

# 1

## INTRODUCTION

*In which we try to explain why we consider artificial intelligence to be a subject most worthy of study, and in which we try to decide what exactly it is, this being a good thing to decide before embarking.*

INTELLIGENCE

We call ourselves *Homo sapiens*—man the wise—because our **intelligence** is so important to us. For thousands of years, we have tried to understand *how we think*; that is, how a mere handful of matter can perceive, understand, predict, and manipulate a world far larger and more complicated than itself. The field of **artificial intelligence**, or AI, goes further still: it attempts not just to understand but also to *build* intelligent entities.

ARTIFICIAL  
INTELLIGENCE

AI is one of the newest fields in science and engineering. Work started in earnest soon after World War II, and the name itself was coined in 1956. Along with molecular biology, AI is regularly cited as the “field I would most like to be in” by scientists in other disciplines. A student in physics might reasonably feel that all the good ideas have already been taken by Galileo, Newton, Einstein, and the rest. AI, on the other hand, still has openings for several full-time Einsteins and Edisons.

AI currently encompasses a huge variety of subfields, ranging from the general (learning and perception) to the specific, such as playing chess, proving mathematical theorems, writing poetry, driving a car on a crowded street, and diagnosing diseases. AI is relevant to any intellectual task; it is truly a universal field.

### 1.1 WHAT IS AI?

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RATIONALITY

We have claimed that AI is exciting, but we have not said what it *is*. In Figure 1.1 we see eight definitions of AI, laid out along two dimensions. The definitions on top are concerned with *thought processes* and *reasoning*, whereas the ones on the bottom address *behavior*. The definitions on the left measure success in terms of fidelity to *human* performance, whereas the ones on the right measure against an *ideal* performance measure, called **rationality**. A system is rational if it does the “right thing,” given what it knows.

Historically, all four approaches to AI have been followed, each by different people with different methods. A human-centered approach must be in part an empirical science, in-

<b>Thinking Humanly</b> “The exciting new effort to make computers think . . . <i>machines with minds</i> , in the full and literal sense.” (Haugeland, 1985) “[The automation of] activities that we associate with human thinking, activities such as decision-making, problem solving, learning . . .” (Bellman, 1978)	<b>Thinking Rationally</b> “The study of mental faculties through the use of computational models.” (Charniak and McDermott, 1985) “The study of the computations that make it possible to perceive, reason, and act.” (Winston, 1992)
<b>Acting Humanly</b> “The art of creating machines that perform functions that require intelligence when performed by people.” (Kurzweil, 1990) “The study of how to make computers do things at which, at the moment, people are better.” (Rich and Knight, 1991)	<b>Acting Rationally</b> “Computational Intelligence is the study of the design of intelligent agents.” (Poole <i>et al.</i> , 1998) “AI . . . is concerned with intelligent behavior in artifacts.” (Nilsson, 1998)
<b>Figure 1.1</b> Some definitions of artificial intelligence, organized into four categories.	

volving observations and hypotheses about human behavior. A rationalist<sup>1</sup> approach involves a combination of mathematics and engineering. The various group have both disparaged and helped each other. Let us look at the four approaches in more detail.

### 1.1.1 Acting humanly: The Turing Test approach

#### TURING TEST

The **Turing Test**, proposed by Alan Turing (1950), was designed to provide a satisfactory operational definition of intelligence. A computer passes the test if a human interrogator, after posing some written questions, cannot tell whether the written responses come from a person or from a computer. Chapter 26 discusses the details of the test and whether a computer would really be intelligent if it passed. For now, we note that programming a computer to pass a rigorously applied test provides plenty to work on. The computer would need to possess the following capabilities:

#### NATURAL LANGUAGE PROCESSING KNOWLEDGE REPRESENTATION AUTOMATED REASONING

- **natural language processing** to enable it to communicate successfully in English;
- **knowledge representation** to store what it knows or hears;
- **automated reasoning** to use the stored information to answer questions and to draw new conclusions;
- **machine learning** to adapt to new circumstances and to detect and extrapolate patterns.

#### MACHINE LEARNING

<sup>1</sup> By distinguishing between *human* and *rational* behavior, we are not suggesting that humans are necessarily “irrational” in the sense of “emotionally unstable” or “insane.” One merely need note that we are not perfect: not all chess players are grandmasters; and, unfortunately, not everyone gets an A on the exam. Some systematic errors in human reasoning are cataloged by Kahneman *et al.* (1982).

Turing's test deliberately avoided direct physical interaction between the interrogator and the computer, because *physical* simulation of a person is unnecessary for intelligence. However, the so-called **total Turing Test** includes a video signal so that the interrogator can test the subject's perceptual abilities, as well as the opportunity for the interrogator to pass physical objects "through the hatch." To pass the total Turing Test, the computer will need

TOTAL TURING TEST

COMPUTER VISION

- **computer vision** to perceive objects, and

ROBOTICS

- **robotics** to manipulate objects and move about.

These six disciplines compose most of AI, and Turing deserves credit for designing a test that remains relevant 60 years later. Yet AI researchers have devoted little effort to passing the Turing Test, believing that it is more important to study the underlying principles of intelligence than to duplicate an exemplar. The quest for "artificial flight" succeeded when the Wright brothers and others stopped imitating birds and started using wind tunnels and learning about aerodynamics. Aeronautical engineering texts do not define the goal of their field as making "machines that fly so exactly like pigeons that they can fool even other pigeons."

### 1.1.2 Thinking humanly: The cognitive modeling approach

COGNITIVE SCIENCE

If we are going to say that a given program thinks like a human, we must have some way of determining how humans think. We need to get *inside* the actual workings of human minds. There are three ways to do this: through introspection—trying to catch our own thoughts as they go by; through psychological experiments—observing a person in action; and through brain imaging—observing the brain in action. Once we have a sufficiently precise theory of the mind, it becomes possible to express the theory as a computer program. If the program's input–output behavior matches corresponding human behavior, that is evidence that some of the program's mechanisms could also be operating in humans. For example, Allen Newell and Herbert Simon, who developed GPS, the "General Problem Solver" (Newell and Simon, 1961), were not content merely to have their program solve problems correctly. They were more concerned with comparing the trace of its reasoning steps to traces of human subjects solving the same problems. The interdisciplinary field of **cognitive science** brings together computer models from AI and experimental techniques from psychology to construct precise and testable theories of the human mind.

Cognitive science is a fascinating field in itself, worthy of several textbooks and at least one encyclopedia (Wilson and Keil, 1999). We will occasionally comment on similarities or differences between AI techniques and human cognition. Real cognitive science, however, is necessarily based on experimental investigation of actual humans or animals. We will leave that for other books, as we assume the reader has only a computer for experimentation.

In the early days of AI there was often confusion between the approaches: an author would argue that an algorithm performs well on a task and that it is *therefore* a good model of human performance, or vice versa. Modern authors separate the two kinds of claims; this distinction has allowed both AI and cognitive science to develop more rapidly. The two fields continue to fertilize each other, most notably in computer vision, which incorporates neurophysiological evidence into computational models.

