Stuart Russell
Peter Norvig

Artificial Intelligence
A Modern Approach
Third Edition

Course Title:	Introduction to Artificial Intelligence and Machine Learning
Course Code:	CC-309
Course Credit:	3
Session Per Week:	4
Total Teaching Hours:	40 Hours

AIM

This course introduces students the fundamentals of artificial intelligence and machine learning and how different business and organizations are trying to use it some way or other to build smart systems, quick decision making etc.

LEARNING OUTCOMES

On the completion of the course students will:

1. Understand the role of basic knowledge representation in AI.
2. Learn how to use AI for problem solving.
3. Deduce the use of NLP applications.
4. Understand the concept machine learning and its types.

DETAIL SYLLABUS

Unit-1 **10 Hours**

Fundamentals of Artificial intelligence and Intelligent Agent
What is AI?

- Acting humanly: The Turing Test approach,
- Thinking humanly: The cognitive modeling approach,
- Thinking rationally: The "laws of thought" approach,
- Acting rationally: The rational agent approach

State of Art (Applications of AI)
Agents and Environments
The Concept of Rationality
The Nature of Environment
The Structure of Agents.
Case Study: Create a new health care market with AI

Unit-2 **10 Hours**

Problem Solving by searching
Problem-Solving Agents

- Well defined problem and solutions
- Formulating problems

Example Problems

- Toy problems

Searching for Solution
Uninformed Search Strategies

- Concept of BFS
- Concept of DFS
- Depth-limited search
- Iterative deepening DFS
- Bidirectional search

Informed (Heuristic) Search Strategies

- Concept of Greedy BFS
- A* search: Minimizing the total estimated solution cost

Case Study: Applications of AI in transportation.

Unit-3 **10 Hours**

Natural language processing
Language Models

- N-gram character models
- N-gram word models

Text classification

- Classification by data compression

Information retrieval

- The page rank algorithm
- The HITS algorithm

Information extraction

- Finite state automata for information extraction
- Probabilistic model for information extraction.

Examples: Applications of Natural Language Processing.
Case Study: Automated Voice Assistants, Chat bots.

Unit-4 **10 Hours**

Machine Learning
Machine Learning in the bigger picture
Areas of machine learning and grades for supervision
Supervised Learning strategies - regression versus classification
Unsupervised problem solving-clustering
Types of Machine Learning:

- Supervised, Unsupervised
- Semi-Supervised Learning
- Reinforcement Learning

How Supervised Learning works.
Why the model works on new data.
Case Study: Recommendation Based Systems, At Microsoft, AI is a Big, Big Deal.

TEXT BOOKS:

1) Artificial Intelligence: A Modern Approach, Stuart Russel, Peter Norvig, Third Edition
2) Machine Learning for Developers: Claudio Delrieux
3) The Hundred-Page Machine Learning Book : Andriy Burkov

REFERENCE BOOKS:

1) Artificial Intelligence, 2nd Edition, Rich and Knight
2) Machine Learning, Tom M Mitchell
3) Artificial Intelligence: A New Synthesis, Nils J. Nilsson

4) Artificial Intelligence in the real world, The Economist Intelligence Briefing Paper, Wipro [Case Study]
5) Getting Smarter by the day: How AI is elevating the performance of global companies. [Case Study]

WEB RESOURCES:

1)https://www.tutorialspoint.com/artificial_intelligence/artificial_intelligence_quick_guide.htm
2)https://www.geeksforgeeks.org/introduction-to-natural-language-processing/
3)https://www.geeksforgeeks.org/introduction-machine-learning/
4)https://www.geeksforgeeks.org/getting-started-machine-learning/
5)https://www.lanner-america.com/blog/examples-artificial-intelligence-applications-transportation/
6)https://medium.com/@datamonsters/artificial-neural-networks-in-natural-language-processing-bcf62aa9151a
7)https://www.tutorialspoint.com/machine_learning/index.htm

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?

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.

RATIONALITY

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-

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

Figure 1.1 Some definitions of artificial intelligence, organized into four categories.

volving observations and hypotheses about human behavior. A rationalist[1] 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
- **natural language processing** to enable it to communicate successfully in English;

KNOWLEDGE REPRESENTATION
- **knowledge representation** to store what it knows or hears;

AUTOMATED REASONING
- **automated reasoning** to use the stored information to answer questions and to draw new conclusions;

MACHINE LEARNING
- **machine learning** to adapt to new circumstances and to detect and extrapolate patterns.

[1] 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,

TOTAL TURING TEST

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

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

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

COGNITIVE SCIENCE

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 **syllogisms** 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 Leibnitz 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.

RATIONALISM

DUALISM

MATERIALISM

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*,[2] 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.[3] 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.

EMPIRICISM

INDUCTION

LOGICAL POSITIVISM

OBSERVATION SENTENCES

CONFIRMATION THEORY

[2] 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.

[3] 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.

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.[4] 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

TRACTABILITY

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.

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

[4] 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?

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

UTILITY

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**

GAME THEORY

theory (see also Luce and Raiffa, 1957) included the surprising result that, for some games,

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.

OPERATIONS RESEARCH

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).

SATISFICING

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."[5] 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.

NEUROSCIENCE

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.[6] 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.[7] Nicolas Rashevsky (1936, 1938) was the first to apply mathematical models to the study of the nervous sytem.

NEURON

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

[6] Many cite Alexander Hood (1824) as a possible prior source.

[7] 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.

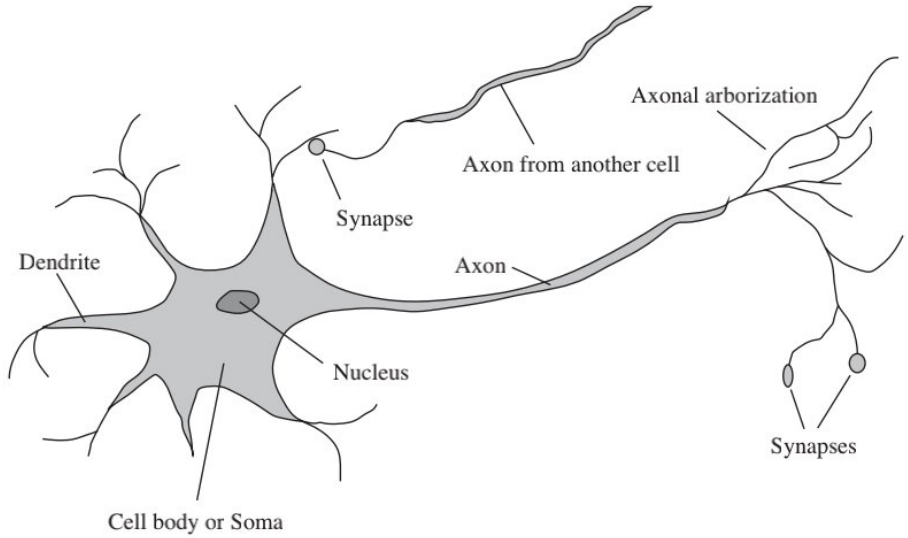


Figure 1.2 The parts of a nerve cell or neuron. Each neuron consists of a cell body, or soma, that contains a cell nucleus. Branching out from the cell body are a number of fibers called dendrites and a single long fiber called the axon. The axon stretches out for a long distance, much longer than the 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^{11} bits RAM	10^{11} neurons
	10^{15} bits disk	10^{13} bits disk	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.)

SINGULARITY

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

BEHAVIORISM

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

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,[8] 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.[9] 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.

[8] Heath Robinson was a cartoonist famous for his depictions of whimsical and absurdly complicated contraptions for everyday tasks such as buttering toast.

[9] 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

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 the 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.

OBJECTIVE FUNCTION

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

mathematics, but von Neumann reportedly said, "If it isn't now, it will be someday." Minsky was later to prove influential theorems showing the limitations of neural network research.

There were a number of early examples of work that can be characterized as AI, but Alan Turing's vision was perhaps the most influential. He gave lectures on the topic as early as 1947 at the London Mathematical Society and articulated a persuasive agenda in his 1950 article "Computing Machinery and Intelligence." Therein, he introduced the Turing Test, machine learning, genetic algorithms, and reinforcement learning. He proposed the *Child Programme* idea, explaining "Instead of trying to produce a programme to simulate the adult mind, why not rather try to produce one which simulated the child's?"

1.3.2 The birth of artificial intelligence (1956)

Princeton was home to another influential figure in AI, John McCarthy. After receiving his PhD there in 1951 and working for two years as an instructor, McCarthy moved to Stanford and then to Dartmouth College, which was to become the official birthplace of the field. McCarthy convinced Minsky, Claude Shannon, and Nathaniel Rochester to help him bring together U.S. researchers interested in automata theory, neural nets, and the study of intelligence. They organized a two-month workshop at Dartmouth in the summer of 1956. The proposal states:[10]

> We propose that a 2 month, 10 man study of artificial intelligence be carried out during the summer of 1956 at Dartmouth College in Hanover, New Hampshire. The study is to proceed on the basis of the conjecture that every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it. An attempt will be made to find how to make machines use language, form abstractions and concepts, solve kinds of problems now reserved for humans, and improve themselves. We think that a significant advance can be made in one or more of these problems if a carefully selected group of scientists work on it together for a summer.

There were 10 attendees in all, including Trenchard More from Princeton, Arthur Samuel from IBM, and Ray Solomonoff and Oliver Selfridge from MIT.

Two researchers from Carnegie Tech,[11] Allen Newell and Herbert Simon, rather stole the show. Although the others had ideas and in some cases programs for particular applications such as checkers, Newell and Simon already had a reasoning program, the Logic Theorist (LT), about which Simon claimed, "We have invented a computer program capable of thinking non-numerically, and thereby solved the venerable mind–body problem."[12] Soon after the workshop, the program was able to prove most of the theorems in Chapter 2 of Rus-

[10] This was the first official usage of McCarthy's term *artificial intelligence*. Perhaps "computational rationality" would have been more precise and less threatening, but "AI" has stuck. At the 50th anniversary of the Dartmouth conference, McCarthy stated that he resisted the terms "computer" or "computational" in deference to Norbert Weiner, who was promoting analog cybernetic devices rather than digital computers.

[11] Now Carnegie Mellon University (CMU).

[12] Newell and Simon also invented a list-processing language, IPL, to write LT. They had no compiler and translated it into machine code by hand. To avoid errors, they worked in parallel, calling out binary numbers to each other as they wrote each instruction to make sure they agreed.

sell and Whitehead's *Principia Mathematica*. Russell was reportedly delighted when Simon showed him that the program had come up with a proof for one theorem that was shorter than the one in *Principia*. The editors of the *Journal of Symbolic Logic* were less impressed; they rejected a paper coauthored by Newell, Simon, and Logic Theorist.

The Dartmouth workshop did not lead to any new breakthroughs, but it did introduce all the major figures to each other. For the next 20 years, the field would be dominated by these people and their students and colleagues at MIT, CMU, Stanford, and IBM.

Looking at the proposal for the Dartmouth workshop (McCarthy *et al.*, 1955), we can see why it was necessary for AI to become a separate field. Why couldn't all the work done in AI have taken place under the name of control theory or operations research or decision theory, which, after all, have objectives similar to those of AI? Or why isn't AI a branch of mathematics? The first answer is that AI from the start embraced the idea of duplicating human faculties such as creativity, self-improvement, and language use. None of the other fields were addressing these issues. The second answer is methodology. AI is the only one of these fields that is clearly a branch of computer science (although operations research does share an emphasis on computer simulations), and AI is the only field to attempt to build machines that will function autonomously in complex, changing environments.

1.3.3 Early enthusiasm, great expectations (1952–1969)

The early years of AI were full of successes—in a limited way. Given the primitive computers and programming tools of the time and the fact that only a few years earlier computers were seen as things that could do arithmetic and no more, it was astonishing whenever a computer did anything remotely clever. The intellectual establishment, by and large, preferred to believe that "a machine can never do X." (See Chapter 26 for a long list of X's gathered by Turing.) AI researchers naturally responded by demonstrating one X after another. John McCarthy referred to this period as the "Look, Ma, no hands!" era.

Newell and Simon's early success was followed up with the General Problem Solver, or GPS. Unlike Logic Theorist, this program was designed from the start to imitate human problem-solving protocols. Within the limited class of puzzles it could handle, it turned out that the order in which the program considered subgoals and possible actions was similar to that in which humans approached the same problems. Thus, GPS was probably the first program to embody the "thinking humanly" approach. The success of GPS and subsequent programs as models of cognition led Newell and Simon (1976) to formulate the famous **physical symbol system** hypothesis, which states that "a physical symbol system has the necessary and sufficient means for general intelligent action." What they meant is that any system (human or machine) exhibiting intelligence must operate by manipulating data structures composed of symbols. We will see later that this hypothesis has been challenged from many directions.

PHYSICAL SYMBOL SYSTEM

At IBM, Nathaniel Rochester and his colleagues produced some of the first AI programs. Herbert Gelernter (1959) constructed the Geometry Theorem Prover, which was able to prove theorems that many students of mathematics would find quite tricky. Starting in 1952, Arthur Samuel wrote a series of programs for checkers (draughts) that eventually learned to play at a strong amateur level. Along the way, he disproved the idea that comput-

ers can do only what they are told to: his program quickly learned to play a better game than its creator. The program was demonstrated on television in February 1956, creating a strong impression. Like Turing, Samuel had trouble finding computer time. Working at night, he used machines that were still on the testing floor at IBM's manufacturing plant. Chapter 5 covers game playing, and Chapter 21 explains the learning techniques used by Samuel.

John McCarthy moved from Dartmouth to MIT and there made three crucial contributions in one historic year: 1958. In MIT AI Lab Memo No. 1, McCarthy defined the high-level language **Lisp**, which was to become the dominant AI programming language for the next 30 years. With Lisp, McCarthy had the tool he needed, but access to scarce and expensive computing resources was also a serious problem. In response, he and others at MIT invented time sharing. Also in 1958, McCarthy published a paper entitled *Programs with Common Sense*, in which he described the Advice Taker, a hypothetical program that can be seen as the first complete AI system. Like the Logic Theorist and Geometry Theorem Prover, McCarthy's program was designed to use knowledge to search for solutions to problems. But unlike the others, it was to embody general knowledge of the world. For example, he showed how some simple axioms would enable the program to generate a plan to drive to the airport. The program was also designed to accept new axioms in the normal course of operation, thereby allowing it to achieve competence in new areas *without being reprogrammed*. The Advice Taker thus embodied the central principles of knowledge representation and reasoning: that it is useful to have a formal, explicit representation of the world and its workings and to be able to manipulate that representation with deductive processes. It is remarkable how much of the 1958 paper remains relevant today.

LISP

1958 also marked the year that Marvin Minsky moved to MIT. His initial collaboration with McCarthy did not last, however. McCarthy stressed representation and reasoning in formal logic, whereas Minsky was more interested in getting programs to work and eventually developed an anti-logic outlook. In 1963, McCarthy started the AI lab at Stanford. His plan to use logic to build the ultimate Advice Taker was advanced by J. A. Robinson's discovery in 1965 of the resolution method (a complete theorem-proving algorithm for first-order logic; see Chapter 9). Work at Stanford emphasized general-purpose methods for logical reasoning. Applications of logic included Cordell Green's question-answering and planning systems (Green, 1969b) and the Shakey robotics project at the Stanford Research Institute (SRI). The latter project, discussed further in Chapter 25, was the first to demonstrate the complete integration of logical reasoning and physical activity.

Minsky supervised a series of students who chose limited problems that appeared to require intelligence to solve. These limited domains became known as **microworlds**. James Slagle's SAINT program (1963) was able to solve closed-form calculus integration problems typical of first-year college courses. Tom Evans's ANALOGY program (1968) solved geometric analogy problems that appear in IQ tests. Daniel Bobrow's STUDENT program (1967) solved algebra story problems, such as the following:

MICROWORLD

> If the number of customers Tom gets is twice the square of 20 percent of the number of advertisements he runs, and the number of advertisements he runs is 45, what is the number of customers Tom gets?

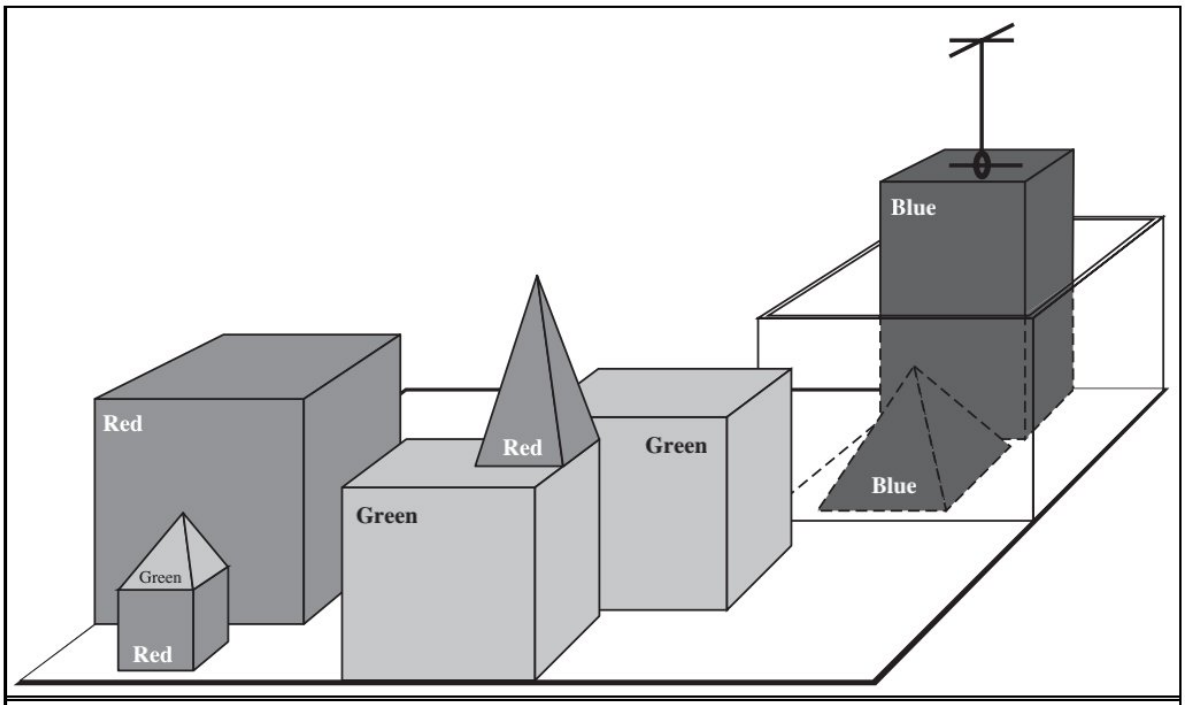


Figure 1.4 A scene from the blocks world. SHRDLU (Winograd, 1972) has just completed the command "Find a block which is taller than the one you are holding and put it in the box."

The most famous microworld was the blocks world, which consists of a set of solid blocks placed on a tabletop (or more often, a simulation of a tabletop), as shown in Figure 1.4. A typical task in this world is to rearrange the blocks in a certain way, using a robot hand that can pick up one block at a time. The blocks world was home to the vision project of David Huffman (1971), the vision and constraint-propagation work of David Waltz (1975), the learning theory of Patrick Winston (1970), the natural-language-understanding program of Terry Winograd (1972), and the planner of Scott Fahlman (1974).

Early work building on the neural networks of McCulloch and Pitts also flourished. The work of Winograd and Cowan (1963) showed how a large number of elements could collectively represent an individual concept, with a corresponding increase in robustness and parallelism. Hebb's learning methods were enhanced by Bernie Widrow (Widrow and Hoff, 1960; Widrow, 1962), who called his networks **adalines**, and by Frank Rosenblatt (1962) with his **perceptrons**. The **perceptron convergence theorem** (Block *et al.*, 1962) says that the learning algorithm can adjust the connection strengths of a perceptron to match any input data, provided such a match exists. These topics are covered in Chapter 20.

1.3.4 A dose of reality (1966–1973)

From the beginning, AI researchers were not shy about making predictions of their coming successes. The following statement by Herbert Simon in 1957 is often quoted:

> It is not my aim to surprise or shock you—but the simplest way I can summarize is to say that there are now in the world machines that think, that learn and that create. Moreover,

> their ability to do these things is going to increase rapidly until—in a visible future—the range of problems they can handle will be coextensive with the range to which the human mind has been applied.

Terms such as "visible future" can be interpreted in various ways, but Simon also made more concrete predictions: that within 10 years a computer would be chess champion, and a significant mathematical theorem would be proved by machine. These predictions came true (or approximately true) within 40 years rather than 10. Simon's overconfidence was due to the promising performance of early AI systems on simple examples. In almost all cases, however, these early systems turned out to fail miserably when tried out on wider selections of problems and on more difficult problems.

The first kind of difficulty arose because most early programs knew nothing of their subject matter; they succeeded by means of simple syntactic manipulations. A typical story occurred in early machine translation efforts, which were generously funded by the U.S. National Research Council in an attempt to speed up the translation of Russian scientific papers in the wake of the Sputnik launch in 1957. It was thought initially that simple syntactic transformations based on the grammars of Russian and English, and word replacement from an electronic dictionary, would suffice to preserve the exact meanings of sentences. The fact is that accurate translation requires background knowledge in order to resolve ambiguity and establish the content of the sentence. The famous retranslation of "the spirit is willing but the flesh is weak" as "the vodka is good but the meat is rotten" illustrates the difficulties encountered. In 1966, a report by an advisory committee found that "there has been no machine translation of general scientific text, and none is in immediate prospect." All U.S. government funding for academic translation projects was canceled. Today, machine translation is an imperfect but widely used tool for technical, commercial, government, and Internet documents.

