feel, a situation that is currently not possible, and the AI would need to be open to sharing feelings with another entity (generally speaking, a human), which is also impossible. The current state of AI technology prohibits an AI from feeling or understanding any sort of emotion, which makes empathy impossible.


REMEMBER

Of course, the issue is why empathy is vital. Without the ability to feel the same as someone else, an AI can't develop the motivation to perform certain tasks. You might order the AI to perform the task, but then the AI would have no motivation on its own. Consequently, the AI would never perform certain tasks, even though the performance of such tasks is a requirement to build the necessary skills and knowledge to achieve human-like intelligence.

Developing true relationships

An AI builds a picture of you via the data it collects. It then creates patterns from this data and, using specific algorithms, develops output that makes it seem to know you — at least as an acquaintance. However, because the AI doesn't feel, it can't appreciate you as a person. It can serve you, should you order it to do so and assuming that the task is within its list of functions, but it can't have any feeling for you.

When dealing with a relationship, people have to consider both intellectual attachment and feelings. The intellectual attachment often comes from a shared benefit between two entities. Unfortunately, no shared benefit exists between an AI and a human (or an AI and any other entity, for that matter). The AI simply processes data using a particular algorithm. Something can't claim to love something else if an order forces it to make the proclamation. Emotional attachment must carry with it the risk of rejection, which implies self-awareness.

Changing perspective

Humans can sometimes change an opinion based on factors other than the facts. Even though the odds would say that a particular course of action is prudent, an emotional need makes another course of action preferable. An AI has no preferences. It therefore can't choose another course of action for any reason other than a change in the probabilities, a *constraint* (a rule forcing it to make the change), or a requirement to provide random output.

Making leaps of faith

Faith is the belief in something as being true without having proven fact to back up such belief. In many cases, faith takes the form of *trust,* which is the belief in the sincerity of another person with no proof that the other person is trustworthy. An AI can't exhibit either faith or trust, which is part of the reason that it can't extrapolate knowledge. The act of extrapolation often relies on a hunch, based on faith, that something is true, despite a lack of any sort of data to support the hunch. Because an AI lacks this ability, it can't exhibit insight — a necessary requirement for human-like thought patterns. (See "How a leap of faith can take science forward" at `phys.org/news/2019-06-faith-science.html`.)


TIP

Examples abound of inventors who made leaps of faith to come up with new creations. However, one of the most prominent was Thomas Edison. For example, he made a thousand (and possibly more) attempts to create the light bulb. An AI would have given up after a certain number of tries, likely due to a constraint.

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Dedications

From Luca: This book is dedicated to the Suda family living in Tokyo: Yoshiki, Takayo, Makiko, and Mikiko.

From Stephanie: This book is dedicated to Barry, who makes all things possible.

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