### 1.1.3 Thinking rationally: The “laws of thought” approach

SYLLOGISM

The Greek philosopher Aristotle was one of the first to attempt to codify “right thinking,” that is, irrefutable reasoning processes. His **sylogisms** provided patterns for argument structures that always yielded correct conclusions when given correct premises—for example, “Socrates is a man; all men are mortal; therefore, Socrates is mortal.” These laws of thought were supposed to govern the operation of the mind; their study initiated the field called **logic**.

LOGIC

Logicians in the 19th century developed a precise notation for statements about all kinds of objects in the world and the relations among them. (Contrast this with ordinary arithmetic notation, which provides only for statements about *numbers*.) By 1965, programs existed that could, in principle, solve *any* solvable problem described in logical notation. (Although if no solution exists, the program might loop forever.) The so-called **logicist** tradition within artificial intelligence hopes to build on such programs to create intelligent systems.

LOGICIST

There are two main obstacles to this approach. First, it is not easy to take informal knowledge and state it in the formal terms required by logical notation, particularly when the knowledge is less than 100% certain. Second, there is a big difference between solving a problem “in principle” and solving it in practice. Even problems with just a few hundred facts can exhaust the computational resources of any computer unless it has some guidance as to which reasoning steps to try first. Although both of these obstacles apply to *any* attempt to build computational reasoning systems, they appeared first in the logicist tradition.

### 1.1.4 Acting rationally: The rational agent approach

AGENT

An **agent** is just something that acts (*agent* comes from the Latin *agere*, to do). Of course, all computer programs do something, but computer agents are expected to do more: operate autonomously, perceive their environment, persist over a prolonged time period, adapt to change, and create and pursue goals. A **rational agent** is one that acts so as to achieve the best outcome or, when there is uncertainty, the best expected outcome.

RATIONAL AGENT

In the “laws of thought” approach to AI, the emphasis was on correct inferences. Making correct inferences is sometimes *part* of being a rational agent, because one way to act rationally is to reason logically to the conclusion that a given action will achieve one’s goals and then to act on that conclusion. On the other hand, correct inference is not *all* of rationality; in some situations, there is no provably correct thing to do, but something must still be done. There are also ways of acting rationally that cannot be said to involve inference. For example, recoiling from a hot stove is a reflex action that is usually more successful than a slower action taken after careful deliberation.

All the skills needed for the Turing Test also allow an agent to act rationally. Knowledge representation and reasoning enable agents to reach good decisions. We need to be able to generate comprehensible sentences in natural language to get by in a complex society. We need learning not only for erudition, but also because it improves our ability to generate effective behavior.

The rational-agent approach has two advantages over the other approaches. First, it is more general than the “laws of thought” approach because correct inference is just one of several possible mechanisms for achieving rationality. Second, it is more amenable to



scientific development than are approaches based on human behavior or human thought. The standard of rationality is mathematically well defined and completely general, and can be “unpacked” to generate agent designs that provably achieve it. Human behavior, on the other hand, is well adapted for one specific environment and is defined by, well, the sum total of all the things that humans do. *This book therefore concentrates on general principles of rational agents and on components for constructing them.* We will see that despite the apparent simplicity with which the problem can be stated, an enormous variety of issues come up when we try to solve it. Chapter 2 outlines some of these issues in more detail.

One important point to keep in mind: We will see before too long that achieving perfect rationality—always doing the right thing—is not feasible in complicated environments. The computational demands are just too high. For most of the book, however, we will adopt the working hypothesis that perfect rationality is a good starting point for analysis. It simplifies the problem and provides the appropriate setting for most of the foundational material in the field. Chapters 5 and 17 deal explicitly with the issue of **limited rationality**—acting appropriately when there is not enough time to do all the computations one might like.

LIMITED  
RATIONALITY

## 1.2 THE FOUNDATIONS OF ARTIFICIAL INTELLIGENCE

In this section, we provide a brief history of the disciplines that contributed ideas, viewpoints, and techniques to AI. Like any history, this one is forced to concentrate on a small number of people, events, and ideas and to ignore others that also were important. We organize the history around a series of questions. We certainly would not wish to give the impression that these questions are the only ones the disciplines address or that the disciplines have all been working toward AI as their ultimate fruition.

### 1.2.1 Philosophy

- Can formal rules be used to draw valid conclusions?
- How does the mind arise from a physical brain?
- Where does knowledge come from?
- How does knowledge lead to action?

Aristotle (384–322 B.C.), whose bust appears on the front cover of this book, was the first to formulate a precise set of laws governing the rational part of the mind. He developed an informal system of syllogisms for proper reasoning, which in principle allowed one to generate conclusions mechanically, given initial premises. Much later, Ramon Lull (d. 1315) had the idea that useful reasoning could actually be carried out by a mechanical artifact. Thomas Hobbes (1588–1679) proposed that reasoning was like numerical computation, that “we add and subtract in our silent thoughts.” The automation of computation itself was already well under way. Around 1500, Leonardo da Vinci (1452–1519) designed but did not build a mechanical calculator; recent reconstructions have shown the design to be functional. The first known calculating machine was constructed around 1623 by the German scientist Wilhelm Schickard (1592–1635), although the Pascaline, built in 1642 by Blaise Pascal (1623–1662),

is more famous. Pascal wrote that “the arithmetical machine produces effects which appear nearer to thought than all the actions of animals.” Gottfried Wilhelm Leibniz (1646–1716) built a mechanical device intended to carry out operations on concepts rather than numbers, but its scope was rather limited. Leibniz did surpass Pascal by building a calculator that could add, subtract, multiply, and take roots, whereas the Pascaline could only add and subtract. Some speculated that machines might not just do calculations but actually be able to think and act on their own. In his 1651 book *Leviathan*, Thomas Hobbes suggested the idea of an “artificial animal,” arguing “For what is the heart but a spring; and the nerves, but so many strings; and the joints, but so many wheels.”

It’s one thing to say that the mind operates, at least in part, according to logical rules, and to build physical systems that emulate some of those rules; it’s another to say that the mind itself *is* such a physical system. René Descartes (1596–1650) gave the first clear discussion of the distinction between mind and matter and of the problems that arise. One problem with a purely physical conception of the mind is that it seems to leave little room for free will: if the mind is governed entirely by physical laws, then it has no more free will than a rock “deciding” to fall toward the center of the earth. Descartes was a strong advocate of the power of reasoning in understanding the world, a philosophy now called **rationalism**, and one that counts Aristotle and Leibniz as members. But Descartes was also a proponent of **dualism**. He held that there is a part of the human mind (or soul or spirit) that is outside of nature, exempt from physical laws. Animals, on the other hand, did not possess this dual quality; they could be treated as machines. An alternative to dualism is **materialism**, which holds that the brain’s operation according to the laws of physics *constitutes* the mind. Free will is simply the way that the perception of available choices appears to the choosing entity.