The second kind of difficulty was the intractability of many of the problems that AI was attempting to solve. Most of the early AI programs solved problems by trying out different combinations of steps until the solution was found. This strategy worked initially because microworlds contained very few objects and hence very few possible actions and very short solution sequences. Before the theory of computational complexity was developed, it was widely thought that "scaling up" to larger problems was simply a matter of faster hardware and larger memories. The optimism that accompanied the development of resolution theorem proving, for example, was soon dampened when researchers failed to prove theorems involving more than a few dozen facts. *The fact that a program can find a solution in principle does not mean that the program contains any of the mechanisms needed to find it in practice.*

MACHINE EVOLUTION
GENETIC ALGORITHM

The illusion of unlimited computational power was not confined to problem-solving programs. Early experiments in **machine evolution** (now called **genetic algorithms**) (Friedberg, 1958; Friedberg *et al.*, 1959) were based on the undoubtedly correct belief that by making an appropriate series of small mutations to a machine-code program, one can generate a program with good performance for any particular task. The idea, then, was to try random mutations with a selection process to preserve mutations that seemed useful. Despite thousands of hours of CPU time, almost no progress was demonstrated. Modern genetic algorithms use better representations and have shown more success.

Failure to come to grips with the "combinatorial explosion" was one of the main criticisms of AI contained in the Lighthill report (Lighthill, 1973), which formed the basis for the decision by the British government to end support for AI research in all but two universities. (Oral tradition paints a somewhat different and more colorful picture, with political ambitions and personal animosities whose description is beside the point.)

A third difficulty arose because of some fundamental limitations on the basic structures being used to generate intelligent behavior. For example, Minsky and Papert's book *Perceptrons* (1969) proved that, although perceptrons (a simple form of neural network) could be shown to learn anything they were capable of representing, they could represent very little. In particular, a two-input perceptron (restricted to be simpler than the form Rosenblatt originally studied) could not be trained to recognize when its two inputs were different. Although their results did not apply to more complex, multilayer networks, research funding for neural-net research soon dwindled to almost nothing. Ironically, the new back-propagation learning algorithms for multilayer networks that were to cause an enormous resurgence in neural-net research in the late 1980s were actually discovered first in 1969 (Bryson and Ho, 1969).

1.3.5 Knowledge-based systems: The key to power? (1969–1979)

The picture of problem solving that had arisen during the first decade of AI research was of a general-purpose search mechanism trying to string together elementary reasoning steps to find complete solutions. Such approaches have been called **weak methods** because, although general, they do not scale up to large or difficult problem instances. The alternative to weak methods is to use more powerful, domain-specific knowledge that allows larger reasoning steps and can more easily handle typically occurring cases in narrow areas of expertise. One might say that to solve a hard problem, you have to almost know the answer already.

WEAK METHOD

The DENDRAL program (Buchanan *et al.*, 1969) was an early example of this approach. It was developed at Stanford, where Ed Feigenbaum (a former student of Herbert Simon), Bruce Buchanan (a philosopher turned computer scientist), and Joshua Lederberg (a Nobel laureate geneticist) teamed up to solve the problem of inferring molecular structure from the information provided by a mass spectrometer. The input to the program consists of the elementary formula of the molecule (e.g., $C_6H_{13}NO_2$) and the mass spectrum giving the masses of the various fragments of the molecule generated when it is bombarded by an electron beam. For example, the mass spectrum might contain a peak at $m = 15$, corresponding to the mass of a methyl (CH_3) fragment.

The naive version of the program generated all possible structures consistent with the formula, and then predicted what mass spectrum would be observed for each, comparing this with the actual spectrum. As one might expect, this is intractable for even moderate-sized molecules. The DENDRAL researchers consulted analytical chemists and found that they worked by looking for well-known patterns of peaks in the spectrum that suggested common substructures in the molecule. For example, the following rule is used to recognize a ketone (C=O) subgroup (which weighs 28):

> **if** there are two peaks at x_1 and x_2 such that
> (a) $x_1 + x_2 = M + 28$ (M is the mass of the whole molecule);

(b) $x_1 - 28$ is a high peak;
(c) $x_2 - 28$ is a high peak;
(d) At least one of x_1 and x_2 is high.
then there is a ketone subgroup

Recognizing that the molecule contains a particular substructure reduces the number of possible candidates enormously. DENDRAL was powerful because

> All the relevant theoretical knowledge to solve these problems has been mapped over from its general form in the [spectrum prediction component] ("first principles") to efficient special forms ("cookbook recipes"). (Feigenbaum *et al.*, 1971)

The significance of DENDRAL was that it was the first successful *knowledge-intensive* system: its expertise derived from large numbers of special-purpose rules. Later systems also incorporated the main theme of McCarthy's Advice Taker approach—the clean separation of the knowledge (in the form of rules) from the reasoning component.

With this lesson in mind, Feigenbaum and others at Stanford began the Heuristic Programming Project (HPP) to investigate the extent to which the new methodology of **expert systems** could be applied to other areas of human expertise. The next major effort was in the area of medical diagnosis. Feigenbaum, Buchanan, and Dr. Edward Shortliffe developed MYCIN to diagnose blood infections. With about 450 rules, MYCIN was able to perform as well as some experts, and considerably better than junior doctors. It also contained two major differences from DENDRAL. First, unlike the DENDRAL rules, no general theoretical model existed from which the MYCIN rules could be deduced. They had to be acquired from extensive interviewing of experts, who in turn acquired them from textbooks, other experts, and direct experience of cases. Second, the rules had to reflect the uncertainty associated with medical knowledge. MYCIN incorporated a calculus of uncertainty called **certainty factors** (see Chapter 14), which seemed (at the time) to fit well with how doctors assessed the impact of evidence on the diagnosis.

EXPERT SYSTEMS

CERTAINTY FACTOR

The importance of domain knowledge was also apparent in the area of understanding natural language. Although Winograd's SHRDLU system for understanding natural language had engendered a good deal of excitement, its dependence on syntactic analysis caused some of the same problems as occurred in the early machine translation work. It was able to overcome ambiguity and understand pronoun references, but this was mainly because it was designed specifically for one area—the blocks world. Several researchers, including Eugene Charniak, a fellow graduate student of Winograd's at MIT, suggested that robust language understanding would require general knowledge about the world and a general method for using that knowledge.

At Yale, linguist-turned-AI-researcher Roger Schank emphasized this point, claiming, "There is no such thing as syntax," which upset a lot of linguists but did serve to start a useful discussion. Schank and his students built a series of programs (Schank and Abelson, 1977; Wilensky, 1978; Schank and Riesbeck, 1981; Dyer, 1983) that all had the task of understanding natural language. The emphasis, however, was less on language *per se* and more on the problems of representing and reasoning with the knowledge required for language understanding. The problems included representing stereotypical situations (Cullingford, 1981),

describing human memory organization (Rieger, 1976; Kolodner, 1983), and understanding plans and goals (Wilensky, 1983).

The widespread growth of applications to real-world problems caused a concurrent increase in the demands for workable knowledge representation schemes. A large number of different representation and reasoning languages were developed. Some were based on logic—for example, the Prolog language became popular in Europe, and the PLANNER family in the United States. Others, following Minsky's idea of **frames** (1975), adopted a more structured approach, assembling facts about particular object and event types and arranging the types into a large taxonomic hierarchy analogous to a biological taxonomy.

FRAMES

1.3.6 AI becomes an industry (1980–present)

The first successful commercial expert system, R1, began operation at the Digital Equipment Corporation (McDermott, 1982). The program helped configure orders for new computer systems; by 1986, it was saving the company an estimated $40 million a year. By 1988, DEC's AI group had 40 expert systems deployed, with more on the way. DuPont had 100 in use and 500 in development, saving an estimated $10 million a year. Nearly every major U.S. corporation had its own AI group and was either using or investigating expert systems.

In 1981, the Japanese announced the "Fifth Generation" project, a 10-year plan to build intelligent computers running Prolog. In response, the United States formed the Microelectronics and Computer Technology Corporation (MCC) as a research consortium designed to assure national competitiveness. In both cases, AI was part of a broad effort, including chip design and human-interface research. In Britain, the Alvey report reinstated the funding that was cut by the Lighthill report.[13] In all three countries, however, the projects never met their ambitious goals.

Overall, the AI industry boomed from a few million dollars in 1980 to billions of dollars in 1988, including hundreds of companies building expert systems, vision systems, robots, and software and hardware specialized for these purposes. Soon after that came a period called the "AI Winter," in which many companies fell by the wayside as they failed to deliver on extravagant promises.

1.3.7 The return of neural networks (1986–present)

BACK-PROPAGATION

In the mid-1980s at least four different groups reinvented the **back-propagation** learning algorithm first found in 1969 by Bryson and Ho. The algorithm was applied to many learning problems in computer science and psychology, and the widespread dissemination of the results in the collection *Parallel Distributed Processing* (Rumelhart and McClelland, 1986) caused great excitement.

CONNECTIONIST

These so-called **connectionist** models of intelligent systems were seen by some as direct competitors both to the symbolic models promoted by Newell and Simon and to the logicist approach of McCarthy and others (Smolensky, 1988). It might seem obvious that at some level humans manipulate symbols—in fact, Terrence Deacon's book *The Symbolic*

[13] To save embarrassment, a new field called IKBS (Intelligent Knowledge-Based Systems) was invented because Artificial Intelligence had been officially canceled.

Species (1997) suggests that this is the *defining characteristic* of humans—but the most ardent connectionists questioned whether symbol manipulation had any real explanatory role in detailed models of cognition. This question remains unanswered, but the current view is that connectionist and symbolic approaches are complementary, not competing. As occurred with the separation of AI and cognitive science, modern neural network research has bifurcated into two fields, one concerned with creating effective network architectures and algorithms and understanding their mathematical properties, the other concerned with careful modeling of the empirical properties of actual neurons and ensembles of neurons.

1.3.8 AI adopts the scientific method (1987–present)

Recent years have seen a revolution in both the content and the methodology of work in artificial intelligence.[14] It is now more common to build on existing theories than to propose brand-new ones, to base claims on rigorous theorems or hard experimental evidence rather than on intuition, and to show relevance to real-world applications rather than toy examples.

AI was founded in part as a rebellion against the limitations of existing fields like control theory and statistics, but now it is embracing those fields. As David McAllester (1998) put it:

> In the early period of AI it seemed plausible that new forms of symbolic computation, e.g., frames and semantic networks, made much of classical theory obsolete. This led to a form of isolationism in which AI became largely separated from the rest of computer science. This isolationism is currently being abandoned. There is a recognition that machine learning should not be isolated from information theory, that uncertain reasoning should not be isolated from stochastic modeling, that search should not be isolated from classical optimization and control, and that automated reasoning should not be isolated from formal methods and static analysis.

In terms of methodology, AI has finally come firmly under the scientific method. To be accepted, hypotheses must be subjected to rigorous empirical experiments, and the results must be analyzed statistically for their importance (Cohen, 1995). It is now possible to replicate experiments by using shared repositories of test data and code.

The field of speech recognition illustrates the pattern. In the 1970s, a wide variety of different architectures and approaches were tried. Many of these were rather *ad hoc* and fragile, and were demonstrated on only a few specially selected examples. In recent years, approaches based on **hidden Markov models** (HMMs) have come to dominate the area. Two aspects of HMMs are relevant. First, they are based on a rigorous mathematical theory. This has allowed speech researchers to build on several decades of mathematical results developed in other fields. Second, they are generated by a process of training on a large corpus of real speech data. This ensures that the performance is robust, and in rigorous blind tests the HMMs have been improving their scores steadily. Speech technology and the related field of handwritten character recognition are already making the transition to widespread industrial

HIDDEN MARKOV MODELS

[14] Some have characterized this change as a victory of the **neats**—those who think that AI theories should be grounded in mathematical rigor—over the **scruffies**—those who would rather try out lots of ideas, write some programs, and then assess what seems to be working. Both approaches are important. A shift toward neatness implies that the field has reached a level of stability and maturity. Whether that stability will be disrupted by a new scruffy idea is another question.

and consumer applications. Note that there is no scientific claim that humans use HMMs to recognize speech; rather, HMMs provide a mathematical framework for understanding the problem and support the engineering claim that they work well in practice.

Machine translation follows the same course as speech recognition. In the 1950s there was initial enthusiasm for an approach based on sequences of words, with models learned according to the principles of information theory. That approach fell out of favor in the 1960s, but returned in the late 1990s and now dominates the field.

Neural networks also fit this trend. Much of the work on neural nets in the 1980s was done in an attempt to scope out what could be done and to learn how neural nets differ from "traditional" techniques. Using improved methodology and theoretical frameworks, the field arrived at an understanding in which neural nets can now be compared with corresponding techniques from statistics, pattern recognition, and machine learning, and the most promising technique can be applied to each application. As a result of these developments, so-called

DATA MINING

data mining technology has spawned a vigorous new industry.

Judea Pearl's (1988) *Probabilistic Reasoning in Intelligent Systems* led to a new acceptance of probability and decision theory in AI, following a resurgence of interest epitomized

BAYESIAN NETWORK

by Peter Cheeseman's (1985) article "In Defense of Probability." The **Bayesian network** formalism was invented to allow efficient representation of, and rigorous reasoning with, uncertain knowledge. This approach largely overcomes many problems of the probabilistic reasoning systems of the 1960s and 1970s; it now dominates AI research on uncertain reasoning and expert systems. The approach allows for learning from experience, and it combines the best of classical AI and neural nets. Work by Judea Pearl (1982a) and by Eric Horvitz and David Heckerman (Horvitz and Heckerman, 1986; Horvitz *et al.*, 1986) promoted the idea of *normative* expert systems: ones that act rationally according to the laws of decision theory and do not try to imitate the thought steps of human experts. The Windows$^{\text{TM}}$ operating system includes several normative diagnostic expert systems for correcting problems. Chapters 13 to 16 cover this area.

Similar gentle revolutions have occurred in robotics, computer vision, and knowledge representation. A better understanding of the problems and their complexity properties, combined with increased mathematical sophistication, has led to workable research agendas and robust methods. Although increased formalization and specialization led fields such as vision and robotics to become somewhat isolated from "mainstream" AI in the 1990s, this trend has reversed in recent years as tools from machine learning in particular have proved effective for many problems. The process of reintegration is already yielding significant benefits

1.3.9 The emergence of intelligent agents (1995–present)

Perhaps encouraged by the progress in solving the subproblems of AI, researchers have also started to look at the "whole agent" problem again. The work of Allen Newell, John Laird, and Paul Rosenbloom on SOAR (Newell, 1990; Laird *et al.*, 1987) is the best-known example of a complete agent architecture. One of the most important environments for intelligent agents is the Internet. AI systems have become so common in Web-based applications that the "-bot" suffix has entered everyday language. Moreover, AI technologies underlie many

Internet tools, such as search engines, recommender systems, and Web site aggregators.

One consequence of trying to build complete agents is the realization that the previously isolated subfields of AI might need to be reorganized somewhat when their results are to be tied together. In particular, it is now widely appreciated that sensory systems (vision, sonar, speech recognition, etc.) cannot deliver perfectly reliable information about the environment. Hence, reasoning and planning systems must be able to handle uncertainty. A second major consequence of the agent perspective is that AI has been drawn into much closer contact with other fields, such as control theory and economics, that also deal with agents. Recent progress in the control of robotic cars has derived from a mixture of approaches ranging from better sensors, control-theoretic integration of sensing, localization and mapping, as well as a degree of high-level planning.

Despite these successes, some influential founders of AI, including John McCarthy (2007), Marvin Minsky (2007), Nils Nilsson (1995, 2005) and Patrick Winston (Beal and Winston, 2009), have expressed discontent with the progress of AI. They think that AI should put less emphasis on creating ever-improved versions of applications that are good at a specific task, such as driving a car, playing chess, or recognizing speech. Instead, they believe AI should return to its roots of striving for, in Simon's words, "machines that think, that learn and that create." They call the effort **human-level AI** or HLAI; their first symposium was in 2004 (Minsky *et al.*, 2004). The effort will require very large knowledge bases; Hendler *et al.* (1995) discuss where these knowledge bases might come from.

HUMAN-LEVEL AI

ARTIFICIAL GENERAL INTELLIGENCE

A related idea is the subfield of **Artificial General Intelligence** or AGI (Goertzel and Pennachin, 2007), which held its first conference and organized the *Journal of Artificial General Intelligence* in 2008. AGI looks for a universal algorithm for learning and acting in any environment, and has its roots in the work of Ray Solomonoff (1964), one of the attendees of the original 1956 Dartmouth conference. Guaranteeing that what we create is really **Friendly AI** is also a concern (Yudkowsky, 2008; Omohundro, 2008), one we will return to in Chapter 26.

FRIENDLY AI

1.3.10 The availability of very large data sets (2001–present)

Throughout the 60-year history of computer science, the emphasis has been on the *algorithm* as the main subject of study. But some recent work in AI suggests that for many problems, it makes more sense to worry about the *data* and be less picky about what algorithm to apply. This is true because of the increasing availability of very large data sources: for example, trillions of words of English and billions of images from the Web (Kilgarriff and Grefenstette, 2006); or billions of base pairs of genomic sequences (Collins *et al.*, 2003).

One influential paper in this line was Yarowsky's (1995) work on word-sense disambiguation: given the use of the word "plant" in a sentence, does that refer to flora or factory? Previous approaches to the problem had relied on human-labeled examples combined with machine learning algorithms. Yarowsky showed that the task can be done, with accuracy above 96%, with no labeled examples at all. Instead, given a very large corpus of unannotated text and just the dictionary definitions of the two senses—"works, industrial plant" and "flora, plant life"—one can label examples in the corpus, and from there **bootstrap** to learn

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."

1.4 The State of the Art

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.

1.5 SUMMARY

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.

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

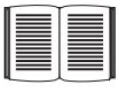
readable account of the philosophical and practical problems of AI. Significant early papers in AI are anthologized in the collections by Webber and Nilsson (1981) and by Luger (1995). The *Encyclopedia of AI* (Shapiro, 1992) contains survey articles on almost every topic in AI, as does Wikipedia. These 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 Nillson (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`, contains news, tutorials, and background information.

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?

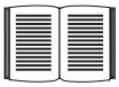
1.9 Why would evolution tend to result in systems that act rationally? What goals are such systems designed to achieve?

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 toe state of the art in AI? Do what degree do they hurt the field by drawing energy away from new ideas?

2 INTELLIGENT AGENTS

In which we discuss the nature of agents, perfect or otherwise, the diversity of environments, and the resulting menagerie of agent types.

Chapter 1 identified the concept of **rational agents** as central to our approach to artificial intelligence. In this chapter, we make this notion more concrete. We will see that the concept of rationality can be applied to a wide variety of agents operating in any imaginable environment. Our plan in this book is to use this concept to develop a small set of design principles for building successful agents—systems that can reasonably be called **intelligent**.

We begin by examining agents, environments, and the coupling between them. The observation that some agents behave better than others leads naturally to the idea of a rational agent—one that behaves as well as possible. How well an agent can behave depends on the nature of the environment; some environments are more difficult than others. We give a crude categorization of environments and show how properties of an environment influence the design of suitable agents for that environment. We describe a number of basic "skeleton" agent designs, which we flesh out in the rest of the book.

2.1 AGENTS AND ENVIRONMENTS

ENVIRONMENT
SENSOR
ACTUATOR

An **agent** is anything that can be viewed as perceiving its **environment** through **sensors** and acting upon that environment through **actuators**. This simple idea is illustrated in Figure 2.1. A human agent has eyes, ears, and other organs for sensors and hands, legs, vocal tract, and so on for actuators. A robotic agent might have cameras and infrared range finders for sensors and various motors for actuators. A software agent receives keystrokes, file contents, and network packets as sensory inputs and acts on the environment by displaying on the screen, writing files, and sending network packets.

PERCEPT
PERCEPT SEQUENCE

We use the term **percept** to refer to the agent's perceptual inputs at any given instant. An agent's **percept sequence** is the complete history of everything the agent has ever perceived. In general, *an agent's choice of action at any given instant can depend on the entire percept sequence observed to date, but not on anything it hasn't perceived.* By specifying the agent's choice of action for every possible percept sequence, we have said more or less everything

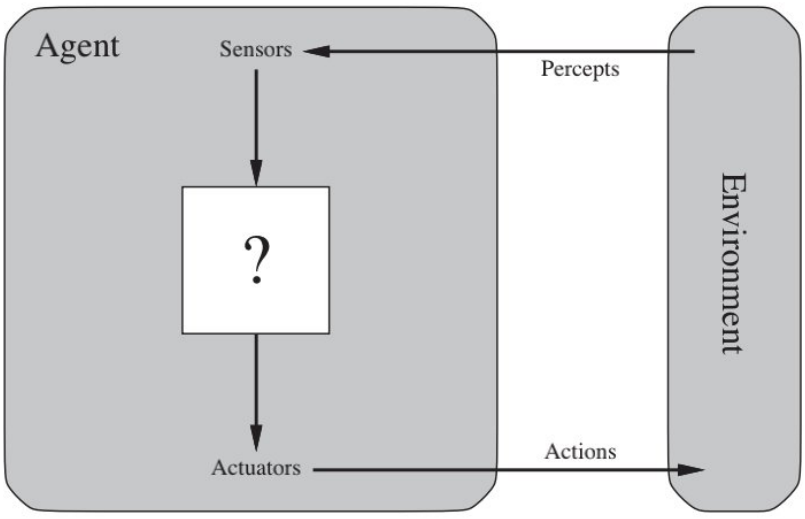


Figure 2.1 Agents interact with environments through sensors and actuators.

there is to say about the agent. Mathematically speaking, we say that an agent's behavior is described by the **agent function** that maps any given percept sequence to an action.