Given a physical mind that manipulates knowledge, the next problem is to establish the source of knowledge. The **empiricism** movement, starting with Francis Bacon’s (1561–1626) *Novum Organum*,<sup>2</sup> is characterized by a dictum of John Locke (1632–1704): “Nothing is in the understanding, which was not first in the senses.” David Hume’s (1711–1776) *A Treatise of Human Nature* (Hume, 1739) proposed what is now known as the principle of **induction**: that general rules are acquired by exposure to repeated associations between their elements. Building on the work of Ludwig Wittgenstein (1889–1951) and Bertrand Russell (1872–1970), the famous Vienna Circle, led by Rudolf Carnap (1891–1970), developed the doctrine of **logical positivism**. This doctrine holds that all knowledge can be characterized by logical theories connected, ultimately, to **observation sentences** that correspond to sensory inputs; thus logical positivism combines rationalism and empiricism.<sup>3</sup> The **confirmation theory** of Carnap and Carl Hempel (1905–1997) attempted to analyze the acquisition of knowledge from experience. Carnap’s book *The Logical Structure of the World* (1928) defined an explicit computational procedure for extracting knowledge from elementary experiences. It was probably the first theory of mind as a computational process.

<sup>2</sup> The *Novum Organum* is an update of Aristotle’s *Organon*, or instrument of thought. Thus Aristotle can be seen as both an empiricist and a rationalist.

<sup>3</sup> In this picture, all meaningful statements can be verified or falsified either by experimentation or by analysis of the meaning of the words. Because this rules out most of metaphysics, as was the intention, logical positivism was unpopular in some circles.

RATIONALISM

DUALISM

MATERIALISM

EMPIRICISM

INDUCTION

LOGICAL POSITIVISM

OBSERVATION  
SENTENCESCONFIRMATION  
THEORY

The final element in the philosophical picture of the mind is the connection between knowledge and action. This question is vital to AI because intelligence requires action as well as reasoning. Moreover, only by understanding how actions are justified can we understand how to build an agent whose actions are justifiable (or rational). Aristotle argued (in *De Motu Animalium*) that actions are justified by a logical connection between goals and knowledge of the action's outcome (the last part of this extract also appears on the front cover of this book, in the original Greek):

But how does it happen that thinking is sometimes accompanied by action and sometimes not, sometimes by motion, and sometimes not? It looks as if almost the same thing happens as in the case of reasoning and making inferences about unchanging objects. But in that case the end is a speculative proposition . . . whereas here the conclusion which results from the two premises is an action. . . . I need covering; a cloak is a covering. I need a cloak. What I need, I have to make; I need a cloak. I have to make a cloak. And the conclusion, the "I have to make a cloak," is an action.

In the *Nicomachean Ethics* (Book III. 3, 1112b), Aristotle further elaborates on this topic, suggesting an algorithm:

We deliberate not about ends, but about means. For a doctor does not deliberate whether he shall heal, nor an orator whether he shall persuade, . . . They assume the end and consider how and by what means it is attained, and if it seems easily and best produced thereby; while if it is achieved by one means only they consider *how* it will be achieved by this and by what means *this* will be achieved, till they come to the first cause, . . . and what is last in the order of analysis seems to be first in the order of becoming. And if we come on an impossibility, we give up the search, e.g., if we need money and this cannot be got; but if a thing appears possible we try to do it.

Aristotle's algorithm was implemented 2300 years later by Newell and Simon in their GPS program. We would now call it a regression planning system (see Chapter 10).

Goal-based analysis is useful, but does not say what to do when several actions will achieve the goal or when no action will achieve it completely. Antoine Arnauld (1612–1694) correctly described a quantitative formula for deciding what action to take in cases like this (see Chapter 16). John Stuart Mill's (1806–1873) book *Utilitarianism* (Mill, 1863) promoted the idea of rational decision criteria in all spheres of human activity. The more formal theory of decisions is discussed in the following section.

### 1.2.2 Mathematics

- What are the formal rules to draw valid conclusions?
- What can be computed?
- How do we reason with uncertain information?

Philosophers staked out some of the fundamental ideas of AI, but the leap to a formal science required a level of mathematical formalization in three fundamental areas: logic, computation, and probability.

The idea of formal logic can be traced back to the philosophers of ancient Greece, but its mathematical development really began with the work of George Boole (1815–1864), who

worked out the details of propositional, or Boolean, logic (Boole, 1847). In 1879, Gottlob Frege (1848–1925) extended Boole’s logic to include objects and relations, creating the first-order logic that is used today.<sup>4</sup> Alfred Tarski (1902–1983) introduced a theory of reference that shows how to relate the objects in a logic to objects in the real world.

ALGORITHM

The next step was to determine the limits of what could be done with logic and computation. The first nontrivial **algorithm** is thought to be Euclid’s algorithm for computing greatest common divisors. The word *algorithm* (and the idea of studying them) comes from al-Khowarazmi, a Persian mathematician of the 9th century, whose writings also introduced Arabic numerals and algebra to Europe. Boole and others discussed algorithms for logical deduction, and, by the late 19th century, efforts were under way to formalize general mathematical reasoning as logical deduction. In 1930, Kurt Gödel (1906–1978) showed that there exists an effective procedure to prove any true statement in the first-order logic of Frege and Russell, but that first-order logic could not capture the principle of mathematical induction needed to characterize the natural numbers. In 1931, Gödel showed that limits on deduction do exist. His **incompleteness theorem** showed that in any formal theory as strong as Peano arithmetic (the elementary theory of natural numbers), there are true statements that are undecidable in the sense that they have no proof within the theory.

INCOMPLETENESS  
THEOREM

This fundamental result can also be interpreted as showing that some functions on the integers cannot be represented by an algorithm—that is, they cannot be computed. This motivated Alan Turing (1912–1954) to try to characterize exactly which functions *are* **computable**—capable of being computed. This notion is actually slightly problematic because the notion of a computation or effective procedure really cannot be given a formal definition. However, the Church–Turing thesis, which states that the Turing machine (Turing, 1936) is capable of computing any computable function, is generally accepted as providing a sufficient definition. Turing also showed that there were some functions that no Turing machine can compute. For example, no machine can tell *in general* whether a given program will return an answer on a given input or run forever.

COMPUTABLE

Although decidability and computability are important to an understanding of computation, the notion of **tractability** has had an even greater impact. Roughly speaking, a problem is called intractable if the time required to solve instances of the problem grows exponentially with the size of the instances. The distinction between polynomial and exponential growth in complexity was first emphasized in the mid-1960s (Cobham, 1964; Edmonds, 1965). It is important because exponential growth means that even moderately large instances cannot be solved in any reasonable time. Therefore, one should strive to divide the overall problem of generating intelligent behavior into tractable subproblems rather than intractable ones.

TRACTABILITY

NP-COMPLETENESS

How can one recognize an intractable problem? The theory of **NP-completeness**, pioneered by Steven Cook (1971) and Richard Karp (1972), provides a method. Cook and Karp showed the existence of large classes of canonical combinatorial search and reasoning problems that are NP-complete. Any problem class to which the class of NP-complete problems can be reduced is likely to be intractable. (Although it has not been proved that NP-complete

<sup>4</sup> Frege’s proposed notation for first-order logic—an arcane combination of textual and geometric features—never became popular.



problems are necessarily intractable, most theoreticians believe it.) These results contrast with the optimism with which the popular press greeted the first computers—“Electronic Super-Brains” that were “Faster than Einstein!” Despite the increasing speed of computers, careful use of resources will characterize intelligent systems. Put crudely, the world is an *extremely* large problem instance! Work in AI has helped explain why some instances of NP-complete problems are hard, yet others are easy (Cheeseman *et al.*, 1991).

PROBABILITY

Besides logic and computation, the third great contribution of mathematics to AI is the theory of **probability**. The Italian Gerolamo Cardano (1501–1576) first framed the idea of probability, describing it in terms of the possible outcomes of gambling events. In 1654, Blaise Pascal (1623–1662), in a letter to Pierre Fermat (1601–1665), showed how to predict the future of an unfinished gambling game and assign average payoffs to the gamblers. Probability quickly became an invaluable part of all the quantitative sciences, helping to deal with uncertain measurements and incomplete theories. James Bernoulli (1654–1705), Pierre Laplace (1749–1827), and others advanced the theory and introduced new statistical methods. Thomas Bayes (1702–1761), who appears on the front cover of this book, proposed a rule for updating probabilities in the light of new evidence. Bayes’ rule underlies most modern approaches to uncertain reasoning in AI systems.

### 1.2.3 Economics

- How should we make decisions so as to maximize payoff?
- How should we do this when others may not go along?
- How should we do this when the payoff may be far in the future?

UTILITY

The science of economics got its start in 1776, when Scottish philosopher Adam Smith (1723–1790) published *An Inquiry into the Nature and Causes of the Wealth of Nations*. While the ancient Greeks and others had made contributions to economic thought, Smith was the first to treat it as a science, using the idea that economies can be thought of as consisting of individual agents maximizing their own economic well-being. Most people think of economics as being about money, but economists will say that they are really studying how people make choices that lead to preferred outcomes. When McDonald’s offers a hamburger for a dollar, they are asserting that they would prefer the dollar and hoping that customers will prefer the hamburger. The mathematical treatment of “preferred outcomes” or **utility** was first formalized by Léon Walras (pronounced “Valrasse”) (1834–1910) and was improved by Frank Ramsey (1931) and later by John von Neumann and Oskar Morgenstern in their book *The Theory of Games and Economic Behavior* (1944).

DECISION THEORY

**Decision theory**, which combines probability theory with utility theory, provides a formal and complete framework for decisions (economic or otherwise) made under uncertainty—that is, in cases where probabilistic descriptions appropriately capture the decision maker’s environment. This is suitable for “large” economies where each agent need pay no attention to the actions of other agents as individuals. For “small” economies, the situation is much more like a **game**: the actions of one player can significantly affect the utility of another (either positively or negatively). Von Neumann and Morgenstern’s development of **game theory** (see also Luce and Raiffa, 1957) included the surprising result that, for some games,

GAME THEORY

a rational agent should adopt policies that are (or least appear to be) randomized. Unlike decision theory, game theory does not offer an unambiguous prescription for selecting actions.

For the most part, economists did not address the third question listed above, namely, how to make rational decisions when payoffs from actions are not immediate but instead result from several actions taken *in sequence*. This topic was pursued in the field of **operations research**, which emerged in World War II from efforts in Britain to optimize radar installations, and later found civilian applications in complex management decisions. The work of Richard Bellman (1957) formalized a class of sequential decision problems called **Markov decision processes**, which we study in Chapters 17 and 21.

Work in economics and operations research has contributed much to our notion of rational agents, yet for many years AI research developed along entirely separate paths. One reason was the apparent complexity of making rational decisions. The pioneering AI researcher Herbert Simon (1916–2001) won the Nobel Prize in economics in 1978 for his early work showing that models based on **satisficing**—making decisions that are “good enough,” rather than laboriously calculating an optimal decision—gave a better description of actual human behavior (Simon, 1947). Since the 1990s, there has been a resurgence of interest in decision-theoretic techniques for agent systems (Wellman, 1995).

#### 1.2.4 Neuroscience

- How do brains process information?

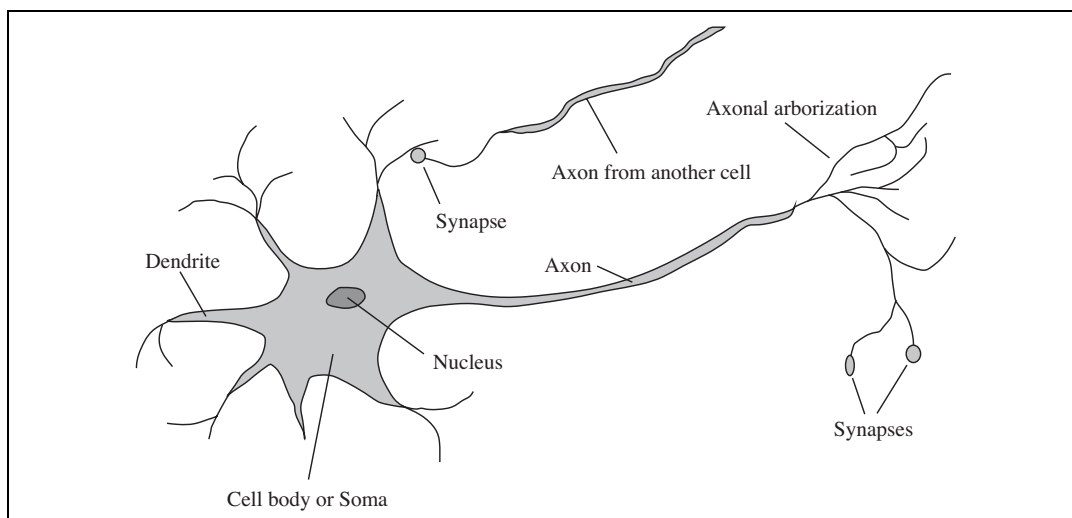
**Neuroscience** is the study of the nervous system, particularly the brain. Although the exact way in which the brain enables thought is one of the great mysteries of science, the fact that it *does* enable thought has been appreciated for thousands of years because of the evidence that strong blows to the head can lead to mental incapacitation. It has also long been known that human brains are somehow different; in about 335 B.C. Aristotle wrote, “Of all the animals, man has the largest brain in proportion to his size.”<sup>5</sup> Still, it was not until the middle of the 18th century that the brain was widely recognized as the seat of consciousness. Before then, candidate locations included the heart and the spleen.

Paul Broca’s (1824–1880) study of aphasia (speech deficit) in brain-damaged patients in 1861 demonstrated the existence of localized areas of the brain responsible for specific cognitive functions. In particular, he showed that speech production was localized to the portion of the left hemisphere now called Broca’s area.<sup>6</sup> By that time, it was known that the brain consisted of nerve cells, or **neurons**, but it was not until 1873 that Camillo Golgi (1843–1926) developed a staining technique allowing the observation of individual neurons in the brain (see Figure 1.2). This technique was used by Santiago Ramon y Cajal (1852–1934) in his pioneering studies of the brain’s neuronal structures.<sup>7</sup> Nicolas Rashevsky (1936, 1938) was the first to apply mathematical models to the study of the nervous system.

<sup>5</sup> Since then, it has been discovered that the tree shrew (*Scandentia*) has a higher ratio of brain to body mass.

<sup>6</sup> Many cite Alexander Hood (1824) as a possible prior source.