AGENT FUNCTION

We can imagine *tabulating* the agent function that describes any given agent; for most agents, this would be a very large table—infinite, in fact, unless we place a bound on the length of percept sequences we want to consider. Given an agent to experiment with, we can, in principle, construct this table by trying out all possible percept sequences and recording which actions the agent does in response.[1] The table is, of course, an *external* characterization of the agent. *Internally*, the agent function for an artificial agent will be implemented by an **agent program**. It is important to keep these two ideas distinct. The agent function is an abstract mathematical description; the agent program is a concrete implementation, running within some physical system.

AGENT PROGRAM

To illustrate these ideas, we use a very simple example—the vacuum-cleaner world shown in Figure 2.2. This world is so simple that we can describe everything that happens; it's also a made-up world, so we can invent many variations. This particular world has just two locations: squares A and B. The vacuum agent perceives which square it is in and whether there is dirt in the square. It can choose to move left, move right, suck up the dirt, or do nothing. One very simple agent function is the following: if the current square is dirty, then suck; otherwise, move to the other square. A partial tabulation of this agent function is shown in Figure 2.3 and an agent program that implements it appears in Figure 2.8 on page 48.

Looking at Figure 2.3, we see that various vacuum-world agents can be defined simply by filling in the right-hand column in various ways. The obvious question, then, is this: *What is the right way to fill out the table?* In other words, what makes an agent good or bad, intelligent or stupid? We answer these questions in the next section.

[1] If the agent uses some randomization to choose its actions, then we would have to try each sequence many times to identify the probability of each action. One might imagine that acting randomly is rather silly, but we show later in this chapter that it can be very intelligent.

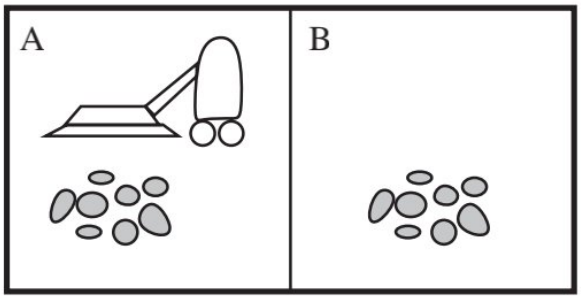


Figure 2.2 A vacuum-cleaner world with just two locations.

Percept sequence	Action
$[A, Clean]$	$Right$
$[A, Dirty]$	$Suck$
$[B, Clean]$	$Left$
$[B, Dirty]$	$Suck$
$[A, Clean], [A, Clean]$	$Right$
$[A, Clean], [A, Dirty]$	$Suck$
⋮	⋮
$[A, Clean], [A, Clean], [A, Clean]$	$Right$
$[A, Clean], [A, Clean], [A, Dirty]$	$Suck$
⋮	⋮

Figure 2.3 Partial tabulation of a simple agent function for the vacuum-cleaner world shown in Figure 2.2.

Before closing this section, we should emphasize that the notion of an agent is meant to be a tool for analyzing systems, not an absolute characterization that divides the world into agents and non-agents. One could view a hand-held calculator as an agent that chooses the action of displaying "4" when given the percept sequence "2 + 2 =," but such an analysis would hardly aid our understanding of the calculator. In a sense, all areas of engineering can be seen as designing artifacts that interact with the world; AI operates at (what the authors consider to be) the most interesting end of the spectrum, where the artifacts have significant computational resources and the task environment requires nontrivial decision making.

2.2 Good Behavior: The Concept of Rationality

RATIONAL AGENT

A **rational agent** is one that does the right thing—conceptually speaking, every entry in the table for the agent function is filled out correctly. Obviously, doing the right thing is better than doing the wrong thing, but what does it mean to do the right thing?

We answer this age-old question in an age-old way: by considering the *consequences* of the agent's behavior. When an agent is plunked down in an environment, it generates a sequence of actions according to the percepts it receives. This sequence of actions causes the environment to go through a sequence of states. If the sequence is desirable, then the agent has performed well. This notion of desirability is captured by a **performance measure** that evaluates any given sequence of environment states.

PERFORMANCE MEASURE

Notice that we said *environment* states, not *agent* states. If we define success in terms of agent's opinion of its own performance, an agent could achieve perfect rationality simply by deluding itself that its performance was perfect. Human agents in particular are notorious for "sour grapes"—believing they did not really want something (e.g., a Nobel Prize) after not getting it.

Obviously, there is not one fixed performance measure for all tasks and agents; typically, a designer will devise one appropriate to the circumstances. This is not as easy as it sounds. Consider, for example, the vacuum-cleaner agent from the preceding section. We might propose to measure performance by the amount of dirt cleaned up in a single eight-hour shift. With a rational agent, of course, what you ask for is what you get. A rational agent can maximize this performance measure by cleaning up the dirt, then dumping it all on the floor, then cleaning it up again, and so on. A more suitable performance measure would reward the agent for having a clean floor. For example, one point could be awarded for each clean square at each time step (perhaps with a penalty for electricity consumed and noise generated). *As a general rule, it is better to design performance measures according to what one actually wants in the environment, rather than according to how one thinks the agent should behave.*

Even when the obvious pitfalls are avoided, there remain some knotty issues to untangle. For example, the notion of "clean floor" in the preceding paragraph is based on average cleanliness over time. Yet the same average cleanliness can be achieved by two different agents, one of which does a mediocre job all the time while the other cleans energetically but takes long breaks. Which is preferable might seem to be a fine point of janitorial science, but in fact it is a deep philosophical question with far-reaching implications. Which is better—a reckless life of highs and lows, or a safe but humdrum existence? Which is better—an economy where everyone lives in moderate poverty, or one in which some live in plenty while others are very poor? We leave these questions as an exercise for the diligent reader.

2.2.1 Rationality

What is rational at any given time depends on four things:

- The performance measure that defines the criterion of success.
- The agent's prior knowledge of the environment.
- The actions that the agent can perform.
- The agent's percept sequence to date.

DEFINITION OF A RATIONAL AGENT

This leads to a **definition of a rational agent**:

> *For each possible percept sequence, a rational agent should select an action that is expected to maximize its performance measure, given the evidence provided by the percept sequence and whatever built-in knowledge the agent has.*

Consider the simple vacuum-cleaner agent that cleans a square if it is dirty and moves to the other square if not; this is the agent function tabulated in Figure 2.3. Is this a rational agent? That depends! First, we need to say what the performance measure is, what is known about the environment, and what sensors and actuators the agent has. Let us assume the following:

- The performance measure awards one point for each clean square at each time step, over a "lifetime" of 1000 time steps.
- The "geography" of the environment is known *a priori* (Figure 2.2) but the dirt distribution and the initial location of the agent are not. Clean squares stay clean and sucking cleans the current square. The $Left$ and $Right$ actions move the agent left and right except when this would take the agent outside the environment, in which case the agent remains where it is.
- The only available actions are $Left$, $Right$, and $Suck$.
- The agent correctly perceives its location and whether that location contains dirt.

We claim that *under these circumstances* the agent is indeed rational; its expected performance is at least as high as any other agent's. Exercise 2.2 asks you to prove this.

One can see easily that the same agent would be irrational under different circumstances. For example, once all the dirt is cleaned up, the agent will oscillate needlessly back and forth; if the performance measure includes a penalty of one point for each movement left or right, the agent will fare poorly. A better agent for this case would do nothing once it is sure that all the squares are clean. If clean squares can become dirty again, the agent should occasionally check and re-clean them if needed. If the geography of the environment is unknown, the agent will need to explore it rather than stick to squares A and B. Exercise 2.2 asks you to design agents for these cases.

2.2.2 Omniscience, learning, and autonomy

OMNISCIENCE

We need to be careful to distinguish between rationality and **omniscience**. An omniscient agent knows the *actual* outcome of its actions and can act accordingly; but omniscience is impossible in reality. Consider the following example: I am walking along the Champs Elysées one day and I see an old friend across the street. There is no traffic nearby and I'm not otherwise engaged, so, being rational, I start to cross the street. Meanwhile, at 33,000 feet, a cargo door falls off a passing airliner,[2] and before I make it to the other side of the street I am flattened. Was I irrational to cross the street? It is unlikely that my obituary would read "Idiot attempts to cross street."

This example shows that rationality is not the same as perfection. Rationality maximizes *expected* performance, while perfection maximizes *actual* performance. Retreating from a requirement of perfection is not just a question of being fair to agents. The point is that if we expect an agent to do what turns out to be the best action after the fact, it will be impossible to design an agent to fulfill this specification—unless we improve the performance of crystal balls or time machines.

[2] See N. Henderson, "New door latches urged for Boeing 747 jumbo jets," *Washington Post*, August 24, 1989.

Our definition of rationality does not require omniscience, then, because the rational choice depends only on the percept sequence *to date*. We must also ensure that we haven't inadvertently allowed the agent to engage in decidedly underintelligent activities. For example, if an agent does not look both ways before crossing a busy road, then its percept sequence will not tell it that there is a large truck approaching at high speed. Does our definition of rationality say that it's now OK to cross the road? Far from it! First, it would not be rational to cross the road given this uninformative percept sequence: the risk of accident from crossing without looking is too great. Second, a rational agent should choose the "looking" action before stepping into the street, because looking helps maximize the expected performance. Doing actions *in order to modify future percepts*—sometimes called **information gathering**—is an important part of rationality and is covered in depth in Chapter 16. A second example of information gathering is provided by the **exploration** that must be undertaken by a vacuum-cleaning agent in an initially unknown environment.

INFORMATION GATHERING

EXPLORATION

LEARNING

Our definition requires a rational agent not only to gather information but also to **learn** as much as possible from what it perceives. The agent's initial configuration could reflect some prior knowledge of the environment, but as the agent gains experience this may be modified and augmented. There are extreme cases in which the environment is completely known *a priori*. In such cases, the agent need not perceive or learn; it simply acts correctly. Of course, such agents are fragile. Consider the lowly dung beetle. After digging its nest and laying its eggs, it fetches a ball of dung from a nearby heap to plug the entrance. If the ball of dung is removed from its grasp *en route*, the beetle continues its task and pantomimes plugging the nest with the nonexistent dung ball, never noticing that it is missing. Evolution has built an assumption into the beetle's behavior, and when it is violated, unsuccessful behavior results. Slightly more intelligent is the sphex wasp. The female sphex will dig a burrow, go out and sting a caterpillar and drag it to the burrow, enter the burrow again to check all is well, drag the caterpillar inside, and lay its eggs. The caterpillar serves as a food source when the eggs hatch. So far so good, but if an entomologist moves the caterpillar a few inches away while the sphex is doing the check, it will revert to the "drag" step of its plan and will continue the plan without modification, even after dozens of caterpillar-moving interventions. The sphex is unable to learn that its innate plan is failing, and thus will not change it.

AUTONOMY

To the extent that an agent relies on the prior knowledge of its designer rather than on its own percepts, we say that the agent lacks **autonomy**. A rational agent should be autonomous—it should learn what it can to compensate for partial or incorrect prior knowledge. For example, a vacuum-cleaning agent that learns to foresee where and when additional dirt will appear will do better than one that does not. As a practical matter, one seldom requires complete autonomy from the start: when the agent has had little or no experience, it would have to act randomly unless the designer gave some assistance. So, just as evolution provides animals with enough built-in reflexes to survive long enough to learn for themselves, it would be reasonable to provide an artificial intelligent agent with some initial knowledge as well as an ability to learn. After sufficient experience of its environment, the behavior of a rational agent can become effectively *independent* of its prior knowledge. Hence, the incorporation of learning allows one to design a single rational agent that will succeed in a vast variety of environments.

2.3 THE NATURE OF ENVIRONMENTS

TASK ENVIRONMENT

Now that we have a definition of rationality, we are almost ready to think about building rational agents. First, however, we must think about **task environments**, which are essentially the "problems" to which rational agents are the "solutions." We begin by showing how to specify a task environment, illustrating the process with a number of examples. We then show that task environments come in a variety of flavors. The flavor of the task environment directly affects the appropriate design for the agent program.

2.3.1 Specifying the task environment

In our discussion of the rationality of the simple vacuum-cleaner agent, we had to specify the performance measure, the environment, and the agent's actuators and sensors. We group all these under the heading of the **task environment**. For the acronymically minded, we call this the **PEAS** (**P**erformance, **E**nvironment, **A**ctuators, **S**ensors) description. In designing an agent, the first step must always be to specify the task environment as fully as possible.

PEAS

The vacuum world was a simple example; let us consider a more complex problem: an automated taxi driver. We should point out, before the reader becomes alarmed, that a fully automated taxi is currently somewhat beyond the capabilities of existing technology. (page 28 describes an existing driving robot.) The full driving task is extremely *open-ended*. There is no limit to the novel combinations of circumstances that can arise—another reason we chose it as a focus for discussion. Figure 2.4 summarizes the PEAS description for the taxi's task environment. We discuss each element in more detail in the following paragraphs.

Agent Type	Performance Measure	Environment	Actuators	Sensors
Taxi driver	Safe, fast, legal, comfortable trip, maximize profits	Roads, other traffic, pedestrians, customers	Steering, accelerator, brake, signal, horn, display	Cameras, sonar, speedometer, GPS, odometer, accelerometer, engine sensors, keyboard

Figure 2.4 PEAS description of the task environment for an automated taxi.

First, what is the **performance measure** to which we would like our automated driver to aspire? Desirable qualities include getting to the correct destination; minimizing fuel consumption and wear and tear; minimizing the trip time or cost; minimizing violations of traffic laws and disturbances to other drivers; maximizing safety and passenger comfort; maximizing profits. Obviously, some of these goals conflict, so tradeoffs will be required.

Next, what is the driving **environment** that the taxi will face? Any taxi driver must deal with a variety of roads, ranging from rural lanes and urban alleys to 12-lane freeways. The roads contain other traffic, pedestrians, stray animals, road works, police cars, puddles,

and potholes. The taxi must also interact with potential and actual passengers. There are also some optional choices. The taxi might need to operate in Southern California, where snow is seldom a problem, or in Alaska, where it seldom is not. It could always be driving on the right, or we might want it to be flexible enough to drive on the left when in Britain or Japan. Obviously, the more restricted the environment, the easier the design problem.

The **actuators** for an automated taxi include those available to a human driver: control over the engine through the accelerator and control over steering and braking. In addition, it will need output to a display screen or voice synthesizer to talk back to the passengers, and perhaps some way to communicate with other vehicles, politely or otherwise.

The basic **sensors** for the taxi will include one or more controllable video cameras so that it can see the road; it might augment these with infrared or sonar sensors to detect distances to other cars and obstacles. To avoid speeding tickets, the taxi should have a speedometer, and to control the vehicle properly, especially on curves, it should have an accelerometer. To determine the mechanical state of the vehicle, it will need the usual array of engine, fuel, and electrical system sensors. Like many human drivers, it might want a global positioning system (GPS) so that it doesn't get lost. Finally, it will need a keyboard or microphone for the passenger to request a destination.

In Figure 2.5, we have sketched the basic PEAS elements for a number of additional agent types. Further examples appear in Exercise 2.4. It may come as a surprise to some readers that our list of agent types includes some programs that operate in the entirely artificial environment defined by keyboard input and character output on a screen. "Surely," one might say, "this is not a real environment, is it?" In fact, what matters is not the distinction between "real" and "artificial" environments, but the complexity of the relationship among the behavior of the agent, the percept sequence generated by the environment, and the performance measure. Some "real" environments are actually quite simple. For example, a robot designed to inspect parts as they come by on a conveyor belt can make use of a number of simplifying assumptions: that the lighting is always just so, that the only thing on the conveyor belt will be parts of a kind that it knows about, and that only two actions (accept or reject) are possible.

SOFTWARE AGENT
SOFTBOT

In contrast, some **software agents** (or software robots or **softbots**) exist in rich, unlimited domains. Imagine a softbot Web site operator designed to scan Internet news sources and show the interesting items to its users, while selling advertising space to generate revenue. To do well, that operator will need some natural language processing abilities, it will need to learn what each user and advertiser is interested in, and it will need to change its plans dynamically—for example, when the connection for one news source goes down or when a new one comes online. The Internet is an environment whose complexity rivals that of the physical world and whose inhabitants include many artificial and human agents.

2.3.2 Properties of task environments

The range of task environments that might arise in AI is obviously vast. We can, however, identify a fairly small number of dimensions along which task environments can be categorized. These dimensions determine, to a large extent, the appropriate agent design and the applicability of each of the principal families of techniques for agent implementation. First,

Agent Type	Performance Measure	Environment	Actuators	Sensors
Medical diagnosis system	Healthy patient, reduced costs	Patient, hospital, staff	Display of questions, tests, diagnoses, treatments, referrals	Keyboard entry of symptoms, findings, patient's answers
Satellite image analysis system	Correct image categorization	Downlink from orbiting satellite	Display of scene categorization	Color pixel arrays
Part-picking robot	Percentage of parts in correct bins	Conveyor belt with parts; bins	Jointed arm and hand	Camera, joint angle sensors
Refinery controller	Purity, yield, safety	Refinery, operators	Valves, pumps, heaters, displays	Temperature, pressure, chemical sensors
Interactive English tutor	Student's score on test	Set of students, testing agency	Display of exercises, suggestions, corrections	Keyboard entry

Figure 2.5 Examples of agent types and their PEAS descriptions.

we list the dimensions, then we analyze several task environments to illustrate the ideas. The definitions here are informal; later chapters provide more precise statements and examples of each kind of environment.

FULLY OBSERVABLE
PARTIALLY OBSERVABLE

Fully observable vs. **partially observable**: If an agent's sensors give it access to the complete state of the environment at each point in time, then we say that the task environment is fully observable. A task environment is effectively fully observable if the sensors detect all aspects that are *relevant* to the choice of action; relevance, in turn, depends on the performance measure. Fully observable environments are convenient because the agent need not maintain any internal state to keep track of the world. An environment might be partially observable because of noisy and inaccurate sensors or because parts of the state are simply missing from the sensor data—for example, a vacuum agent with only a local dirt sensor cannot tell whether there is dirt in other squares, and an automated taxi cannot see what other drivers are thinking. If the agent has no sensors at all then the environment is **unobservable**. One might think that in such cases the agent's plight is hopeless, but, as we discuss in Chapter 4, the agent's goals may still be achievable, sometimes with certainty.

UNOBSERVABLE

SINGLE AGENT
MULTIAGENT

Single agent vs. **multiagent**: The distinction between single-agent and multiagent en-

vironments may seem simple enough. For example, an agent solving a crossword puzzle by itself is clearly in a single-agent environment, whereas an agent playing chess is in a two-agent environment. There are, however, some subtle issues. First, we have described how an entity *may* be viewed as an agent, but we have not explained which entities *must* be viewed as agents. Does an agent A (the taxi driver for example) have to treat an object B (another vehicle) as an agent, or can it be treated merely as an object behaving according to the laws of physics, analogous to waves at the beach or leaves blowing in the wind? The key distinction is whether B's behavior is best described as maximizing a performance measure whose value depends on agent A's behavior. For example, in chess, the opponent entity B is trying to maximize its performance measure, which, by the rules of chess, minimizes agent A's performance measure. Thus, chess is a **competitive** multiagent environment. In the taxi-driving environment, on the other hand, avoiding collisions maximizes the performance measure of all agents, so it is a partially **cooperative** multiagent environment. It is also partially competitive because, for example, only one car can occupy a parking space. The agent-design problems in multiagent environments are often quite different from those in single-agent environments; for example, **communication** often emerges as a rational behavior in multiagent environments; in some competitive environments, **randomized behavior** is rational because it avoids the pitfalls of predictability.

COMPETITIVE

COOPERATIVE

Deterministic vs. **stochastic**. If the next state of the environment is completely determined by the current state and the action executed by the agent, then we say the environment is deterministic; otherwise, it is stochastic. In principle, an agent need not worry about uncertainty in a fully observable, deterministic environment. (In our definition, we ignore uncertainty that arises purely from the actions of other agents in a multiagent environment; thus, a game can be deterministic even though each agent may be unable to predict the actions of the others.) If the environment is partially observable, however, then it could *appear* to be stochastic. Most real situations are so complex that it is impossible to keep track of all the unobserved aspects; for practical purposes, they must be treated as stochastic. Taxi driving is clearly stochastic in this sense, because one can never predict the behavior of traffic exactly; moreover, one's tires blow out and one's engine seizes up without warning. The vacuum world as we described it is deterministic, but variations can include stochastic elements such as randomly appearing dirt and an unreliable suction mechanism (Exercise 2.13). We say an environment is **uncertain** if it is not fully observable or not deterministic. One final note: our use of the word "stochastic" generally implies that uncertainty about outcomes is quantified in terms of probabilities; a **nondeterministic** environment is one in which actions are characterized by their *possible* outcomes, but no probabilities are attached to them. Nondeterministic environment descriptions are usually associated with performance measures that require the agent to succeed for *all possible* outcomes of its actions.