<sup>7</sup> Golgi persisted in his belief that the brain’s functions were carried out primarily in a continuous medium in which neurons were embedded, whereas Cajal propounded the “neuronal doctrine.” The two shared the Nobel prize in 1906 but gave mutually antagonistic acceptance speeches.



**Figure 1.2** The parts of a nerve cell or neuron. Each neuron consists of a cell body, or soma, that contains a cell nucleus. Branching out from the cell body are a number of fibers called dendrites and a single long fiber called the axon. The axon stretches out for a long distance, much longer than the scale in this diagram indicates. Typically, an axon is 1 cm long (100 times the diameter of the cell body), but can reach up to 1 meter. A neuron makes connections with 10 to 100,000 other neurons at junctions called synapses. Signals are propagated from neuron to neuron by a complicated electrochemical reaction. The signals control brain activity in the short term and also enable long-term changes in the connectivity of neurons. These mechanisms are thought to form the basis for learning in the brain. Most information processing goes on in the cerebral cortex, the outer layer of the brain. The basic organizational unit appears to be a column of tissue about 0.5 mm in diameter, containing about 20,000 neurons and extending the full depth of the cortex about 4 mm in humans).

We now have some data on the mapping between areas of the brain and the parts of the body that they control or from which they receive sensory input. Such mappings are able to change radically over the course of a few weeks, and some animals seem to have multiple maps. Moreover, we do not fully understand how other areas can take over functions when one area is damaged. There is almost no theory on how an individual memory is stored.

The measurement of intact brain activity began in 1929 with the invention by Hans Berger of the electroencephalograph (EEG). The recent development of functional magnetic resonance imaging (fMRI) (Ogawa *et al.*, 1990; Cabeza and Nyberg, 2001) is giving neuroscientists unprecedentedly detailed images of brain activity, enabling measurements that correspond in interesting ways to ongoing cognitive processes. These are augmented by advances in single-cell recording of neuron activity. Individual neurons can be stimulated electrically, chemically, or even optically (Han and Boyden, 2007), allowing neuronal input–output relationships to be mapped. Despite these advances, we are still a long way from understanding how cognitive processes actually work.



The truly amazing conclusion is that *a collection of simple cells can lead to thought, action, and consciousness* or, in the pithy words of John Searle (1992), *brains cause minds*.

	Supercomputer	Personal Computer	Human Brain
Computational units	$10^4$ CPUs, $10^{12}$ transistors	4 CPUs, $10^9$ transistors	$10^{11}$ neurons
Storage units	$10^{14}$ bits RAM $10^{15}$ bits disk	$10^{11}$ bits RAM $10^{13}$ bits disk	$10^{11}$ neurons $10^{14}$ synapses
Cycle time	$10^{-9}$ sec	$10^{-9}$ sec	$10^{-3}$ sec
Operations/sec	$10^{15}$	$10^{10}$	$10^{17}$
Memory updates/sec	$10^{14}$	$10^{10}$	$10^{14}$

**Figure 1.3** A crude comparison of the raw computational resources available to the IBM BLUE GENE supercomputer, a typical personal computer of 2008, and the human brain. The brain's numbers are essentially fixed, whereas the supercomputer's numbers have been increasing by a factor of 10 every 5 years or so, allowing it to achieve rough parity with the brain. The personal computer lags behind on all metrics except cycle time.

The only real alternative theory is mysticism: that minds operate in some mystical realm that is beyond physical science.

Brains and digital computers have somewhat different properties. Figure 1.3 shows that computers have a cycle time that is a million times faster than a brain. The brain makes up for that with far more storage and interconnection than even a high-end personal computer, although the largest supercomputers have a capacity that is similar to the brain's. (It should be noted, however, that the brain does not seem to use all of its neurons simultaneously.) Futurists make much of these numbers, pointing to an approaching **singularity** at which computers reach a superhuman level of performance (Vinge, 1993; Kurzweil, 2005), but the raw comparisons are not especially informative. Even with a computer of virtually unlimited capacity, we still would not know how to achieve the brain's level of intelligence.

### 1.2.5 Psychology

- How do humans and animals think and act?

The origins of scientific psychology are usually traced to the work of the German physicist Hermann von Helmholtz (1821–1894) and his student Wilhelm Wundt (1832–1920). Helmholtz applied the scientific method to the study of human vision, and his *Handbook of Physiological Optics* is even now described as “the single most important treatise on the physics and physiology of human vision” (Nalwa, 1993, p.15). In 1879, Wundt opened the first laboratory of experimental psychology, at the University of Leipzig. Wundt insisted on carefully controlled experiments in which his workers would perform a perceptual or associative task while introspecting on their thought processes. The careful controls went a long way toward making psychology a science, but the subjective nature of the data made it unlikely that an experimenter would ever disconfirm his or her own theories. Biologists studying animal behavior, on the other hand, lacked introspective data and developed an objective methodology, as described by H. S. Jennings (1906) in his influential work *Behavior of the Lower Organisms*. Applying this viewpoint to humans, the **behaviorism** movement, led by John Watson (1878–1958), rejected *any* theory involving mental processes on the grounds

that introspection could not provide reliable evidence. Behaviorists insisted on studying only objective measures of the percepts (or *stimulus*) given to an animal and its resulting actions (or *response*). Behaviorism discovered a lot about rats and pigeons but had less success at understanding humans.

**Cognitive psychology**, which views the brain as an information-processing device, can be traced back at least to the works of William James (1842–1910). Helmholtz also insisted that perception involved a form of unconscious logical inference. The cognitive viewpoint was largely eclipsed by behaviorism in the United States, but at Cambridge's Applied Psychology Unit, directed by Frederic Bartlett (1886–1969), cognitive modeling was able to flourish. *The Nature of Explanation*, by Bartlett's student and successor Kenneth Craik (1943), forcefully reestablished the legitimacy of such "mental" terms as beliefs and goals, arguing that they are just as scientific as, say, using pressure and temperature to talk about gases, despite their being made of molecules that have neither. Craik specified the three key steps of a knowledge-based agent: (1) the stimulus must be translated into an internal representation, (2) the representation is manipulated by cognitive processes to derive new internal representations, and (3) these are in turn retranslated back into action. He clearly explained why this was a good design for an agent:

If the organism carries a "small-scale model" of external reality and of its own possible actions within its head, it is able to try out various alternatives, conclude which is the best of them, react to future situations before they arise, utilize the knowledge of past events in dealing with the present and future, and in every way to react in a much fuller, safer, and more competent manner to the emergencies which face it. (Craik, 1943)

After Craik's death in a bicycle accident in 1945, his work was continued by Donald Broadbent, whose book *Perception and Communication* (1958) was one of the first works to model psychological phenomena as information processing. Meanwhile, in the United States, the development of computer modeling led to the creation of the field of **cognitive science**. The field can be said to have started at a workshop in September 1956 at MIT. (We shall see that this is just two months after the conference at which AI itself was "born.") At the workshop, George Miller presented *The Magic Number Seven*, Noam Chomsky presented *Three Models of Language*, and Allen Newell and Herbert Simon presented *The Logic Theory Machine*. These three influential papers showed how computer models could be used to address the psychology of memory, language, and logical thinking, respectively. It is now a common (although far from universal) view among psychologists that "a cognitive theory should be like a computer program" (Anderson, 1980); that is, it should describe a detailed information-processing mechanism whereby some cognitive function might be implemented.

### 1.2.6 Computer engineering

- How can we build an efficient computer?

For artificial intelligence to succeed, we need two things: intelligence and an artifact. The computer has been the artifact of choice. The modern digital electronic computer was invented independently and almost simultaneously by scientists in three countries embattled in

World War II. The first *operational* computer was the electromechanical Heath Robinson,<sup>8</sup> built in 1940 by Alan Turing's team for a single purpose: deciphering German messages. In 1943, the same group developed the Colossus, a powerful general-purpose machine based on vacuum tubes.<sup>9</sup> The first operational *programmable* computer was the Z-3, the invention of Konrad Zuse in Germany in 1941. Zuse also invented floating-point numbers and the first high-level programming language, Plankalkül. The first *electronic* computer, the ABC, was assembled by John Atanasoff and his student Clifford Berry between 1940 and 1942 at Iowa State University. Atanasoff's research received little support or recognition; it was the ENIAC, developed as part of a secret military project at the University of Pennsylvania by a team including John Mauchly and John Eckert, that proved to be the most influential forerunner of modern computers.

Since that time, each generation of computer hardware has brought an increase in speed and capacity and a decrease in price. Performance doubled every 18 months or so until around 2005, when power dissipation problems led manufacturers to start multiplying the number of CPU cores rather than the clock speed. Current expectations are that future increases in power will come from massive parallelism—a curious convergence with the properties of the brain.

Of course, there were calculating devices before the electronic computer. The earliest automated machines, dating from the 17th century, were discussed on page 6. The first *programmable* machine was a loom, devised in 1805 by Joseph Marie Jacquard (1752–1834), that used punched cards to store instructions for the pattern to be woven. In the mid-19th century, Charles Babbage (1792–1871) designed two machines, neither of which he completed. The Difference Engine was intended to compute mathematical tables for engineering and scientific projects. It was finally built and shown to work in 1991 at the Science Museum in London (Swade, 2000). Babbage's Analytical Engine was far more ambitious: it included addressable memory, stored programs, and conditional jumps and was the first artifact capable of universal computation. Babbage's colleague Ada Lovelace, daughter of the poet Lord Byron, was perhaps the world's first programmer. (The programming language Ada is named after her.) She wrote programs for the unfinished Analytical Engine and even speculated that the machine could play chess or compose music.

AI also owes a debt to the software side of computer science, which has supplied the operating systems, programming languages, and tools needed to write modern programs (and papers about them). But this is one area where the debt has been repaid: work in AI has pioneered many ideas that have made their way back to mainstream computer science, including time sharing, interactive interpreters, personal computers with windows and mice, rapid development environments, the linked list data type, automatic storage management, and key concepts of symbolic, functional, declarative, and object-oriented programming.

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<sup>8</sup> Heath Robinson was a cartoonist famous for his depictions of whimsical and absurdly complicated contraptions for everyday tasks such as buttering toast.

<sup>9</sup> In the postwar period, Turing wanted to use these computers for AI research—for example, one of the first chess programs (Turing *et al.*, 1953). His efforts were blocked by the British government.

### 1.2.7 Control theory and cybernetics

- How can artifacts operate under their own control?

Ktesibios of Alexandria (c. 250 B.C.) built the first self-controlling machine: a water clock with a regulator that maintained a constant flow rate. This invention changed the definition of what an artifact could do. Previously, only living things could modify their behavior in response to changes in the environment. Other examples of self-regulating feedback control systems include the steam engine governor, created by James Watt (1736–1819), and the thermostat, invented by Cornelis Drebbel (1572–1633), who also invented the submarine. The mathematical theory of stable feedback systems was developed in the 19th century.

CONTROL THEORY

The central figure in the creation of what is now called **control theory** was Norbert Wiener (1894–1964). Wiener was a brilliant mathematician who worked with Bertrand Russell, among others, before developing an interest in biological and mechanical control systems and their connection to cognition. Like Craik (who also used control systems as psychological models), Wiener and his colleagues Arturo Rosenblueth and Julian Bigelow challenged the behaviorist orthodoxy (Rosenblueth *et al.*, 1943). They viewed purposive behavior as arising from a regulatory mechanism trying to minimize “error”—the difference between current state and goal state. In the late 1940s, Wiener, along with Warren McCulloch, Walter Pitts, and John von Neumann, organized a series of influential conferences that explored the new mathematical and computational models of cognition. Wiener’s book *Cybernetics* (1948) became a bestseller and awoke the public to the possibility of artificially intelligent machines. Meanwhile, in Britain, W. Ross Ashby (Ashby, 1940) pioneered similar ideas. Ashby, Alan Turing, Grey Walter, and others formed the Ratio Club for “those who had Wiener’s ideas before Wiener’s book appeared.” Ashby’s *Design for a Brain* (1948, 1952) elaborated on his idea that intelligence could be created by the use of **homeostatic** devices containing appropriate feedback loops to achieve stable adaptive behavior.

CYBERNETICS

HOMEOSTATIC

OBJECTIVE  
FUNCTION

Modern control theory, especially the branch known as stochastic optimal control, has as its goal the design of systems that maximize an **objective function** over time. This roughly matches our view of AI: designing systems that behave optimally. Why, then, are AI and control theory two different fields, despite the close connections among their founders? The answer lies in the close coupling between the mathematical techniques that were familiar to the participants and the corresponding sets of problems that were encompassed in each world view. Calculus and matrix algebra, the tools of control theory, lend themselves to systems that are describable by fixed sets of continuous variables, whereas AI was founded in part as a way to escape from these perceived limitations. The tools of logical inference and computation allowed AI researchers to consider problems such as language, vision, and planning that fell completely outside the control theorist’s purview.

### 1.2.8 Linguistics

- How does language relate to thought?

In 1957, B. F. Skinner published *Verbal Behavior*. This was a comprehensive, detailed account of the behaviorist approach to language learning, written by the foremost expert in

the field. But curiously, a review of the book became as well known as the book itself, and served to almost kill off interest in behaviorism. The author of the review was the linguist Noam Chomsky, who had just published a book on his own theory, *Syntactic Structures*. Chomsky pointed out that the behaviorist theory did not address the notion of creativity in language—it did not explain how a child could understand and make up sentences that he or she had never heard before. Chomsky’s theory—based on syntactic models going back to the Indian linguist Panini (c. 350 B.C.)—could explain this, and unlike previous theories, it was formal enough that it could in principle be programmed.

COMPUTATIONAL  
LINGUISTICS

Modern linguistics and AI, then, were “born” at about the same time, and grew up together, intersecting in a hybrid field called **computational linguistics** or **natural language processing**. The problem of understanding language soon turned out to be considerably more complex than it seemed in 1957. Understanding language requires an understanding of the subject matter and context, not just an understanding of the structure of sentences. This might seem obvious, but it was not widely appreciated until the 1960s. Much of the early work in **knowledge representation** (the study of how to put knowledge into a form that a computer can reason with) was tied to language and informed by research in linguistics, which was connected in turn to decades of work on the philosophical analysis of language.