DETERMINISTIC

STOCHASTIC

UNCERTAIN

NONDETERMINISTIC

Episodic vs. **sequential**: In an episodic task environment, the agent's experience is divided into atomic episodes. In each episode the agent receives a percept and then performs a single action. Crucially, the next episode does not depend on the actions taken in previous episodes. Many classification tasks are episodic. For example, an agent that has to spot defective parts on an assembly line bases each decision on the current part, regardless of previous decisions; moreover, the current decision doesn't affect whether the next part is

EPISODIC

SEQUENTIAL

defective. In sequential environments, on the other hand, the current decision could affect all future decisions.[3] Chess and taxi driving are sequential: in both cases, short-term actions can have long-term consequences. Episodic environments are much simpler than sequential environments because the agent does not need to think ahead.

STATIC
DYNAMIC

Static vs. **dynamic**: If the environment can change while an agent is deliberating, then we say the environment is dynamic for that agent; otherwise, it is static. Static environments are easy to deal with because the agent need not keep looking at the world while it is deciding on an action, nor need it worry about the passage of time. Dynamic environments, on the other hand, are continuously asking the agent what it wants to do; if it hasn't decided yet, that counts as deciding to do nothing. If the environment itself does not change with the passage of time but the agent's performance score does, then we say the environment is **semidynamic**. Taxi driving is clearly dynamic: the other cars and the taxi itself keep moving while the driving algorithm dithers about what to do next. Chess, when played with a clock, is semidynamic. Crossword puzzles are static.

SEMIDYNAMIC
DISCRETE
CONTINUOUS

Discrete vs. **continuous**: The discrete/continuous distinction applies to the *state* of the environment, to the way *time* is handled, and to the *percepts* and *actions* of the agent. For example, the chess environment has a finite number of distinct states (excluding the clock). Chess also has a discrete set of percepts and actions. Taxi driving is a continuous-state and continuous-time problem: the speed and location of the taxi and of the other vehicles sweep through a range of continuous values and do so smoothly over time. Taxi-driving actions are also continuous (steering angles, etc.). Input from digital cameras is discrete, strictly speaking, but is typically treated as representing continuously varying intensities and locations.

KNOWN
UNKNOWN

Known vs. **unknown**: Strictly speaking, this distinction refers not to the environment itself but to the agent's (or designer's) state of knowledge about the "laws of physics" of the environment. In a known environment, the outcomes (or outcome probabilities if the environment is stochastic) for all actions are given. Obviously, if the environment is unknown, the agent will have to learn how it works in order to make good decisions. Note that the distinction between known and unknown environments is not the same as the one between fully and partially observable environments. It is quite possible for a *known* environment to be *partially* observable—for example, in solitaire card games, I know the rules but am still unable to see the cards that have not yet been turned over. Conversely, an *unknown* environment can be *fully* observable—in a new video game, the screen may show the entire game state but I still don't know what the buttons do until I try them.

As one might expect, the hardest case is *partially observable*, *multiagent*, *stochastic*, *sequential*, *dynamic*, *continuous*, and *unknown*. Taxi driving is hard in all these senses, except that for the most part the driver's environment is known. Driving a rented car in a new country with unfamiliar geography and traffic laws is a lot more exciting.

Figure 2.6 lists the properties of a number of familiar environments. Note that the answers are not always cut and dried. For example, we describe the part-picking robot as episodic, because it normally considers each part in isolation. But if one day there is a large

[3] The word "sequential" is also used in computer science as the antonym of "parallel." The two meanings are largely unrelated.

Task Environment	Observable	Agents	Deterministic	Episodic	Static	Discrete
Crossword puzzle	Fully	Single	Deterministic	Sequential	Static	Discrete
Chess with a clock	Fully	Multi	Deterministic	Sequential	Semi	Discrete
Poker	Partially	Multi	Stochastic	Sequential	Static	Discrete
Backgammon	Fully	Multi	Stochastic	Sequential	Static	Discrete
Taxi driving	Partially	Multi	Stochastic	Sequential	Dynamic	Continuous
Medical diagnosis	Partially	Single	Stochastic	Sequential	Dynamic	Continuous
Image analysis	Fully	Single	Deterministic	Episodic	Semi	Continuous
Part-picking robot	Partially	Single	Stochastic	Episodic	Dynamic	Continuous
Refinery controller	Partially	Single	Stochastic	Sequential	Dynamic	Continuous
Interactive English tutor	Partially	Multi	Stochastic	Sequential	Dynamic	Discrete

Figure 2.6 Examples of task environments and their characteristics.

batch of defective parts, the robot should learn from several observations that the distribution of defects has changed, and should modify its behavior for subsequent parts. We have not included a "known/unknown" column because, as explained earlier, this is not strictly a property of the environment. For some environments, such as chess and poker, it is quite easy to supply the agent with full knowledge of the rules, but it is nonetheless interesting to consider how an agent might learn to play these games without such knowledge.

Several of the answers in the table depend on how the task environment is defined. We have listed the medical-diagnosis task as single-agent because the disease process in a patient is not profitably modeled as an agent; but a medical-diagnosis system might also have to deal with recalcitrant patients and skeptical staff, so the environment could have a multiagent aspect. Furthermore, medical diagnosis is episodic if one conceives of the task as selecting a diagnosis given a list of symptoms; the problem is sequential if the task can include proposing a series of tests, evaluating progress over the course of treatment, and so on. Also, many environments are episodic at higher levels than the agent's individual actions. For example, a chess tournament consists of a sequence of games; each game is an episode because (by and large) the contribution of the moves in one game to the agent's overall performance is not affected by the moves in its previous game. On the other hand, decision making within a single game is certainly sequential.

The code repository associated with this book (aima.cs.berkeley.edu) includes implementations of a number of environments, together with a general-purpose environment simulator that places one or more agents in a simulated environment, observes their behavior over time, and evaluates them according to a given performance measure. Such experiments are often carried out not for a single environment but for many environments drawn from an **environment class**. For example, to evaluate a taxi driver in simulated traffic, we would want to run many simulations with different traffic, lighting, and weather conditions. If we designed the agent for a single scenario, we might be able to take advantage of specific properties of the particular case but might not identify a good design for driving in general. For this

ENVIRONMENT CLASS

ENVIRONMENT GENERATOR

reason, the code repository also includes an **environment generator** for each environment class that selects particular environments (with certain likelihoods) in which to run the agent. For example, the vacuum environment generator initializes the dirt pattern and agent location randomly. We are then interested in the agent's average performance over the environment class. A rational agent for a given environment class maximizes this average performance. Exercises 2.8 to 2.13 take you through the process of developing an environment class and evaluating various agents therein.

2.4 THE STRUCTURE OF AGENTS

So far we have talked about agents by describing *behavior*—the action that is performed after any given sequence of percepts. Now we must bite the bullet and talk about how the insides

AGENT PROGRAM

work. The job of AI is to design an **agent program** that implements the agent function—the mapping from percepts to actions. We assume this program will run on some sort of

ARCHITECTURE

computing device with physical sensors and actuators—we call this the **architecture**:

$$agent = architecture + program\ .$$

Obviously, the program we choose has to be one that is appropriate for the architecture. If the program is going to recommend actions like *Walk*, the architecture had better have legs. The architecture might be just an ordinary PC, or it might be a robotic car with several onboard computers, cameras, and other sensors. In general, the architecture makes the percepts from the sensors available to the program, runs the program, and feeds the program's action choices to the actuators as they are generated. Most of this book is about designing agent programs, although Chapters 24 and 25 deal directly with the sensors and actuators.

2.4.1 Agent programs

The agent programs that we design in this book all have the same skeleton: they take the current percept as input from the sensors and return an action to the actuators.[4] Notice the difference between the agent program, which takes the current percept as input, and the agent function, which takes the entire percept history. The agent program takes just the current percept as input because nothing more is available from the environment; if the agent's actions need to depend on the entire percept sequence, the agent will have to remember the percepts.

We describe the agent programs in the simple pseudocode language that is defined in Appendix B. (The online code repository contains implementations in real programming languages.) For example, Figure 2.7 shows a rather trivial agent program that keeps track of the percept sequence and then uses it to index into a table of actions to decide what to do. The table—an example of which is given for the vacuum world in Figure 2.3—represents explicitly the agent function that the agent program embodies. To build a rational agent in

[4] There are other choices for the agent program skeleton; for example, we could have the agent programs be **coroutines** that run asynchronously with the environment. Each such coroutine has an input and output port and consists of a loop that reads the input port for percepts and writes actions to the output port.

```
function TABLE-DRIVEN-AGENT(percept) returns an action
  persistent: percepts, a sequence, initially empty
              table, a table of actions, indexed by percept sequences, initially fully specified

  append percept to the end of percepts
  action ← LOOKUP(percepts, table)
  return action
```

Figure 2.7 The TABLE-DRIVEN-AGENT program is invoked for each new percept and returns an action each time. It retains the complete percept sequence in memory.

this way, we as designers must construct a table that contains the appropriate action for every possible percept sequence.

It is instructive to consider why the table-driven approach to agent construction is doomed to failure. Let $\mathcal{P}$ be the set of possible percepts and let T be the lifetime of the agent (the total number of percepts it will receive). The lookup table will contain $\sum_{t=1}^{T} |\mathcal{P}|^t$ entries. Consider the automated taxi: the visual input from a single camera comes in at the rate of roughly 27 megabytes per second (30 frames per second, 640×480 pixels with 24 bits of color information). This gives a lookup table with over $10^{250,000,000,000}$ entries for an hour's driving. Even the lookup table for chess—a tiny, well-behaved fragment of the real world—would have at least 10^{150} entries. The daunting size of these tables (the number of atoms in the observable universe is less than 10^{80}) means that (a) no physical agent in this universe will have the space to store the table, (b) the designer would not have time to create the table, (c) no agent could ever learn all the right table entries from its experience, and (d) even if the environment is simple enough to yield a feasible table size, the designer still has no guidance about how to fill in the table entries.

Despite all this, TABLE-DRIVEN-AGENT *does* do what we want: it implements the desired agent function. The key challenge for AI is to find out how to write programs that, to the extent possible, produce rational behavior from a smallish program rather than from a vast table. We have many examples showing that this can be done successfully in other areas: for example, the huge tables of square roots used by engineers and schoolchildren prior to the 1970s have now been replaced by a five-line program for Newton's method running on electronic calculators. The question is, can AI do for general intelligent behavior what Newton did for square roots? We believe the answer is yes.

In the remainder of this section, we outline four basic kinds of agent programs that embody the principles underlying almost all intelligent systems:

- Simple reflex agents;
- Model-based reflex agents;
- Goal-based agents; and
- Utility-based agents.

Each kind of agent program combines particular components in particular ways to generate actions. Section 2.4.6 explains in general terms how to convert all these agents into *learning*

```
function REFLEX-VACUUM-AGENT([location,status]) returns an action
  if status = Dirty then return Suck
  else if location = A then return Right
  else if location = B then return Left
```

Figure 2.8 The agent program for a simple reflex agent in the two-state vacuum environment. This program implements the agent function tabulated in Figure 2.3.

agents that can improve the performance of their components so as to generate better actions. Finally, Section 2.4.7 describes the variety of ways in which the components themselves can be represented within the agent. This variety provides a major organizing principle for the field and for the book itself.

2.4.2 Simple reflex agents

SIMPLE REFLEX AGENT

The simplest kind of agent is the **simple reflex agent**. These agents select actions on the basis of the *current* percept, ignoring the rest of the percept history. For example, the vacuum agent whose agent function is tabulated in Figure 2.3 is a simple reflex agent, because its decision is based only on the current location and on whether that location contains dirt. An agent program for this agent is shown in Figure 2.8.

Notice that the vacuum agent program is very small indeed compared to the corresponding table. The most obvious reduction comes from ignoring the percept history, which cuts down the number of possibilities from 4^T to just 4. A further, small reduction comes from the fact that when the current square is dirty, the action does not depend on the location.

Simple reflex behaviors occur even in more complex environments. Imagine yourself as the driver of the automated taxi. If the car in front brakes and its brake lights come on, then you should notice this and initiate braking. In other words, some processing is done on the visual input to establish the condition we call "The car in front is braking." Then, this triggers some established connection in the agent program to the action "initiate braking." We call such a connection a **condition–action rule**,[5] written as

CONDITION–ACTION RULE

if *car-in-front-is-braking* **then** *initiate-braking*.

Humans also have many such connections, some of which are learned responses (as for driving) and some of which are innate reflexes (such as blinking when something approaches the eye). In the course of the book, we show several different ways in which such connections can be learned and implemented.

The program in Figure 2.8 is specific to one particular vacuum environment. A more general and flexible approach is first to build a general-purpose interpreter for condition–action rules and then to create rule sets for specific task environments. Figure 2.9 gives the structure of this general program in schematic form, showing how the condition–action rules allow the agent to make the connection from percept to action. (Do not worry if this seems

[5] Also called **situation–action rules**, **productions**, or **if–then rules**.

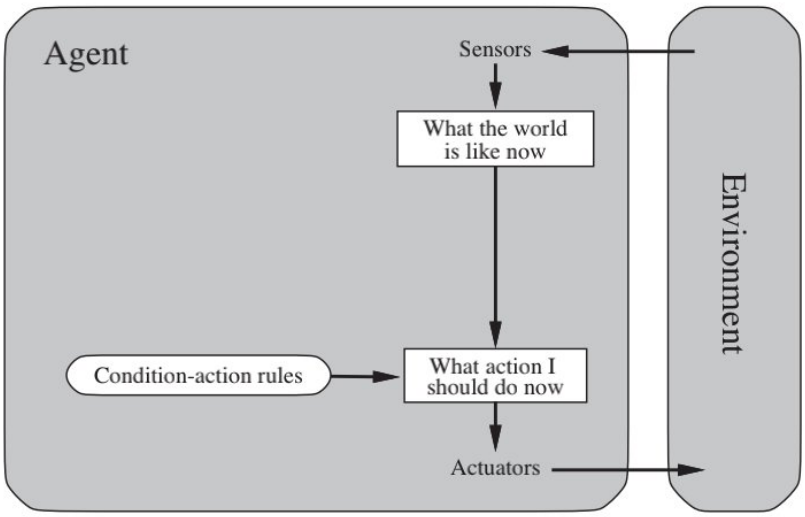


Figure 2.9 Schematic diagram of a simple reflex agent.

```
function SIMPLE-REFLEX-AGENT(percept) returns an action
  persistent: rules, a set of condition–action rules

  state ← INTERPRET-INPUT(percept)
  rule ← RULE-MATCH(state, rules)
  action ← rule.ACTION
  return action
```

Figure 2.10 A simple reflex agent. It acts according to a rule whose condition matches the current state, as defined by the percept.

trivial; it gets more interesting shortly.) We use rectangles to denote the current internal state of the agent's decision process, and ovals to represent the background information used in the process. The agent program, which is also very simple, is shown in Figure 2.10. The INTERPRET-INPUT function generates an abstracted description of the current state from the percept, and the RULE-MATCH function returns the first rule in the set of rules that matches the given state description. Note that the description in terms of "rules" and "matching" is purely conceptual; actual implementations can be as simple as a collection of logic gates implementing a Boolean circuit.

Simple reflex agents have the admirable property of being simple, but they turn out to be of limited intelligence. The agent in Figure 2.10 will work *only if the correct decision can be made on the basis of only the current percept—that is, only if the environment is fully observable.* Even a little bit of unobservability can cause serious trouble. For example, the braking rule given earlier assumes that the condition *car-in-front-is-braking* can be determined from the current percept—a single frame of video. This works if the car in front has a centrally mounted brake light. Unfortunately, older models have different configurations of taillights,

brake lights, and turn-signal lights, and it is not always possible to tell from a single image whether the car is braking. A simple reflex agent driving behind such a car would either brake continuously and unnecessarily, or, worse, never brake at all.

We can see a similar problem arising in the vacuum world. Suppose that a simple reflex vacuum agent is deprived of its location sensor and has only a dirt sensor. Such an agent has just two possible percepts: $[Dirty]$ and $[Clean]$. It can $Suck$ in response to $[Dirty]$; what should it do in response to $[Clean]$? Moving $Left$ fails (forever) if it happens to start in square A, and moving $Right$ fails (forever) if it happens to start in square B. Infinite loops are often unavoidable for simple reflex agents operating in partially observable environments.

RANDOMIZATION

Escape from infinite loops is possible if the agent can **randomize** its actions. For example, if the vacuum agent perceives $[Clean]$, it might flip a coin to choose between $Left$ and $Right$. It is easy to show that the agent will reach the other square in an average of two steps. Then, if that square is dirty, the agent will clean it and the task will be complete. Hence, a randomized simple reflex agent might outperform a deterministic simple reflex agent.

We mentioned in Section 2.3 that randomized behavior of the right kind can be rational in some multiagent environments. In single-agent environments, randomization is usually *not* rational. It is a useful trick that helps a simple reflex agent in some situations, but in most cases we can do much better with more sophisticated deterministic agents.

2.4.3 Model-based reflex agents

The most effective way to handle partial observability is for the agent to *keep track of the part of the world it can't see now*. That is, the agent should maintain some sort of **internal state** that depends on the percept history and thereby reflects at least some of the unobserved aspects of the current state. For the braking problem, the internal state is not too extensive—just the previous frame from the camera, allowing the agent to detect when two red lights at the edge of the vehicle go on or off simultaneously. For other driving tasks such as changing lanes, the agent needs to keep track of where the other cars are if it can't see them all at once. And for any driving to be possible at all, the agent needs to keep track of where its keys are.

INTERNAL STATE

Updating this internal state information as time goes by requires two kinds of knowledge to be encoded in the agent program. First, we need some information about how the world evolves independently of the agent—for example, that an overtaking car generally will be closer behind than it was a moment ago. Second, we need some information about how the agent's own actions affect the world—for example, that when the agent turns the steering wheel clockwise, the car turns to the right, or that after driving for five minutes northbound on the freeway, one is usually about five miles north of where one was five minutes ago. This knowledge about "how the world works"—whether implemented in simple Boolean circuits or in complete scientific theories—is called a **model** of the world. An agent that uses such a model is called a **model-based agent**.

MODEL-BASED AGENT

Figure 2.11 gives the structure of the model-based reflex agent with internal state, showing how the current percept is combined with the old internal state to generate the updated description of the current state, based on the agent's model of how the world works. The agent program is shown in Figure 2.12. The interesting part is the function UPDATE-STATE, which

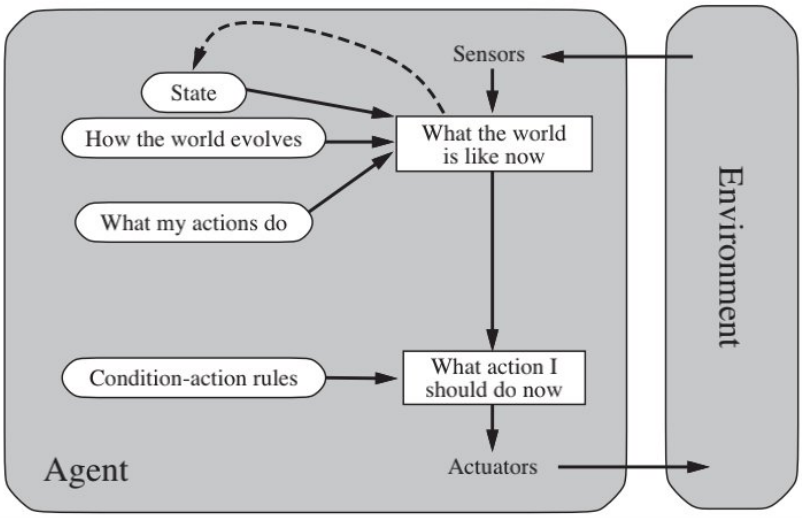


Figure 2.11 A model-based reflex agent.

function MODEL-BASED-REFLEX-AGENT(*percept*) **returns** an action
persistent: *state*, the agent's current conception of the world state
model, a description of how the next state depends on current state and action
rules, a set of condition–action rules
action, the most recent action, initially none

state ← UPDATE-STATE(*state*, *action*, *percept*, *model*)
rule ← RULE-MATCH(*state*, *rules*)
action ← *rule*.ACTION
return *action*

Figure 2.12 A model-based reflex agent. It keeps track of the current state of the world, using an internal model. It then chooses an action in the same way as the reflex agent.

is responsible for creating the new internal state description. The details of how models and states are represented vary widely depending on the type of environment and the particular technology used in the agent design. Detailed examples of models and updating algorithms appear in Chapters 4, 12, 11, 15, 17, and 25.

Regardless of the kind of representation used, it is seldom possible for the agent to determine the current state of a partially observable environment *exactly*. Instead, the box labeled "what the world is like now" (Figure 2.11) represents the agent's "best guess" (or sometimes best guesses). For example, an automated taxi may not be able to see around the large truck that has stopped in front of it and can only guess about what may be causing the hold-up. Thus, uncertainty about the current state may be unavoidable, but the agent still has to make a decision.