## 1.3 THE HISTORY OF ARTIFICIAL INTELLIGENCE

With the background material behind us, we are ready to cover the development of AI itself.

### 1.3.1 The gestation of artificial intelligence (1943–1955)

The first work that is now generally recognized as AI was done by Warren McCulloch and Walter Pitts (1943). They drew on three sources: knowledge of the basic physiology and function of neurons in the brain; a formal analysis of propositional logic due to Russell and Whitehead; and Turing’s theory of computation. They proposed a model of artificial neurons in which each neuron is characterized as being “on” or “off,” with a switch to “on” occurring in response to stimulation by a sufficient number of neighboring neurons. The state of a neuron was conceived of as “factually equivalent to a proposition which proposed its adequate stimulus.” They showed, for example, that any computable function could be computed by some network of connected neurons, and that all the logical connectives (and, or, not, etc.) could be implemented by simple net structures. McCulloch and Pitts also suggested that suitably defined networks could learn. Donald Hebb (1949) demonstrated a simple updating rule for modifying the connection strengths between neurons. His rule, now called **Hebbian learning**, remains an influential model to this day.

HEBBIAN LEARNING

Two undergraduate students at Harvard, Marvin Minsky and Dean Edmonds, built the first neural network computer in 1950. The SNARC, as it was called, used 3000 vacuum tubes and a surplus automatic pilot mechanism from a B-24 bomber to simulate a network of 40 neurons. Later, at Princeton, Minsky studied universal computation in neural networks. His Ph.D. committee was skeptical about whether this kind of work should be considered



new patterns that help label new examples. Banko and Brill (2001) show that techniques like this perform even better as the amount of available text goes from a million words to a billion and that the increase in performance from using more data exceeds any difference in algorithm choice; a mediocre algorithm with 100 million words of unlabeled training data outperforms the best known algorithm with 1 million words.

As another example, Hays and Efros (2007) discuss the problem of filling in holes in a photograph. Suppose you use Photoshop to mask out an ex-friend from a group photo, but now you need to fill in the masked area with something that matches the background. Hays and Efros defined an algorithm that searches through a collection of photos to find something that will match. They found the performance of their algorithm was poor when they used a collection of only ten thousand photos, but crossed a threshold into excellent performance when they grew the collection to two million photos.

Work like this suggests that the “knowledge bottleneck” in AI—the problem of how to express all the knowledge that a system needs—may be solved in many applications by learning methods rather than hand-coded knowledge engineering, provided the learning algorithms have enough data to go on (Halevy *et al.*, 2009). Reporters have noticed the surge of new applications and have written that “AI Winter” may be yielding to a new Spring (Havenstein, 2005). As Kurzweil (2005) writes, “today, many thousands of AI applications are deeply embedded in the infrastructure of every industry.”

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## 1.4 THE STATE OF THE ART

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What can AI do today? A concise answer is difficult because there are so many activities in so many subfields. Here we sample a few applications; others appear throughout the book.

**Robotic vehicles:** A driverless robotic car named STANLEY sped through the rough terrain of the Mojave dessert at 22 mph, finishing the 132-mile course first to win the 2005 DARPA Grand Challenge. STANLEY is a Volkswagen Touareg outfitted with cameras, radar, and laser rangefinders to sense the environment and onboard software to command the steering, braking, and acceleration (Thrun, 2006). The following year CMU’s BOSS won the Urban Challenge, safely driving in traffic through the streets of a closed Air Force base, obeying traffic rules and avoiding pedestrians and other vehicles.

**Speech recognition:** A traveler calling United Airlines to book a flight can have the entire conversation guided by an automated speech recognition and dialog management system.

**Autonomous planning and scheduling:** A hundred million miles from Earth, NASA’s Remote Agent program became the first on-board autonomous planning program to control the scheduling of operations for a spacecraft (Jonsson *et al.*, 2000). REMOTE AGENT generated plans from high-level goals specified from the ground and monitored the execution of those plans—detecting, diagnosing, and recovering from problems as they occurred. Successor program MAPGEN (Al-Chang *et al.*, 2004) plans the daily operations for NASA’s Mars Exploration Rovers, and MEXAR2 (Cesta *et al.*, 2007) did mission planning—both logistics and science planning—for the European Space Agency’s Mars Express mission in 2008.

**Game playing:** IBM's DEEP BLUE became the first computer program to defeat the world champion in a chess match when it bested Garry Kasparov by a score of 3.5 to 2.5 in an exhibition match (Goodman and Keene, 1997). Kasparov said that he felt a "new kind of intelligence" across the board from him. *Newsweek* magazine described the match as "The brain's last stand." The value of IBM's stock increased by \$18 billion. Human champions studied Kasparov's loss and were able to draw a few matches in subsequent years, but the most recent human-computer matches have been won convincingly by the computer.

**Spam fighting:** Each day, learning algorithms classify over a billion messages as spam, saving the recipient from having to waste time deleting what, for many users, could comprise 80% or 90% of all messages, if not classified away by algorithms. Because the spammers are continually updating their tactics, it is difficult for a static programmed approach to keep up, and learning algorithms work best (Sahami *et al.*, 1998; Goodman and Heckerman, 2004).

**Logistics planning:** During the Persian Gulf crisis of 1991, U.S. forces deployed a Dynamic Analysis and Replanning Tool, DART (Cross and Walker, 1994), to do automated logistics planning and scheduling for transportation. This involved up to 50,000 vehicles, cargo, and people at a time, and had to account for starting points, destinations, routes, and conflict resolution among all parameters. The AI planning techniques generated in hours a plan that would have taken weeks with older methods. The Defense Advanced Research Project Agency (DARPA) stated that this single application more than paid back DARPA's 30-year investment in AI.

**Robotics:** The iRobot Corporation has sold over two million Roomba robotic vacuum cleaners for home use. The company also deploys the more rugged PackBot to Iraq and Afghanistan, where it is used to handle hazardous materials, clear explosives, and identify the location of snipers.

**Machine Translation:** A computer program automatically translates from Arabic to English, allowing an English speaker to see the headline "Ardogan Confirms That Turkey Would Not Accept Any Pressure, Urging Them to Recognize Cyprus." The program uses a statistical model built from examples of Arabic-to-English translations and from examples of English text totaling two trillion words (Brants *et al.*, 2007). None of the computer scientists on the team speak Arabic, but they do understand statistics and machine learning algorithms.

These are just a few examples of artificial intelligence systems that exist today. Not magic or science fiction—but rather science, engineering, and mathematics, to which this book provides an introduction.

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## 1.5 SUMMARY

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This chapter defines AI and establishes the cultural background against which it has developed. Some of the important points are as follows:

- Different people approach AI with different goals in mind. Two important questions to ask are: Are you concerned with thinking or behavior? Do you want to model humans or work from an ideal standard?

- In this book, we adopt the view that intelligence is concerned mainly with **rational action**. Ideally, an **intelligent agent** takes the best possible action in a situation. We study the problem of building agents that are intelligent in this sense.
- Philosophers (going back to 400 B.C.) made AI conceivable by considering the ideas that the mind is in some ways like a machine, that it operates on knowledge encoded in some internal language, and that thought can be used to choose what actions to take.
- Mathematicians provided the tools to manipulate statements of logical certainty as well as uncertain, probabilistic statements. They also set the groundwork for understanding computation and reasoning about algorithms.
- Economists formalized the problem of making decisions that maximize the expected outcome to the decision maker.
- Neuroscientists discovered some facts about how the brain works and the ways in which it is similar to and different from computers.
- Psychologists adopted the idea that humans and animals can be considered information-processing machines. Linguists showed that language use fits into this model.
- Computer engineers provided the ever-more-powerful machines that make AI applications possible.
- Control theory deals with designing devices that act optimally on the basis of feedback from the environment. Initially, the mathematical tools of control theory were quite different from AI, but the fields are coming closer together.
- The history of AI has had cycles of success, misplaced optimism, and resulting cutbacks in enthusiasm and funding. There have also been cycles of introducing new creative approaches and systematically refining the best ones.
- AI has advanced more rapidly in the past decade because of greater use of the scientific method in experimenting with and comparing approaches.
- Recent progress in understanding the theoretical basis for intelligence has gone hand in hand with improvements in the capabilities of real systems. The subfields of AI have become more integrated, and AI has found common ground with other disciplines.

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## BIBLIOGRAPHICAL AND HISTORICAL NOTES

The methodological status of artificial intelligence is investigated in *The Sciences of the Artificial*, by Herb Simon (1981), which discusses research areas concerned with complex artifacts. It explains how AI can be viewed as both science and mathematics. Cohen (1995) gives an overview of experimental methodology within AI.

The Turing Test (Turing, 1950) is discussed by Shieber (1994), who severely criticizes the usefulness of its instantiation in the Loebner Prize competition, and by Ford and Hayes (1995), who argue that the test itself is not helpful for AI. Bringsjord (2008) gives advice for a Turing Test judge. Shieber (2004) and Epstein *et al.* (2008) collect a number of essays on the Turing Test. *Artificial Intelligence: The Very Idea*, by John Haugeland (1985), gives a

readable account of the philosophical and practical problems of AI. Significant early papers in AI are anthologized in the collections by Webber and Nilsson (1981) and by Luger (1995). The *Encyclopedia of AI* (Shapiro, 1992) contains survey articles on almost every topic in AI, as does Wikipedia. These articles usually provide a good entry point into the research literature on each topic. An insightful and comprehensive history of AI is given by Nils Nilsson (2009), one of the early pioneers of the field.

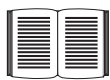
The most recent work appears in the proceedings of the major AI conferences: the biennial International Joint Conference on AI (IJCAI), the annual European Conference on AI (ECAI), and the National Conference on AI, more often known as AAAI, after its sponsoring organization. The major journals for general AI are *Artificial Intelligence*, *Computational Intelligence*, the *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *IEEE Intelligent Systems*, and the electronic *Journal of Artificial Intelligence Research*. There are also many conferences and journals devoted to specific areas, which we cover in the appropriate chapters. The main professional societies for AI are the American Association for Artificial Intelligence (AAAI), the ACM Special Interest Group in Artificial Intelligence (SIGART), and the Society for Artificial Intelligence and Simulation of Behaviour (AISB). AAAI's *AI Magazine* contains many topical and tutorial articles, and its Web site, [aaai.org](http://aaai.org), contains news, tutorials, and background information.

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## EXERCISES

These exercises are intended to stimulate discussion, and some might be set as term projects. Alternatively, preliminary attempts can be made now, and these attempts can be reviewed after the completion of the book.

**1.1** Define in your own words: (a) intelligence, (b) artificial intelligence, (c) agent, (d) rationality, (e) logical reasoning.



**1.2** Read Turing's original paper on AI (Turing, 1950). In the paper, he discusses several objections to his proposed enterprise and his test for intelligence. Which objections still carry weight? Are his refutations valid? Can you think of new objections arising from developments since he wrote the paper? In the paper, he predicts that, by the year 2000, a computer will have a 30% chance of passing a five-minute Turing Test with an unskilled interrogator. What chance do you think a computer would have today? In another 50 years?

**1.3** Are reflex actions (such as flinching from a hot stove) rational? Are they intelligent?

**1.4** Suppose we extend Evans's ANALOGY program so that it can score 200 on a standard IQ test. Would we then have a program more intelligent than a human? Explain.

**1.5** The neural structure of the sea slug *Aplysia* has been widely studied (first by Nobel Laureate Eric Kandel) because it has only about 20,000 neurons, most of them large and easily manipulated. Assuming that the cycle time for an *Aplysia* neuron is roughly the same as for a human neuron, how does the computational power, in terms of memory updates per second, compare with the high-end computer described in Figure 1.3?

**1.6** How could introspection—reporting on one’s inner thoughts—be inaccurate? Could I be wrong about what I’m thinking? Discuss.

**1.7** To what extent are the following computer systems instances of artificial intelligence:

- Supermarket bar code scanners.
- Web search engines.
- Voice-activated telephone menus.
- Internet routing algorithms that respond dynamically to the state of the network.

**1.8** Many of the computational models of cognitive activities that have been proposed involve quite complex mathematical operations, such as convolving an image with a Gaussian or finding a minimum of the entropy function. Most humans (and certainly all animals) never learn this kind of mathematics at all, almost no one learns it before college, and almost no one can compute the convolution of a function with a Gaussian in their head. What sense does it make to say that the “vision system” is doing this kind of mathematics, whereas the actual person has no idea how to do it?

**1.9** Why would evolution tend to result in systems that act rationally? What goals are such systems designed to achieve?

**1.10** Is AI a science, or is it engineering? Or neither or both? Explain.

**1.11** “Surely computers cannot be intelligent—they can do only what their programmers tell them.” Is the latter statement true, and does it imply the former?

**1.12** “Surely animals cannot be intelligent—they can do only what their genes tell them.” Is the latter statement true, and does it imply the former?

**1.13** “Surely animals, humans, and computers cannot be intelligent—they can do only what their constituent atoms are told to do by the laws of physics.” Is the latter statement true, and does it imply the former?



**1.14** Examine the AI literature to discover whether the following tasks can currently be solved by computers:

- a. Playing a decent game of table tennis (Ping-Pong).
- b. Driving in the center of Cairo, Egypt.
- c. Driving in Victorville, California.
- d. Buying a week’s worth of groceries at the market.
- e. Buying a week’s worth of groceries on the Web.
- f. Playing a decent game of bridge at a competitive level.
- g. Discovering and proving new mathematical theorems.
- h. Writing an intentionally funny story.
- i. Giving competent legal advice in a specialized area of law.
- j. Translating spoken English into spoken Swedish in real time.
- k. Performing a complex surgical operation.

For the currently infeasible tasks, try to find out what the difficulties are and predict when, if ever, they will be overcome.

**1.15** Various subfields of AI have held contests by defining a standard task and inviting researchers to do their best. Examples include the DARPA Grand Challenge for robotic cars, The International Planning Competition, the Robocup robotic soccer league, the TREC information retrieval event, and contests in machine translation, speech recognition. Investigate five of these contests, and describe the progress made over the years. To what degree have the contests advanced the state of the art in AI? To what degree do they hurt the field by drawing energy away from new ideas?