A perhaps less obvious point about the internal "state" maintained by a model-based agent is that it does not have to describe "what the world is like now" in a literal sense. For

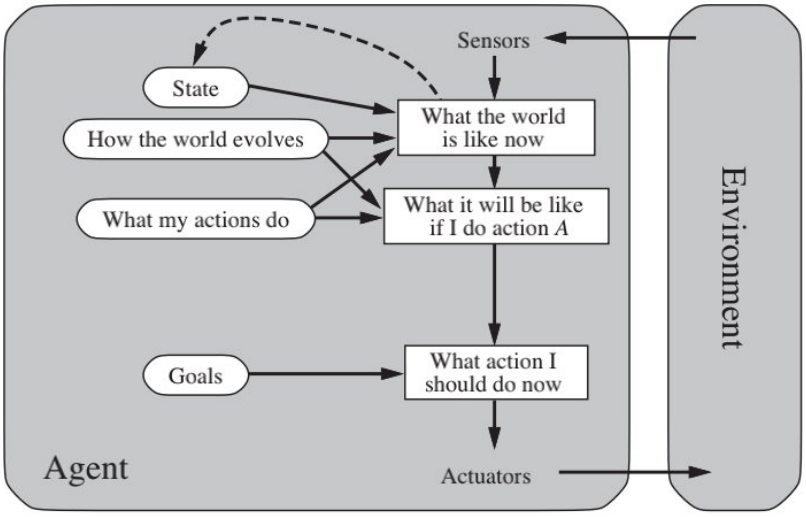


Figure 2.13 A model-based, goal-based agent. It keeps track of the world state as well as a set of goals it is trying to achieve, and chooses an action that will (eventually) lead to the achievement of its goals.

example, the taxi may be driving back home, and it may have a rule telling it to fill up with gas on the way home unless it has at least half a tank. Although "driving back home" may *seem* to an aspect of the world state, the fact of the taxi's *destination* is actually an aspect of the agent's internal state. If you find this puzzling, consider that the taxi could be in exactly the same place at the same time, but intending to reach a different destination.

2.4.4 Goal-based agents

Knowing something about the current state of the environment is not always enough to decide what to do. For example, at a road junction, the taxi can turn left, turn right, or go straight on. The correct decision depends on where the taxi is trying to get to. In other words, as well as a current state description, the agent needs some sort of **goal** information that describes situations that are desirable—for example, being at the passenger's destination. The agent program can combine this with the model (the same information as was used in the model-based reflex agent) to choose actions that achieve the goal. Figure 2.13 shows the goal-based agent's structure.

GOAL

Sometimes goal-based action selection is straightforward—for example, when goal satisfaction results immediately from a single action. Sometimes it will be more tricky—for example, when the agent has to consider long sequences of twists and turns in order to find a way to achieve the goal. **Search** (Chapters 3 to 5) and **planning** (Chapters 10 and 11) are the subfields of AI devoted to finding action sequences that achieve the agent's goals.

Notice that decision making of this kind is fundamentally different from the condition–action rules described earlier, in that it involves consideration of the future—both "What will happen if I do such-and-such?" and "Will that make me happy?" In the reflex agent designs, this information is not explicitly represented, because the built-in rules map directly from

percepts to actions. The reflex agent brakes when it sees brake lights. A goal-based agent, in principle, could reason that if the car in front has its brake lights on, it will slow down. Given the way the world usually evolves, the only action that will achieve the goal of not hitting other cars is to brake.

Although the goal-based agent appears less efficient, it is more flexible because the knowledge that supports its decisions is represented explicitly and can be modified. If it starts to rain, the agent can update its knowledge of how effectively its brakes will operate; this will automatically cause all of the relevant behaviors to be altered to suit the new conditions. For the reflex agent, on the other hand, we would have to rewrite many condition–action rules. The goal-based agent's behavior can easily be changed to go to a different destination, simply by specifying that destination as the goal. The reflex agent's rules for when to turn and when to go straight will work only for a single destination; they must all be replaced to go somewhere new.

2.4.5 Utility-based agents

Goals alone are not enough to generate high-quality behavior in most environments. For example, many action sequences will get the taxi to its destination (thereby achieving the goal) but some are quicker, safer, more reliable, or cheaper than others. Goals just provide a crude binary distinction between "happy" and "unhappy" states. A more general performance measure should allow a comparison of different world states according to exactly how happy they would make the agent. Because "happy" does not sound very scientific, economists and computer scientists use the term **utility** instead.[6]

UTILITY

We have already seen that a performance measure assigns a score to any given sequence of environment states, so it can easily distinguish between more and less desirable ways of getting to the taxi's destination. An agent's **utility function** is essentially an internalization of the performance measure. If the internal utility function and the external performance measure are in agreement, then an agent that chooses actions to maximize its utility will be rational according to the external performance measure.

UTILITY FUNCTION

Let us emphasize again that this is not the *only* way to be rational—we have already seen a rational agent program for the vacuum world (Figure 2.8) that has no idea what its utility function is—but, like goal-based agents, a utility-based agent has many advantages in terms of flexibility and learning. Furthermore, in two kinds of cases, goals are inadequate but a utility-based agent can still make rational decisions. First, when there are conflicting goals, only some of which can be achieved (for example, speed and safety), the utility function specifies the appropriate tradeoff. Second, when there are several goals that the agent can aim for, none of which can be achieved with certainty, utility provides a way in which the likelihood of success can be weighed against the importance of the goals.

Partial observability and stochasticity are ubiquitous in the real world, and so, therefore, is decision making under uncertainty. Technically speaking, a rational utility-based agent chooses the action that maximizes the **expected utility** of the action outcomes—that is, the utility the agent expects to derive, on average, given the probabilities and utilities of each

EXPECTED UTILITY

[6] The word "utility" here refers to "the quality of being useful," not to the electric company or waterworks.

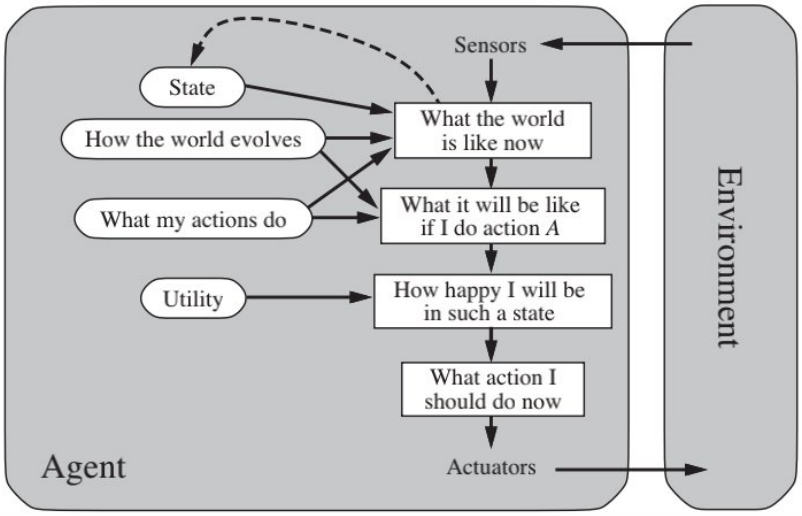


Figure 2.14 A model-based, utility-based agent. It uses a model of the world, along with a utility function that measures its preferences among states of the world. Then it chooses the action that leads to the best expected utility, where expected utility is computed by averaging over all possible outcome states, weighted by the probability of the outcome.

outcome. (Appendix A defines expectation more precisely.) In Chapter 16, we show that any rational agent must behave *as if* it possesses a utility function whose expected value it tries to maximize. An agent that possesses an *explicit* utility function can make rational decisions with a general-purpose algorithm that does not depend on the specific utility function being maximized. In this way, the "global" definition of rationality—designating as rational those agent functions that have the highest performance—is turned into a "local" constraint on rational-agent designs that can be expressed in a simple program.

The utility-based agent structure appears in Figure 2.14. Utility-based agent programs appear in Part IV, where we design decision-making agents that must handle the uncertainty inherent in stochastic or partially observable environments.

At this point, the reader may be wondering, "Is it that simple? We just build agents that maximize expected utility, and we're done?" It's true that such agents would be intelligent, but it's not simple. A utility-based agent has to model and keep track of its environment, tasks that have involved a great deal of research on perception, representation, reasoning, and learning. The results of this research fill many of the chapters of this book. Choosing the utility-maximizing course of action is also a difficult task, requiring ingenious algorithms that fill several more chapters. Even with these algorithms, perfect rationality is usually unachievable in practice because of computational complexity, as we noted in Chapter 1.

2.4.6 Learning agents

We have described agent programs with various methods for selecting actions. We have not, so far, explained how the agent programs *come into being*. In his famous early paper, Turing (1950) considers the idea of actually programming his intelligent machines by hand.

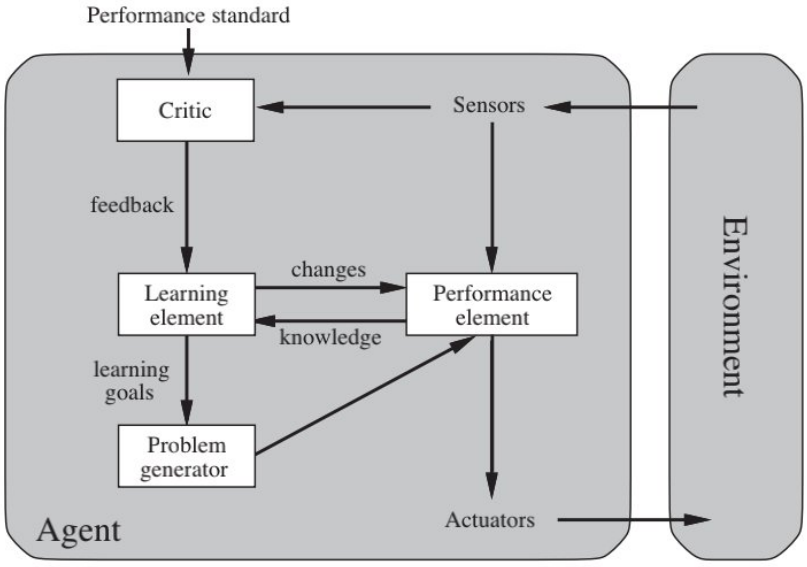


Figure 2.15 A general learning agent.

He estimates how much work this might take and concludes "Some more expeditious method seems desirable." The method he proposes is to build learning machines and then to teach them. In many areas of AI, this is now the preferred method for creating state-of-the-art systems. Learning has another advantage, as we noted earlier: it allows the agent to operate in initially unknown environments and to become more competent than its initial knowledge alone might allow. In this section, we briefly introduce the main ideas of learning agents. Throughout the book, we comment on opportunities and methods for learning in particular kinds of agents. Part V goes into much more depth on the learning algorithms themselves.

LEARNING ELEMENT
PERFORMANCE ELEMENT
CRITIC

A learning agent can be divided into four conceptual components, as shown in Figure 2.15. The most important distinction is between the **learning element**, which is responsible for making improvements, and the **performance element**, which is responsible for selecting external actions. The performance element is what we have previously considered to be the entire agent: it takes in percepts and decides on actions. The learning element uses feedback from the **critic** on how the agent is doing and determines how the performance element should be modified to do better in the future.

The design of the learning element depends very much on the design of the performance element. When trying to design an agent that learns a certain capability, the first question is not "How am I going to get it to learn this?" but "What kind of performance element will my agent need to do this once it has learned how?" Given an agent design, learning mechanisms can be constructed to improve every part of the agent.

The critic tells the learning element how well the agent is doing with respect to a fixed performance standard. The critic is necessary because the percepts themselves provide no indication of the agent's success. For example, a chess program could receive a percept indicating that it has checkmated its opponent, but it needs a performance standard to know that this is a good thing; the percept itself does not say so. It is important that the performance

standard be fixed. Conceptually, one should think of it as being outside the agent altogether because the agent must not modify it to fit its own behavior.

PROBLEM GENERATOR

The last component of the learning agent is the **problem generator**. It is responsible for suggesting actions that will lead to new and informative experiences. The point is that if the performance element had its way, it would keep doing the actions that are best, given what it knows. But if the agent is willing to explore a little and do some perhaps suboptimal actions in the short run, it might discover much better actions for the long run. The problem generator's job is to suggest these exploratory actions. This is what scientists do when they carry out experiments. Galileo did not think that dropping rocks from the top of a tower in Pisa was valuable in itself. He was not trying to break the rocks or to modify the brains of unfortunate passers-by. His aim was to modify his own brain by identifying a better theory of the motion of objects.

To make the overall design more concrete, let us return to the automated taxi example. The performance element consists of whatever collection of knowledge and procedures the taxi has for selecting its driving actions. The taxi goes out on the road and drives, using this performance element. The critic observes the world and passes information along to the learning element. For example, after the taxi makes a quick left turn across three lanes of traffic, the critic observes the shocking language used by other drivers. From this experience, the learning element is able to formulate a rule saying this was a bad action, and the performance element is modified by installation of the new rule. The problem generator might identify certain areas of behavior in need of improvement and suggest experiments, such as trying out the brakes on different road surfaces under different conditions.

The learning element can make changes to any of the "knowledge" components shown in the agent diagrams (Figures 2.9, 2.11, 2.13, and 2.14). The simplest cases involve learning directly from the percept sequence. Observation of pairs of successive states of the environment can allow the agent to learn "How the world evolves," and observation of the results of its actions can allow the agent to learn "What my actions do." For example, if the taxi exerts a certain braking pressure when driving on a wet road, then it will soon find out how much deceleration is actually achieved. Clearly, these two learning tasks are more difficult if the environment is only partially observable.

The forms of learning in the preceding paragraph do not need to access the external performance standard—in a sense, the standard is the universal one of making predictions that agree with experiment. The situation is slightly more complex for a utility-based agent that wishes to learn utility information. For example, suppose the taxi-driving agent receives no tips from passengers who have been thoroughly shaken up during the trip. The external performance standard must inform the agent that the loss of tips is a negative contribution to its overall performance; then the agent might be able to learn that violent maneuvers do not contribute to its own utility. In a sense, the performance standard distinguishes part of the incoming percept as a **reward** (or **penalty**) that provides direct feedback on the quality of the agent's behavior. Hard-wired performance standards such as pain and hunger in animals can be understood in this way. This issue is discussed further in Chapter 21.

In summary, agents have a variety of components, and those components can be represented in many ways within the agent program, so there appears to be great variety among

learning methods. There is, however, a single unifying theme. Learning in intelligent agents can be summarized as a process of modification of each component of the agent to bring the components into closer agreement with the available feedback information, thereby improving the overall performance of the agent.

2.4.7 How the components of agent programs work

We have described agent programs (in very high-level terms) as consisting of various components, whose function it is to answer questions such as: "What is the world like now?" "What action should I do now?" "What do my actions do?" The next question for a student of AI is, "How on earth do these components work?" It takes about a thousand pages to begin to answer that question properly, but here we want to draw the reader's attention to some basic distinctions among the various ways that the components can represent the environment that the agent inhabits.

Roughly speaking, we can place the representations along an axis of increasing complexity and expressive power—**atomic**, **factored**, and **structured**. To illustrate these ideas, it helps to consider a particular agent component, such as the one that deals with "What my actions do." This component describes the changes that might occur in the environment as the result of taking an action, and Figure 2.16 provides schematic depictions of how those transitions might be represented.

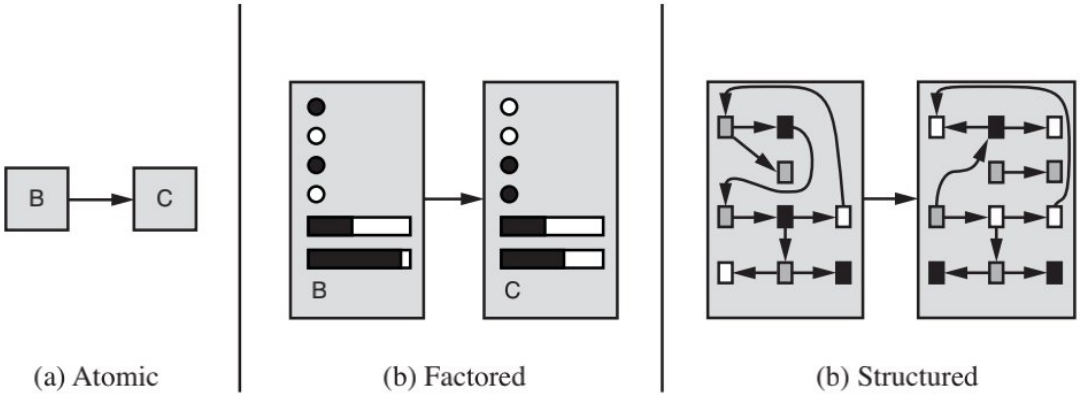


Figure 2.16 Three ways to represent states and the transitions between them. (a) Atomic representation: a state (such as B or C) is a black box with no internal structure; (b) Factored representation: a state consists of a vector of attribute values; values can be Boolean, real-valued, or one of a fixed set of symbols. (c) Structured representation: a state includes objects, each of which may have attributes of its own as well as relationships to other objects.

ATOMIC REPRESENTATION

In an **atomic representation** each state of the world is indivisible—it has no internal structure. Consider the problem of finding a driving route from one end of a country to the other via some sequence of cities (we address this problem in Figure 3.2 on page 68). For the purposes of solving this problem, it may suffice to reduce the state of world to just the name of the city we are in—a single atom of knowledge; a "black box" whose only discernible property is that of being identical to or different from another black box. The algorithms

underlying **search** and **game-playing** (Chapters 3–5), **Hidden Markov models** (Chapter 15), and **Markov decision processes** (Chapter 17) all work with atomic representations—or, at least, they treat representations *as if* they were atomic.

Now consider a higher-fidelity description for the same problem, where we need to be concerned with more than just atomic location in one city or another; we might need to pay attention to how much gas is in the tank, our current GPS coordinates, whether or not the oil warning light is working, how much spare change we have for toll crossings, what station is on the radio, and so on. A **factored representation** splits up each state into a fixed set of **variables** or **attributes**, each of which can have a **value**. While two different atomic states have nothing in common—they are just different black boxes—two different factored states can share some attributes (such as being at some particular GPS location) and not others (such as having lots of gas or having no gas); this makes it much easier to work out how to turn one state into another. With factored representations, we can also represent *uncertainty*—for example, ignorance about the amount of gas in the tank can be represented by leaving that attribute blank. Many important areas of AI are based on factored representations, including **constraint satisfaction** algorithms (Chapter 6), **propositional logic** (Chapter 7), **planning** (Chapters 10 and 11), **Bayesian networks** (Chapters 13–16), and the **machine learning** algorithms in Chapters 18, 20, and 21.

FACTORED REPRESENTATION

VARIABLE

ATTRIBUTE

VALUE

For many purposes, we need to understand the world as having *things* in it that are *related* to each other, not just variables with values. For example, we might notice that a large truck ahead of us is reversing into the driveway of a dairy farm but a cow has got loose and is blocking the truck's path. A factored representation is unlikely to be pre-equipped with the attribute $TruckAheadBackingIntoDairyFarmDrivewayBlockedByLooseCow$ with value $true$ or $false$. Instead, we would need a **structured representation**, in which objects such as cows and trucks and their various and varying relationships can be described explicitly. (See Figure 2.16(c).) Structured representations underlie **relational databases** and **first-order logic** (Chapters 8, 9, and 12), **first-order probability models** (Chapter 14), **knowledge-based learning** (Chapter 19) and much of **natural language understanding** (Chapters 22 and 23). In fact, almost everything that humans express in natural language concerns objects and their relationships.

STRUCTURED REPRESENTATION

As we mentioned earlier, the axis along which atomic, factored, and structured representations lie is the axis of increasing **expressiveness**. Roughly speaking, a more expressive representation can capture, at least as concisely, everything a less expressive one can capture, plus some more. Often, the more expressive language is *much* more concise; for example, the rules of chess can be written in a page or two of a structured-representation language such as first-order logic but require thousands of pages when written in a factored-representation language such as propositional logic. On the other hand, reasoning and learning become more complex as the expressive power of the representation increases. To gain the benefits of expressive representations while avoiding their drawbacks, intelligent systems for the real world may need to operate at all points along the axis simultaneously.

EXPRESSIVENESS

2.5 SUMMARY

This chapter has been something of a whirlwind tour of AI, which we have conceived of as the science of agent design. The major points to recall are as follows:

- An **agent** is something that perceives and acts in an environment. The **agent function** for an agent specifies the action taken by the agent in response to any percept sequence.
- The **performance measure** evaluates the behavior of the agent in an environment. A **rational agent** acts so as to maximize the expected value of the performance measure, given the percept sequence it has seen so far.
- A **task environment** specification includes the performance measure, the external environment, the actuators, and the sensors. In designing an agent, the first step must always be to specify the task environment as fully as possible.
- Task environments vary along several significant dimensions. They can be fully or partially observable, single-agent or multiagent, deterministic or stochastic, episodic or sequential, static or dynamic, discrete or continuous, and known or unknown.
- The **agent program** implements the agent function. There exists a variety of basic agent-program designs reflecting the kind of information made explicit and used in the decision process. The designs vary in efficiency, compactness, and flexibility. The appropriate design of the agent program depends on the nature of the environment.
- **Simple reflex agents** respond directly to percepts, whereas **model-based reflex agents** maintain internal state to track aspects of the world that are not evident in the current percept. **Goal-based agents** act to achieve their goals, and **utility-based agents** try to maximize their own expected "happiness."
- All agents can improve their performance through **learning**.

BIBLIOGRAPHICAL AND HISTORICAL NOTES

The central role of action in intelligence—the notion of practical reasoning—goes back at least as far as Aristotle's *Nicomachean Ethics*. Practical reasoning was also the subject of McCarthy's (1958) influential paper "Programs with Common Sense." The fields of robotics and control theory are, by their very nature, concerned principally with physical agents. The concept of a **controller** in control theory is identical to that of an agent in AI. Perhaps surprisingly, AI has concentrated for most of its history on isolated components of agents—question-answering systems, theorem-provers, vision systems, and so on—rather than on whole agents. The discussion of agents in the text by Genesereth and Nilsson (1987) was an influential exception. The whole-agent view is now widely accepted and is a central theme in recent texts (Poole *et al.*, 1998; Nilsson, 1998; Padgham and Winikoff, 2004; Jones, 2007).

CONTROLLER

Chapter 1 traced the roots of the concept of rationality in philosophy and economics. In AI, the concept was of peripheral interest until the mid-1980s, when it began to suffuse many

discussions about the proper technical foundations of the field. A paper by Jon Doyle (1983) predicted that rational agent design would come to be seen as the core mission of AI, while other popular topics would spin off to form new disciplines.

Careful attention to the properties of the environment and their consequences for rational agent design is most apparent in the control theory tradition—for example, classical control systems (Dorf and Bishop, 2004; Kirk, 2004) handle fully observable, deterministic environments; stochastic optimal control (Kumar and Varaiya, 1986; Bertsekas and Shreve, 2007) handles partially observable, stochastic environments; and hybrid control (Henzinger and Sastry, 1998; Cassandras and Lygeros, 2006) deals with environments containing both discrete and continuous elements. The distinction between fully and partially observable environments is also central in the **dynamic programming** literature developed in the field of operations research (Puterman, 1994), which we discuss in Chapter 17.

Reflex agents were the primary model for psychological behaviorists such as Skinner (1953), who attempted to reduce the psychology of organisms strictly to input/output or stimulus/response mappings. The advance from behaviorism to functionalism in psychology, which was at least partly driven by the application of the computer metaphor to agents (Putnam, 1960; Lewis, 1966), introduced the internal state of the agent into the picture. Most work in AI views the idea of pure reflex agents with state as too simple to provide much leverage, but work by Rosenschein (1985) and Brooks (1986) questioned this assumption (see Chapter 25). In recent years, a great deal of work has gone into finding efficient algorithms for keeping track of complex environments (Hamscher *et al.*, 1992; Simon, 2006). The Remote Agent program (described on page 28) that controlled the Deep Space One spacecraft is a particularly impressive example (Muscettola *et al.*, 1998; Jonsson *et al.*, 2000).

Goal-based agents are presupposed in everything from Aristotle's view of practical reasoning to McCarthy's early papers on logical AI. Shakey the Robot (Fikes and Nilsson, 1971; Nilsson, 1984) was the first robotic embodiment of a logical, goal-based agent. A full logical analysis of goal-based agents appeared in Genesereth and Nilsson (1987), and a goal-based programming methodology called agent-oriented programming was developed by Shoham (1993). The agent-based approach is now extremely popular in software engineering (Ciancarini and Wooldridge, 2001). It has also infiltrated the area of operating systems,

AUTONOMIC COMPUTING

where **autonomic computing** refers to computer systems and networks that monitor and control themselves with a perceive–act loop and machine learning methods (Kephart and Chess, 2003). Noting that a collection of agent programs designed to work well together in a true multiagent environment necessarily exhibits modularity—the programs share no internal state and communicate with each other only through the environment—it is common within the

MULTIAGENT SYSTEMS

field of **multiagent systems** to design the agent program of a single agent as a collection of autonomous sub-agents. In some cases, one can even prove that the resulting system gives the same optimal solutions as a monolithic design.

The goal-based view of agents also dominates the cognitive psychology tradition in the area of problem solving, beginning with the enormously influential *Human Problem Solving* (Newell and Simon, 1972) and running through all of Newell's later work (Newell, 1990). Goals, further analyzed as *desires* (general) and *intentions* (currently pursued), are central to the theory of agents developed by Bratman (1987). This theory has been influential both in

natural language understanding and multiagent systems.

Horvitz *et al.* (1988) specifically suggest the use of rationality conceived as the maximization of expected utility as a basis for AI. The text by Pearl (1988) was the first in AI to cover probability and utility theory in depth; its exposition of practical methods for reasoning and decision making under uncertainty was probably the single biggest factor in the rapid shift towards utility-based agents in the 1990s (see Part IV).

The general design for learning agents portrayed in Figure 2.15 is classic in the machine learning literature (Buchanan *et al.*, 1978; Mitchell, 1997). Examples of the design, as embodied in programs, go back at least as far as Arthur Samuel's (1959, 1967) learning program for playing checkers. Learning agents are discussed in depth in Part V.

Interest in agents and in agent design has risen rapidly in recent years, partly because of the growth of the Internet and the perceived need for automated and mobile **softbot** (Etzioni and Weld, 1994). Relevant papers are collected in *Readings in Agents* (Huhns and Singh, 1998) and *Foundations of Rational Agency* (Wooldridge and Rao, 1999). Texts on multiagent systems usually provide a good introduction to many aspects of agent design (Weiss, 2000a; Wooldridge, 2002). Several conference series devoted to agents began in the 1990s, including the International Workshop on Agent Theories, Architectures, and Languages (ATAL), the International Conference on Autonomous Agents (AGENTS), and the International Conference on Multi-Agent Systems (ICMAS). In 2002, these three merged to form the International Joint Conference on Autonomous Agents and Multi-Agent Systems (AAMAS). The journal *Autonomous Agents and Multi-Agent Systems* was founded in 1998. Finally, *Dung Beetle Ecology* (Hanski and Cambefort, 1991) provides a wealth of interesting information on the behavior of dung beetles. YouTube features inspiring video recordings of their activities.

EXERCISES

2.1 Suppose that the performance measure is concerned with just the first T time steps of the environment and ignores everything thereafter. Show that a rational agent's action may depend not just on the state of the environment but also on the time step it has reached.

2.2 Let us examine the rationality of various vacuum-cleaner agent functions.

a. Show that the simple vacuum-cleaner agent function described in Figure 2.3 is indeed rational under the assumptions listed on page 38.

b. Describe a rational agent function for the case in which each movement costs one point. Does the corresponding agent program require internal state?

c. Discuss possible agent designs for the cases in which clean squares can become dirty and the geography of the environment is unknown. Does it make sense for the agent to learn from its experience in these cases? If so, what should it learn? If not, why not?

2.3 For each of the following assertions, say whether it is true or false and support your answer with examples or counterexamples where appropriate.

a. An agent that senses only partial information about the state cannot be perfectly rational.

b. There exist task environments in which no pure reflex agent can behave rationally.

c. There exists a task environment in which every agent is rational.

d. The input to an agent program is the same as the input to the agent function.

e. Every agent function is implementable by some program/machine combination.

f. Suppose an agent selects its action uniformly at random from the set of possible actions. There exists a deterministic task environment in which this agent is rational.

g. It is possible for a given agent to be perfectly rational in two distinct task environments.

h. Every agent is rational in an unobservable environment.

i. A perfectly rational poker-playing agent never loses.

2.4 For each of the following activities, give a PEAS description of the task environment and characterize it in terms of the properties listed in Section 2.3.2.

- Playing soccer.
- Exploring the subsurface oceans of Titan.
- Shopping for used AI books on the Internet.
- Playing a tennis match.
- Practicing tennis against a wall.
- Performing a high jump.
- Knitting a sweater.
- Bidding on an item at an auction.

2.5 Define in your own words the following terms: agent, agent function, agent program, rationality, autonomy, reflex agent, model-based agent, goal-based agent, utility-based agent, learning agent.

2.6 This exercise explores the differences between agent functions and agent programs.

a. Can there be more than one agent program that implements a given agent function? Give an example, or show why one is not possible.

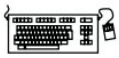
b. Are there agent functions that cannot be implemented by any agent program?

c. Given a fixed machine architecture, does each agent program implement exactly one agent function?

d. Given an architecture with n bits of storage, how many different possible agent programs are there?

e. Suppose we keep the agent program fixed but speed up the machine by a factor of two. Does that change the agent function?

2.7 Write pseudocode agent programs for the goal-based and utility-based agents.



The following exercises all concern the implementation of environments and agents for the vacuum-cleaner world.

2.8 Implement a performance-measuring environment simulator for the vacuum-cleaner world depicted in Figure 2.2 and specified on page 38. Your implementation should be modular so that the sensors, actuators, and environment characteristics (size, shape, dirt placement, etc.) can be changed easily. (*Note:* for some choices of programming language and operating system there are already implementations in the online code repository.)

2.9 Implement a simple reflex agent for the vacuum environment in Exercise 2.8. Run the environment with this agent for all possible initial dirt configurations and agent locations. Record the performance score for each configuration and the overall average score.

2.10 Consider a modified version of the vacuum environment in Exercise 2.8, in which the agent is penalized one point for each movement.

a. Can a simple reflex agent be perfectly rational for this environment? Explain.

b. What about a reflex agent with state? Design such an agent.

c. How do your answers to **a** and **b** change if the agent's percepts give it the clean/dirty status of every square in the environment?

2.11 Consider a modified version of the vacuum environment in Exercise 2.8, in which the geography of the environment—its extent, boundaries, and obstacles—is unknown, as is the initial dirt configuration. (The agent can go Up and $Down$ as well as $Left$ and $Right$.)

a. Can a simple reflex agent be perfectly rational for this environment? Explain.

b. Can a simple reflex agent with a *randomized* agent function outperform a simple reflex agent? Design such an agent and measure its performance on several environments.

c. Can you design an environment in which your randomized agent will perform poorly? Show your results.

d. Can a reflex agent with state outperform a simple reflex agent? Design such an agent and measure its performance on several environments. Can you design a rational agent of this type?

2.12 Repeat Exercise 2.11 for the case in which the location sensor is replaced with a "bump" sensor that detects the agent's attempts to move into an obstacle or to cross the boundaries of the environment. Suppose the bump sensor stops working; how should the agent behave?

2.13 The vacuum environments in the preceding exercises have all been deterministic. Discuss possible agent programs for each of the following stochastic versions:

a. Murphy's law: twenty-five percent of the time, the $Suck$ action fails to clean the floor if it is dirty and deposits dirt onto the floor if the floor is clean. How is your agent program affected if the dirt sensor gives the wrong answer 10% of the time?

b. Small children: At each time step, each clean square has a 10% chance of becoming dirty. Can you come up with a rational agent design for this case?

3 SOLVING PROBLEMS BY SEARCHING

In which we see how an agent can find a sequence of actions that achieves its goals when no single action will do.

The simplest agents discussed in Chapter 2 were the reflex agents, which base their actions on a direct mapping from states to actions. Such agents cannot operate well in environments for which this mapping would be too large to store and would take too long to learn. Goal-based agents, on the other hand, consider future actions and the desirability of their outcomes.

PROBLEM-SOLVING AGENT

This chapter describes one kind of goal-based agent called a **problem-solving agent**. Problem-solving agents use **atomic** representations, as described in Section 2.4.7—that is, states of the world are considered as wholes, with no internal structure visible to the problem-solving algorithms. Goal-based agents that use more advanced **factored** or **structured** representations are usually called **planning agents** and are discussed in Chapters 7 and 10.

Our discussion of problem solving begins with precise definitions of **problems** and their **solutions** and give several examples to illustrate these definitions. We then describe several general-purpose search algorithms that can be used to solve these problems. We will see several **uninformed** search algorithms—algorithms that are given no information about the problem other than its definition. Although some of these algorithms can solve any solvable problem, none of them can do so efficiently. **Informed** search algorithms, on the other hand, can do quite well given some guidance on where to look for solutions.

In this chapter, we limit ourselves to the simplest kind of task environment, for which the solution to a problem is always a *fixed sequence* of actions. The more general case—where the agent's future actions may vary depending on future percepts—is handled in Chapter 4.

This chapter uses the concepts of asymptotic complexity (that is, $O()$ notation) and NP-completeness. Readers unfamiliar with these concepts should consult Appendix A.

3.1 PROBLEM-SOLVING AGENTS

Intelligent agents are supposed to maximize their performance measure. As we mentioned in Chapter 2, achieving this is sometimes simplified if the agent can adopt a **goal** and aim at satisfying it. Let us first look at why and how an agent might do this.

Imagine an agent in the city of Arad, Romania, enjoying a touring holiday. The agent's performance measure contains many factors: it wants to improve its suntan, improve its Romanian, take in the sights, enjoy the nightlife (such as it is), avoid hangovers, and so on. The decision problem is a complex one involving many tradeoffs and careful reading of guidebooks. Now, suppose the agent has a nonrefundable ticket to fly out of Bucharest the following day. In that case, it makes sense for the agent to adopt the **goal** of getting to Bucharest. Courses of action that don't reach Bucharest on time can be rejected without further consideration and the agent's decision problem is greatly simplified. Goals help organize behavior by limiting the objectives that the agent is trying to achieve and hence the actions it needs to consider. **Goal formulation**, based on the current situation and the agent's performance measure, is the first step in problem solving.

GOAL FORMULATION

We will consider a goal to be a set of world states—exactly those states in which the goal is satisfied. The agent's task is to find out how to act, now and in the future, so that it reaches a goal state. Before it can do this, it needs to decide (or we need to decide on its behalf) what sorts of actions and states it should consider. If it were to consider actions at the level of "move the left foot forward an inch" or "turn the steering wheel one degree left," the agent would probably never find its way out of the parking lot, let alone to Bucharest, because at that level of detail there is too much uncertainty in the world and there would be too many steps in a solution. **Problem formulation** is the process of deciding what actions and states to consider, given a goal. We discuss this process in more detail later. For now, let us assume that the agent will consider actions at the level of driving from one major town to another. Each state therefore corresponds to being in a particular town.

PROBLEM FORMULATION

Our agent has now adopted the goal of driving to Bucharest and is considering where to go from Arad. Three roads lead out of Arad, one toward Sibiu, one to Timisoara, and one to Zerind. None of these achieves the goal, so unless the agent is familiar with the geography of Romania, it will not know which road to follow.[1] In other words, the agent will not know which of its possible actions is best, because it does not yet know enough about the state that results from taking each action. If the agent has no additional information—i.e., if the environment is **unknown** in the sense defined in Section 2.3—then it is has no choice but to try one of the actions at random. This sad situation is discussed in Chapter 4.

But suppose the agent has a map of Romania. The point of a map is to provide the agent with information about the states it might get itself into and the actions it can take. The agent can use this information to consider *subsequent* stages of a hypothetical journey via each of the three towns, trying to find a journey that eventually gets to Bucharest. Once it has found a path on the map from Arad to Bucharest, it can achieve its goal by carrying out the driving actions that correspond to the legs of the journey. In general, *an agent with several immediate options of unknown value can decide what to do by first examining* future *actions that eventually lead to states of known value.*

To be more specific about what we mean by "examining future actions," we have to be more specific about properties of the environment, as defined in Section 2.3. For now,

[1] We are assuming that most readers are in the same position and can easily imagine themselves to be as clueless as our agent. We apologize to Romanian readers who are unable to take advantage of this pedagogical device.

we assume that the environment is **observable**, so the agent always knows the current state. For the agent driving in Romania, it's reasonable to suppose that each city on the map has a sign indicating its presence to arriving drivers. We also assume the environment is **discrete**, so at any given state there are only finitely many actions to choose from. This is true for navigating in Romania because each city is connected to a small number of other cities. We will assume the environment is **known**, so the agent knows which states are reached by each action. (Having an accurate map suffices to meet this condition for navigation problems.) Finally, we assume that the environment is **deterministic**, so each action has exactly one outcome. Under ideal conditions, this is true for the agent in Romania—it means that if it chooses to drive from Arad to Sibiu, it does end up in Sibiu. Of course, conditions are not always ideal, as we show in Chapter 4.

Under these assumptions, the solution to any problem is a fixed sequence of actions. "Of course!" one might say, "What else could it be?" Well, in general it could be a branching strategy that recommends different actions in the future depending on what percepts arrive. For example, under less than ideal conditions, the agent might plan to drive from Arad to Sibiu and then to Rimnicu Vilcea but may also need to have a contingency plan in case it arrives by accident in Zerind instead of Sibiu. Fortunately, if the agent knows the initial state and the environment is known and deterministic, it knows exactly where it will be after the first action and what it will perceive. Since only one percept is possible after the first action, the solution can specify only one possible second action, and so on.

SEARCH

SOLUTION

EXECUTION

The process of looking for a sequence of actions that reaches the goal is called **search**. A search algorithm takes a problem as input and returns a **solution** in the form of an action sequence. Once a solution is found, the actions it recommends can be carried out. This is called the **execution** phase. Thus, we have a simple "formulate, search, execute" design for the agent, as shown in Figure 3.1. After formulating a goal and a problem to solve, the agent calls a search procedure to solve it. It then uses the solution to guide its actions, doing whatever the solution recommends as the next thing to do—typically, the first action of the sequence—and then removing that step from the sequence. Once the solution has been executed, the agent will formulate a new goal.

Notice that while the agent is executing the solution sequence it *ignores its percepts* when choosing an action because it knows in advance what they will be. An agent that carries out its plans with its eyes closed, so to speak, must be quite certain of what is going on. Control theorists call this an **open-loop** system, because ignoring the percepts breaks the loop between agent and environment.

OPEN-LOOP

We first describe the process of problem formulation, and then devote the bulk of the chapter to various algorithms for the SEARCH function. We do not discuss the workings of the UPDATE-STATE and FORMULATE-GOAL functions further in this chapter.

3.1.1 Well-defined problems and solutions

PROBLEM

A **problem** can be defined formally by five components:

INITIAL STATE

- The **initial state** that the agent starts in. For example, the initial state for our agent in Romania might be described as $In(Arad)$.

```
function SIMPLE-PROBLEM-SOLVING-AGENT(percept) returns an action
  persistent: seq, an action sequence, initially empty
              state, some description of the current world state
              goal, a goal, initially null
              problem, a problem formulation

  state ← UPDATE-STATE(state, percept)
  if seq is empty then
      goal ← FORMULATE-GOAL(state)
      problem ← FORMULATE-PROBLEM(state, goal)
      seq ← SEARCH(problem)
      if seq = failure then return a null action
  action ← FIRST(seq)
  seq ← REST(seq)
  return action
```

Figure 3.1 A simple problem-solving agent. It first formulates a goal and a problem, searches for a sequence of actions that would solve the problem, and then executes the actions one at a time. When this is complete, it formulates another goal and starts over.

ACTIONS

- A description of the possible **actions** available to the agent. Given a particular state s, ACTIONS(s) returns the set of actions that can be executed in s. We say that each of these actions is **applicable** in s. For example, from the state $In(Arad)$, the applicable actions are $\{Go(Sibiu), Go(Timisoara), Go(Zerind)\}$.

APPLICABLE

TRANSITION MODEL

SUCCESSOR

- A description of what each action does; the formal name for this is the **transition model**, specified by a function RESULT(s, a) that returns the state that results from doing action a in state s. We also use the term **successor** to refer to any state reachable from a given state by a single action.[2] For example, we have

$$\text{RESULT}(In(Arad), Go(Zerind)) = In(Zerind) .$$

STATE SPACE

GRAPH

PATH

Together, the initial state, actions, and transition model implicitly define the **state space** of the problem—the set of all states reachable from the initial state by any sequence of actions. The state space forms a directed network or **graph** in which the nodes are states and the links between nodes are actions. (The map of Romania shown in Figure 3.2 can be interpreted as a state-space graph if we view each road as standing for two driving actions, one in each direction.) A **path** in the state space is a sequence of states connected by a sequence of actions.

GOAL TEST

- The **goal test**, which determines whether a given state is a goal state. Sometimes there is an explicit set of possible goal states, and the test simply checks whether the given state is one of them. The agent's goal in Romania is the singleton set $\{In(Bucharest)\}$.

[2] Many treatments of problem solving, including previous editions of this book, use a **successor function**, which returns the set of all successors, instead of separate ACTIONS and RESULT functions. The successor function makes it difficult to describe an agent that knows what actions it can try but not what they achieve. Also, note some author use RESULT(a, s) instead of RESULT(s, a), and some use DO instead of RESULT.

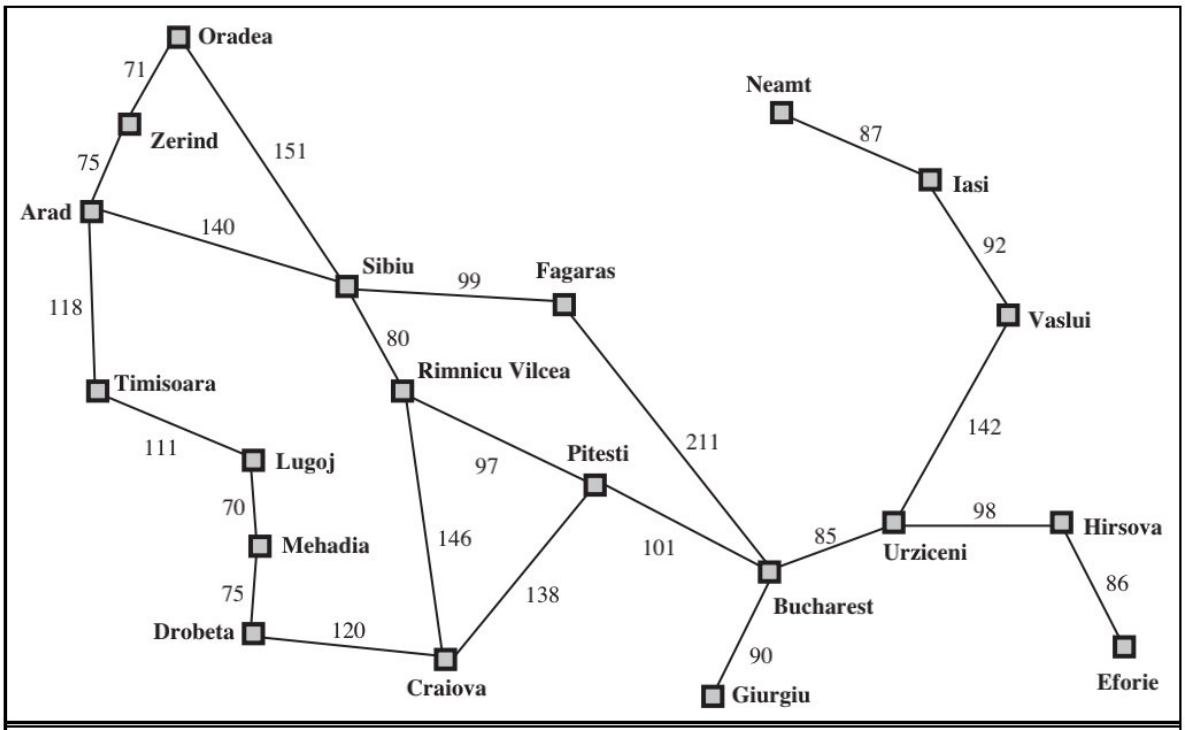


Figure 3.2 A simplified road map of part of Romania.

Sometimes the goal is specified by an abstract property rather than an explicitly enumerated set of states. For example, in chess, the goal is to reach a state called "checkmate," where the opponent's king is under attack and can't escape.

PATH COST

- A **path cost** function that assigns a numeric cost to each path. The problem-solving agent chooses a cost function that reflects its own performance measure. For the agent trying to get to Bucharest, time is of the essence, so the cost of a path might be its length in kilometers. In this chapter, we assume that the cost of a path can be described as the *sum* of the costs of the individual actions along the path.[3] The **step cost** of taking action a in state s to reach state s' is denoted by $c(s, a, s')$. The step costs for Romania are shown in Figure 3.2 as route distances. We assume that step costs are nonnegative.[4]

STEP COST

The preceding elements define a problem and can be gathered into a single data structure that is given as input to a problem-solving algorithm. A **solution** to a problem is an action sequence that leads from the initial state to a goal state. Solution quality is measured by the path cost function, and an **optimal solution** has the lowest path cost among all solutions.

OPTIMAL SOLUTION

3.1.2 Formulating problems

In the preceding section we proposed a formulation of the problem of getting to Bucharest in terms of the initial state, actions, transition model, goal test, and path cost. This formulation seems reasonable, but it is still a *model*—an abstract mathematical description—and not the

[3] This assumption is algorithmically convenient but also theoretically justifiable—see page 649 in Chapter 17.

[4] The implications of negative costs are explored in Exercise 3.8.

real thing. Compare the simple state description we have chosen, *In(Arad)*, to an actual cross-country trip, where the state of the world includes so many things: the traveling companions, the current radio program, the scenery out of the window, the proximity of law enforcement officers, the distance to the next rest stop, the condition of the road, the weather, and so on. All these considerations are left out of our state descriptions because they are irrelevant to the problem of finding a route to Bucharest. The process of removing detail from a representation is called **abstraction**.

ABSTRACTION

In addition to abstracting the state description, we must abstract the actions themselves. A driving action has many effects. Besides changing the location of the vehicle and its occupants, it takes up time, consumes fuel, generates pollution, and changes the agent (as they say, travel is broadening). Our formulation takes into account only the change in location. Also, there are many actions that we omit altogether: turning on the radio, looking out of the window, slowing down for law enforcement officers, and so on. And of course, we don't specify actions at the level of "turn steering wheel to the left by one degree."

Can we be more precise about defining the appropriate level of abstraction? Think of the abstract states and actions we have chosen as corresponding to large sets of detailed world states and detailed action sequences. Now consider a solution to the abstract problem: for example, the path from Arad to Sibiu to Rimnicu Vilcea to Pitesti to Bucharest. This abstract solution corresponds to a large number of more detailed paths. For example, we could drive with the radio on between Sibiu and Rimnicu Vilcea, and then switch it off for the rest of the trip. The abstraction is *valid* if we can expand any abstract solution into a solution in the more detailed world; a sufficient condition is that for every detailed state that is "in Arad," there is a detailed path to some state that is "in Sibiu," and so on.[5] The abstraction is *useful* if carrying out each of the actions in the solution is easier than the original problem; in this case they are easy enough that they can be carried out without further search or planning by an average driving agent. The choice of a good abstraction thus involves removing as much detail as possible while retaining validity and ensuring that the abstract actions are easy to carry out. Were it not for the ability to construct useful abstractions, intelligent agents would be completely swamped by the real world.

3.2 EXAMPLE PROBLEMS

The problem-solving approach has been applied to a vast array of task environments. We list some of the best known here, distinguishing between *toy* and *real-world* problems. A **toy problem** is intended to illustrate or exercise various problem-solving methods. It can be given a concise, exact description and hence is usable by different researchers to compare the performance of algorithms. A **real-world problem** is one whose solutions people actually care about. Such problems tend not to have a single agreed-upon description, but we can give the general flavor of their formulations.

TOY PROBLEM

REAL-WORLD PROBLEM

[5] See Section 11.2 for a more complete set of definitions and algorithms.

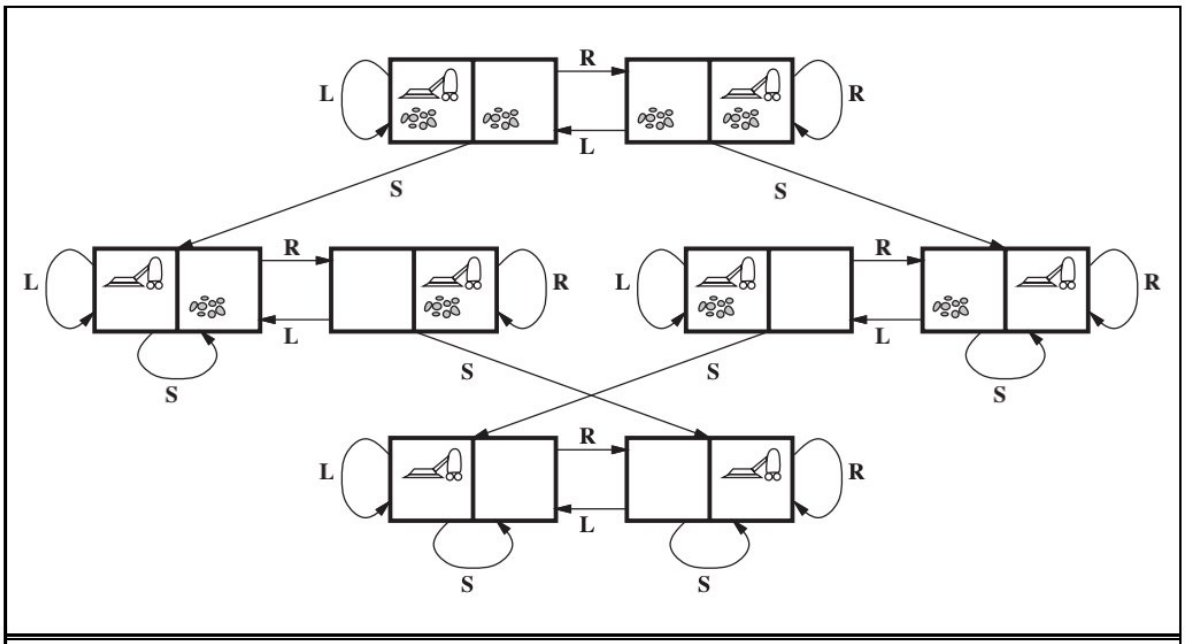


Figure 3.3 The state space for the vacuum world. Links denote actions: L = *Left*, R = *Right*, S = *Suck*.

3.2.1 Toy problems

The first example we examine is the **vacuum world** first introduced in Chapter 2. (See Figure 2.2.) This can be formulated as a problem as follows:

- **States**: The state is determined by both the agent location and the dirt locations. The agent is in one of two locations, each of which might or might not contain dirt. Thus, there are $2 \times 2^2 = 8$ possible world states. A larger environment with n locations has $n \cdot 2^n$ states.
- **Initial state**: Any state can be designated as the initial state.
- **Actions**: In this simple environment, each state has just three actions: *Left*, *Right*, and *Suck*. Larger environments might also include *Up* and *Down*.
- **Transition model**: The actions have their expected effects, except that moving *Left* in the leftmost square, moving *Right* in the rightmost square, and *Suck*ing in a clean square have no effect. The complete state space is shown in Figure 3.3.
- **Goal test**: This checks whether all the squares are clean.
- **Path cost**: Each step costs 1, so the path cost is the number of steps in the path.

Compared with the real world, this toy problem has discrete locations, discrete dirt, reliable cleaning, and it never gets any dirtier. Chapter 4 relaxes some of these assumptions.

8-PUZZLE

The **8-puzzle**, an instance of which is shown in Figure 3.4, consists of a 3×3 board with eight numbered tiles and a blank space. A tile adjacent to the blank space can slide into the space. The object is to reach a specified goal state, such as the one shown on the right of the figure. The standard formulation is as follows:

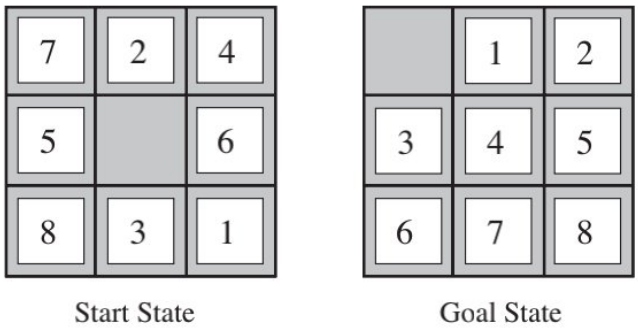


Figure 3.4 A typical instance of the 8-puzzle.

- **States**: A state description specifies the location of each of the eight tiles and the blank in one of the nine squares.
- **Initial state**: Any state can be designated as the initial state. Note that any given goal can be reached from exactly half of the possible initial states (Exercise 3.4).
- **Actions**: The simplest formulation defines the actions as movements of the blank space *Left*, *Right*, *Up*, or *Down*. Different subsets of these are possible depending on where the blank is.
- **Transition model**: Given a state and action, this returns the resulting state; for example, if we apply *Left* to the start state in Figure 3.4, the resulting state has the 5 and the blank switched.
- **Goal test**: This checks whether the state matches the goal configuration shown in Figure 3.4. (Other goal configurations are possible.)
- **Path cost**: Each step costs 1, so the path cost is the number of steps in the path.

What abstractions have we included here? The actions are abstracted to their beginning and final states, ignoring the intermediate locations where the block is sliding. We have abstracted away actions such as shaking the board when pieces get stuck and ruled out extracting the pieces with a knife and putting them back again. We are left with a description of the rules of the puzzle, avoiding all the details of physical manipulations.

SLIDING-BLOCK PUZZLES

The 8-puzzle belongs to the family of **sliding-block puzzles**, which are often used as test problems for new search algorithms in AI. This family is known to be NP-complete, so one does not expect to find methods significantly better in the worst case than the search algorithms described in this chapter and the next. The 8-puzzle has $9!/2 = 181,440$ reachable states and is easily solved. The 15-puzzle (on a 4×4 board) has around 1.3 trillion states, and random instances can be solved optimally in a few milliseconds by the best search algorithms. The 24-puzzle (on a 5×5 board) has around 10^{25} states, and random instances take several hours to solve optimally.

8-QUEENS PROBLEM

The goal of the **8-queens problem** is to place eight queens on a chessboard such that no queen attacks any other. (A queen attacks any piece in the same row, column or diagonal.) Figure 3.5 shows an attempted solution that fails: the queen in the rightmost column is attacked by the queen at the top left.

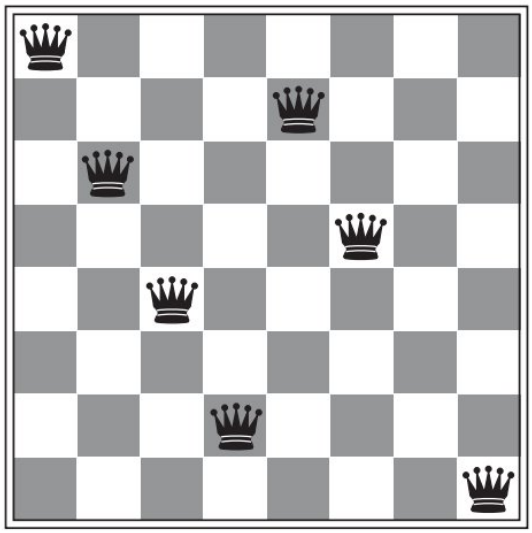


Figure 3.5 Almost a solution to the 8-queens problem. (Solution is left as an exercise.)

Although efficient special-purpose algorithms exist for this problem and for the whole n-queens family, it remains a useful test problem for search algorithms. There are two main kinds of formulation. An **incremental formulation** involves operators that *augment* the state description, starting with an empty state; for the 8-queens problem, this means that each action adds a queen to the state. A **complete-state formulation** starts with all 8 queens on the board and moves them around. In either case, the path cost is of no interest because only the final state counts. The first incremental formulation one might try is the following:

INCREMENTAL FORMULATION

COMPLETE-STATE FORMULATION

- **States**: Any arrangement of 0 to 8 queens on the board is a state.
- **Initial state**: No queens on the board.
- **Actions**: Add a queen to any empty square.
- **Transition model**: Returns the board with a queen added to the specified square.
- **Goal test**: 8 queens are on the board, none attacked.

In this formulation, we have $64 \cdot 63 \cdots 57 \approx 1.8 \times 10^{14}$ possible sequences to investigate. A better formulation would prohibit placing a queen in any square that is already attacked:

- **States**: All possible arrangements of n queens $(0 \leq n \leq 8)$, one per column in the leftmost n columns, with no queen attacking another.
- **Actions**: Add a queen to any square in the leftmost empty column such that it is not attacked by any other queen.

This formulation reduces the 8-queens state space from 1.8×10^{14} to just 2,057, and solutions are easy to find. On the other hand, for 100 queens the reduction is from roughly 10^{400} states to about 10^{52} states (Exercise 3.5)—a big improvement, but not enough to make the problem tractable. Section 4.1 describes the complete-state formulation, and Chapter 6 gives a simple algorithm that solves even the million-queens problem with ease.

Our final toy problem was devised by Donald Knuth (1964) and illustrates how infinite state spaces can arise. Knuth conjectured that, starting with the number 4, a sequence of factorial, square root, and floor operations will reach any desired positive integer. For example, we can reach 5 from 4 as follows:

$$\left\lfloor \sqrt{\sqrt{\sqrt{\sqrt{\sqrt{(4!)!}}}}} \right\rfloor = 5 \ .$$

The problem definition is very simple:

- **States**: Positive numbers.
- **Initial state**: 4.
- **Actions**: Apply factorial, square root, or floor operation (factorial for integers only).
- **Transition model**: As given by the mathematical definitions of the operations.
- **Goal test**: State is the desired positive integer.

To our knowledge there is no bound on how large a number might be constructed in the process of reaching a given target—for example, the number 620,448,401,733,239,439,360,000 is generated in the expression for 5—so the state space for this problem is infinite. Such state spaces arise frequently in tasks involving the generation of mathematical expressions, circuits, proofs, programs, and other recursively defined objects.

3.2.2 Real-world problems

ROUTE-FINDING PROBLEM

We have already seen how the **route-finding problem** is defined in terms of specified locations and transitions along links between them. Route-finding algorithms are used in a variety of applications. Some, such as Web sites and in-car systems that provide driving directions, are relatively straightforward extensions of the Romania example. Others, such as routing video streams in computer networks, military operations planning, and airline travel-planning systems, involve much more complex specifications. Consider the airline travel problems that must be solved by a travel-planning Web site:

- **States**: Each state obviously includes a location (e.g., an airport) and the current time. Furthermore, because the cost of an action (a flight segment) may depend on previous segments, their fare bases, and their status as domestic or international, the state must record extra information about these "historical" aspects.
- **Initial state**: This is specified by the user's query.
- **Actions**: Take any flight from the current location, in any seat class, leaving after the current time, leaving enough time for within-airport transfer if needed.
- **Transition model**: The state resulting from taking a flight will have the flight's destination as the current location and the flight's arrival time as the current time.
- **Goal test**: Are we at the final destination specified by the user?
- **Path cost**: This depends on monetary cost, waiting time, flight time, customs and immigration procedures, seat quality, time of day, type of airplane, frequent-flyer mileage awards, and so on.

Commercial travel advice systems use a problem formulation of this kind, with many additional complications to handle the byzantine fare structures that airlines impose. Any seasoned traveler knows, however, that not all air travel goes according to plan. A really good system should include contingency plans—such as backup reservations on alternate flights—to the extent that these are justified by the cost and likelihood of failure of the original plan.

TOURING PROBLEM

Touring problems are closely related to route-finding problems, but with an important difference. Consider, for example, the problem "Visit every city in Figure 3.2 at least once, starting and ending in Bucharest." As with route finding, the actions correspond to trips between adjacent cities. The state space, however, is quite different. Each state must include not just the current location but also the *set of cities the agent has visited*. So the initial state would be $In(Bucharest), Visited(\{Bucharest\})$, a typical intermediate state would be $In(Vaslui), Visited(\{Bucharest, Urziceni, Vaslui\})$, and the goal test would check whether the agent is in Bucharest and all 20 cities have been visited.

TRAVELING SALESPERSON PROBLEM

The **traveling salesperson problem** (TSP) is a touring problem in which each city must be visited exactly once. The aim is to find the *shortest* tour. The problem is known to be NP-hard, but an enormous amount of effort has been expended to improve the capabilities of TSP algorithms. In addition to planning trips for traveling salespersons, these algorithms have been used for tasks such as planning movements of automatic circuit-board drills and of stocking machines on shop floors.

VLSI LAYOUT

A **VLSI layout** problem requires positioning millions of components and connections on a chip to minimize area, minimize circuit delays, minimize stray capacitances, and maximize manufacturing yield. The layout problem comes after the logical design phase and is usually split into two parts: **cell layout** and **channel routing**. In cell layout, the primitive components of the circuit are grouped into cells, each of which performs some recognized function. Each cell has a fixed footprint (size and shape) and requires a certain number of connections to each of the other cells. The aim is to place the cells on the chip so that they do not overlap and so that there is room for the connecting wires to be placed between the cells. Channel routing finds a specific route for each wire through the gaps between the cells. These search problems are extremely complex, but definitely worth solving. Later in this chapter, we present some algorithms capable of solving them.

ROBOT NAVIGATION

Robot navigation is a generalization of the route-finding problem described earlier. Rather than following a discrete set of routes, a robot can move in a continuous space with (in principle) an infinite set of possible actions and states. For a circular robot moving on a flat surface, the space is essentially two-dimensional. When the robot has arms and legs or wheels that must also be controlled, the search space becomes many-dimensional. Advanced techniques are required just to make the search space finite. We examine some of these methods in Chapter 25. In addition to the complexity of the problem, real robots must also deal with errors in their sensor readings and motor controls.

AUTOMATIC ASSEMBLY SEQUENCING

Automatic assembly sequencing of complex objects by a robot was first demonstrated by FREDDY (Michie, 1972). Progress since then has been slow but sure, to the point where the assembly of intricate objects such as electric motors is economically feasible. In assembly problems, the aim is to find an order in which to assemble the parts of some object. If the wrong order is chosen, there will be no way to add some part later in the sequence without

undoing some of the work already done. Checking a step in the sequence for feasibility is a difficult geometrical search problem closely related to robot navigation. Thus, the generation of legal actions is the expensive part of assembly sequencing. Any practical algorithm must avoid exploring all but a tiny fraction of the state space. Another important assembly problem is **protein design**, in which the goal is to find a sequence of amino acids that will fold into a three-dimensional protein with the right properties to cure some disease.

PROTEIN DESIGN

3.3 SEARCHING FOR SOLUTIONS

Having formulated some problems, we now need to solve them. A solution is an action sequence, so search algorithms work by considering various possible action sequences. The possible action sequences starting at the initial state form a **search tree** with the initial state at the root; the branches are actions and the **nodes** correspond to states in the state space of the problem. Figure 3.6 shows the first few steps in growing the search tree for finding a route from Arad to Bucharest. The root node of the tree corresponds to the initial state, *In(Arad)*. The first step is to test whether this is a goal state. (Clearly it is not, but it is important to check so that we can solve trick problems like "starting in Arad, get to Arad.") Then we need to consider taking various actions. We do this by **expanding** the current state; that is, applying each legal action to the current state, thereby **generating** a new set of states. In this case, we add three branches from the **parent node** *In(Arad)* leading to three new **child nodes**: *In(Sibiu), In(Timisoara),* and *In(Zerind)*. Now we must choose which of these three possibilities to consider further.

SEARCH TREE
NODE
EXPANDING
GENERATING
PARENT NODE
CHILD NODE

This is the essence of search—following up one option now and putting the others aside for later, in case the first choice does not lead to a solution. Suppose we choose Sibiu first. We check to see whether it is a goal state (it is not) and then expand it to get *In(Arad)*, *In(Fagaras)*, *In(Oradea)*, and *In(RimnicuVilcea)*. We can then choose any of these four or go back and choose Timisoara or Zerind. Each of these six nodes is a **leaf node**, that is, a node with no children in the tree. The set of all leaf nodes available for expansion at any given point is called the **frontier**. (Many authors call it the **open list**, which is both geographically less evocative and less accurate, because other data structures are better suited than a list.) In Figure 3.6, the frontier of each tree consists of those nodes with bold outlines.

LEAF NODE
FRONTIER
OPEN LIST

The process of expanding nodes on the frontier continues until either a solution is found or there are no more states to expand. The general TREE-SEARCH algorithm is shown informally in Figure 3.7. Search algorithms all share this basic structure; they vary primarily according to how they choose which state to expand next—the so-called **search strategy**.

SEARCH STRATEGY

The eagle-eyed reader will notice one peculiar thing about the search tree shown in Figure 3.6: it includes the path from Arad to Sibiu and back to Arad again! We say that *In(Arad)* is a **repeated state** in the search tree, generated in this case by a **loopy path**. Considering such loopy paths means that the complete search tree for Romania is *infinite* because there is no limit to how often one can traverse a loop. On the other hand, the state space—the map shown in Figure 3.2—has only 20 states. As we discuss in Section 3.4, loops can cause

REPEATED STATE
LOOPY PATH

certain algorithms to fail, making otherwise solvable problems unsolvable. Fortunately, there is no need to consider loopy paths. We can rely on more than intuition for this: because path costs are additive and step costs are nonnegative, a loopy path to any given state is never better than the same path with the loop removed.

REDUNDANT PATH

Loopy paths are a special case of the more general concept of **redundant paths**, which exist whenever there is more than one way to get from one state to another. Consider the paths Arad–Sibiu (140 km long) and Arad–Zerind–Oradea–Sibiu (297 km long). Obviously, the second path is redundant—it's just a worse way to get to the same state. If you are concerned about reaching the goal, there's never any reason to keep more than one path to any given state, because any goal state that is reachable by extending one path is also reachable by extending the other.

In some cases, it is possible to define the problem itself so as to eliminate redundant paths. For example, if we formulate the 8-queens problem (page 71) so that a queen can be placed in any column, then each state with n queens can be reached by $n!$ different paths; but if we reformulate the problem so that each new queen is placed in the leftmost empty column, then each state can be reached only through one path.

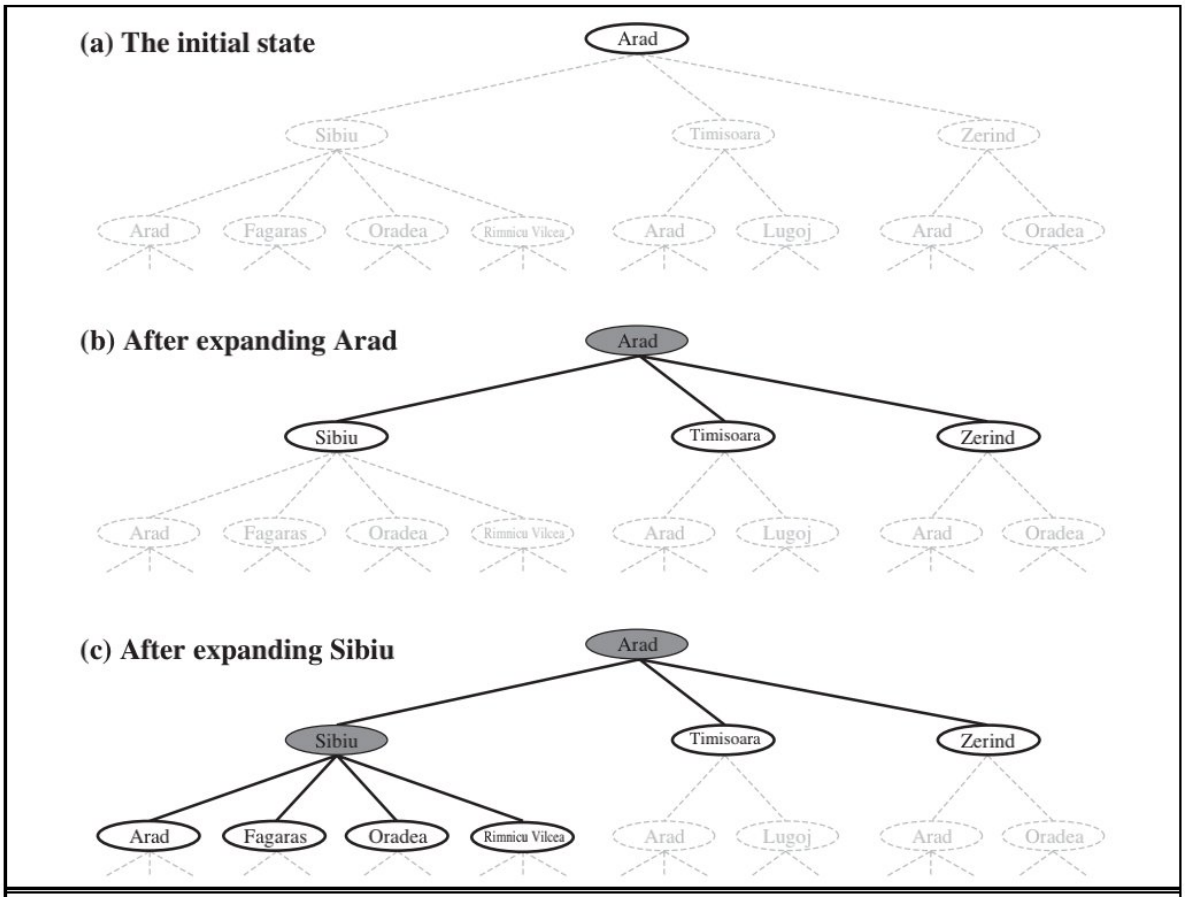


Figure 3.6 Partial search trees for finding a route from Arad to Bucharest. Nodes that have been expanded are shaded; nodes that have been generated but not yet expanded are outlined in bold; nodes that have not yet been generated are shown in faint dashed lines.

```
function TREE-SEARCH(problem) returns a solution, or failure
  initialize the frontier using the initial state of problem
  loop do
    if the frontier is empty then return failure
    choose a leaf node and remove it from the frontier
    if the node contains a goal state then return the corresponding solution
    expand the chosen node, adding the resulting nodes to the frontier
```

```
function GRAPH-SEARCH(problem) returns a solution, or failure
  initialize the frontier using the initial state of problem
  initialize the explored set to be empty
  loop do
    if the frontier is empty then return failure
    choose a leaf node and remove it from the frontier
    if the node contains a goal state then return the corresponding solution
    add the node to the explored set
    expand the chosen node, adding the resulting nodes to the frontier
      only if not in the frontier or explored set
```

Figure 3.7 An informal description of the general tree-search and graph-search algorithms. The parts of GRAPH-SEARCH marked in bold italic are the additions needed to handle repeated states.

In other cases, redundant paths are unavoidable. This includes all problems where the actions are reversible, such as route-finding problems and sliding-block puzzles. Route-finding on a **rectangular grid** (like the one used later for Figure 3.9) is a particularly important example in computer games. In such a grid, each state has four successors, so a search tree of depth d that includes repeated states has 4^d leaves; but there are only about $2d^2$ distinct states within d steps of any given state. For $d = 20$, this means about a trillion nodes but only about 800 distinct states. Thus, following redundant paths can cause a tractable problem to become intractable. This is true even for algorithms that know how to avoid infinite loops.

RECTANGULAR GRID

As the saying goes, *algorithms that forget their history are doomed to repeat it.* The way to avoid exploring redundant paths is to remember where one has been. To do this, we augment the TREE-SEARCH algorithm with a data structure called the **explored set** (also known as the **closed list**), which remembers every expanded node. Newly generated nodes that match previously generated nodes—ones in the explored set or the frontier—can be discarded instead of being added to the frontier. The new algorithm, called GRAPH-SEARCH, is shown informally in Figure 3.7. The specific algorithms in this chapter draw on this general design.

EXPLORED SET

CLOSED LIST

Clearly, the search tree constructed by the GRAPH-SEARCH algorithm contains at most one copy of each state, so we can think of it as growing a tree directly on the state-space graph, as shown in Figure 3.8. The algorithm has another nice property: the frontier **separates** the state-space graph into the explored region and the unexplored region, so that every path from

SEPARATOR

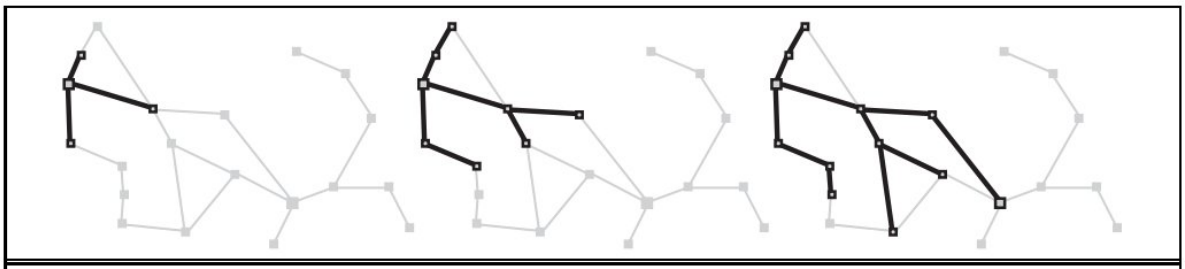


Figure 3.8 A sequence of search trees generated by a graph search on the Romania problem of Figure 3.2. At each stage, we have extended each path by one step. Notice that at the third stage, the northernmost city (Oradea) has become a dead end: both of its successors are already explored via other paths.

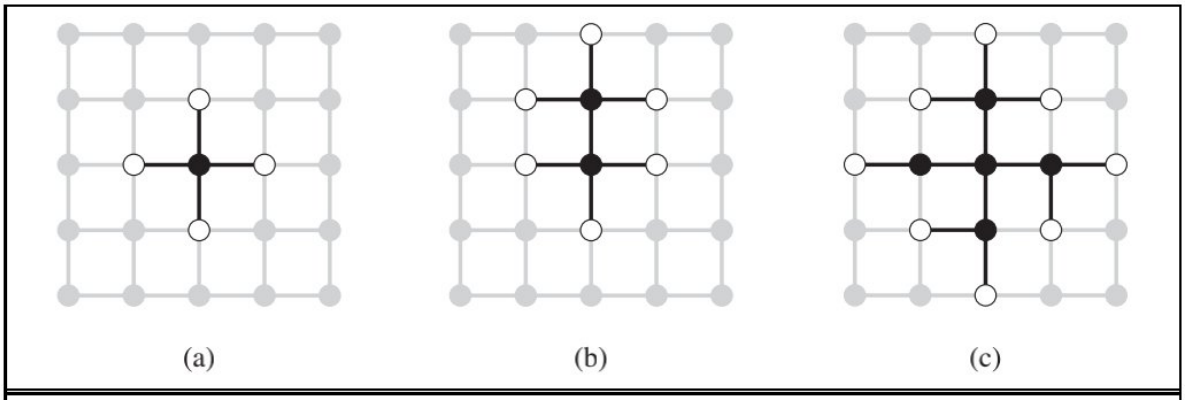


Figure 3.9 The separation property of GRAPH-SEARCH, illustrated on a rectangular-grid problem. The frontier (white nodes) always separates the explored region of the state space (black nodes) from the unexplored region (gray nodes). In (a), just the root has been expanded. In (b), one leaf node has been expanded. In (c), the remaining successors of the root have been expanded in clockwise order.

the initial state to an unexplored state has to pass through a state in the frontier. (If this seems completely obvious, try Exercise 3.13 now.) This property is illustrated in Figure 3.9. As every step moves a state from the frontier into the explored region while moving some states from the unexplored region into the frontier, we see that the algorithm is *systematically* examining the states in the state space, one by one, until it finds a solution.

3.3.1 Infrastructure for search algorithms

Search algorithms require a data structure to keep track of the search tree that is being constructed. For each node n of the tree, we have a structure that contains four components:

- n.STATE: the state in the state space to which the node corresponds;
- n.PARENT: the node in the search tree that generated this node;
- n.ACTION: the action that was applied to the parent to generate the node;
- n.PATH-COST: the cost, traditionally denoted by $g(n)$, of the path from the initial state to the node, as indicated by the parent pointers.

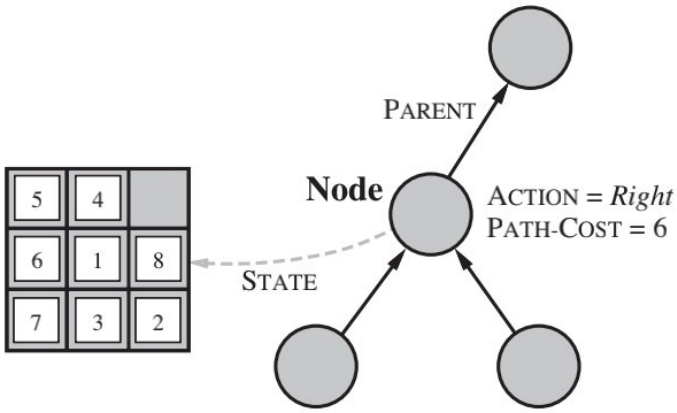


Figure 3.10 Nodes are the data structures from which the search tree is constructed. Each has a parent, a state, and various bookkeeping fields. Arrows point from child to parent.

Given the components for a parent node, it is easy to see how to compute the necessary components for a child node. The function CHILD-NODE takes a parent node and an action and returns the resulting child node:

```
function CHILD-NODE(problem, parent, action) returns a node
  return a node with
      STATE = problem.RESULT(parent.STATE, action),
      PARENT = parent, ACTION = action,
      PATH-COST = parent.PATH-COST + problem.STEP-COST(parent.STATE, action)
```

The node data structure is depicted in Figure 3.10. Notice how the PARENT pointers string the nodes together into a tree structure. These pointers also allow the solution path to be extracted when a goal node is found; we use the SOLUTION function to return the sequence of actions obtained by following parent pointers back to the root.

Up to now, we have not been very careful to distinguish between nodes and states, but in writing detailed algorithms it's important to make that distinction. A node is a bookkeeping data structure used to represent the search tree. A state corresponds to a configuration of the world. Thus, nodes are on particular paths, as defined by PARENT pointers, whereas states are not. Furthermore, two different nodes can contain the same world state if that state is generated via two different search paths.

Now that we have nodes, we need somewhere to put them. The frontier needs to be stored in such a way that the search algorithm can easily choose the next node to expand according to its preferred strategy. The appropriate data structure for this is a **queue**. The operations on a queue are as follows:

QUEUE

- EMPTY?($queue$) returns true only if there are no more elements in the queue.
- POP($queue$) removes the first element of the queue and returns it.
- INSERT($element$, $queue$) inserts an element and returns the resulting queue.

Queues are characterized by the *order* in which they store the inserted nodes. Three common variants are the first-in, first-out or **FIFO queue**, which pops the *oldest* element of the queue; the last-in, first-out or **LIFO queue** (also known as a **stack**), which pops the *newest* element of the queue; and the **priority queue**, which pops the element of the queue with the highest priority according to some ordering function.

FIFO QUEUE
LIFO QUEUE
PRIORITY QUEUE

The explored set can be implemented with a hash table to allow efficient checking for repeated states. With a good implementation, insertion and lookup can be done in roughly constant time no matter how many states are stored. One must take care to implement the hash table with the right notion of equality between states. For example, in the traveling salesperson problem (page 74), the hash table needs to know that the set of visited cities {Bucharest,Urziceni,Vaslui} is the same as {Urziceni,Vaslui,Bucharest}. Sometimes this can be achieved most easily by insisting that the data structures for states be in some **canonical form**; that is, logically equivalent states should map to the same data structure. In the case of states described by sets, for example, a bit-vector representation or a sorted list without repetition would be canonical, whereas an unsorted list would not.

CANONICAL FORM

3.3.2 Measuring problem-solving performance

Before we get into the design of specific search algorithms, we need to consider the criteria that might be used to choose among them. We can evaluate an algorithm's performance in four ways:

COMPLETENESS
OPTIMALITY
TIME COMPLEXITY
SPACE COMPLEXITY

- **Completeness**: Is the algorithm guaranteed to find a solution when there is one?
- **Optimality**: Does the strategy find the optimal solution, as defined on page 68?
- **Time complexity**: How long does it take to find a solution?
- **Space complexity**: How much memory is needed to perform the search?

Time and space complexity are always considered with respect to some measure of the problem difficulty. In theoretical computer science, the typical measure is the size of the state space graph, $|V| + |E|$, where V is the set of vertices (nodes) of the graph and E is the set of edges (links). This is appropriate when the graph is an explicit data structure that is input to the search program. (The map of Romania is an example of this.) In AI, the graph is often represented *implicitly* by the initial state, actions, and transition model and is frequently infinite. For these reasons, complexity is expressed in terms of three quantities: b, the **branching factor** or maximum number of successors of any node; d, the **depth** of the shallowest goal node (i.e., the number of steps along the path from the root); and m, the maximum length of any path in the state space. Time is often measured in terms of the number of nodes generated during the search, and space in terms of the maximum number of nodes stored in memory. For the most part, we describe time and space complexity for search on a tree; for a graph, the answer depends on how "redundant" the paths in the state space are.

BRANCHING FACTOR
DEPTH

SEARCH COST
TOTAL COST

To assess the effectiveness of a search algorithm, we can consider just the **search cost**—which typically depends on the time complexity but can also include a term for memory usage—or we can use the **total cost**, which combines the search cost and the path cost of the solution found. For the problem of finding a route from Arad to Bucharest, the search cost is the amount of time taken by the search and the solution cost is the total length of the path

in kilometers. Thus, to compute the total cost, we have to add milliseconds and kilometers. There is no "official exchange rate" between the two, but it might be reasonable in this case to convert kilometers into milliseconds by using an estimate of the car's average speed (because time is what the agent cares about). This enables the agent to find an optimal tradeoff point at which further computation to find a shorter path becomes counterproductive. The more general problem of tradeoffs between different goods is taken up in Chapter 16.

3.4 UNINFORMED SEARCH STRATEGIES

UNINFORMED SEARCH
BLIND SEARCH

This section covers several search strategies that come under the heading of **uninformed search** (also called **blind search**). The term means that the strategies have no additional information about states beyond that provided in the problem definition. All they can do is generate successors and distinguish a goal state from a non-goal state. All search strategies are distinguished by the *order* in which nodes are expanded. Strategies that know whether one non-goal state is "more promising" than another are called **informed search** or **heuristic search** strategies; they are covered in Section 3.5.

INFORMED SEARCH
HEURISTIC SEARCH

3.4.1 Breadth-first search

BREADTH-FIRST SEARCH

Breadth-first search is a simple strategy in which the root node is expanded first, then all the successors of the root node are expanded next, then *their* successors, and so on. In general, all the nodes are expanded at a given depth in the search tree before any nodes at the next level are expanded.

Breadth-first search is an instance of the general graph-search algorithm (Figure 3.7) in which the *shallowest* unexpanded node is chosen for expansion. This is achieved very simply by using a FIFO queue for the frontier. Thus, new nodes (which are always deeper than their parents) go to the back of the queue, and old nodes, which are shallower than the new nodes, get expanded first. There is one slight tweak on the general graph-search algorithm, which is that the goal test is applied to each node when it is *generated* rather than when it is selected for expansion. This decision is explained below, where we discuss time complexity. Note also that the algorithm, following the general template for graph search, discards any new path to a state already in the frontier or explored set; it is easy to see that any such path must be at least as deep as the one already found. Thus, breadth-first search always has the shallowest path to every node on the frontier.

Pseudocode is given in Figure 3.11. Figure 3.12 shows the progress of the search on a simple binary tree.

How does breadth-first search rate according to the four criteria from the previous section? We can easily see that it is *complete*—if the shallowest goal node is at some finite depth d, breadth-first search will eventually find it after generating all shallower nodes (provided the branching factor b is finite). Note that as soon as a goal node is generated, we know it is the shallowest goal node because all shallower nodes must have been generated already and failed the goal test. Now, the *shallowest* goal node is not necessarily the *optimal* one;

```
function BREADTH-FIRST-SEARCH(problem) returns a solution, or failure
  node ← a node with STATE = problem.INITIAL-STATE, PATH-COST = 0
  if problem.GOAL-TEST(node.STATE) then return SOLUTION(node)
  frontier ← a FIFO queue with node as the only element
  explored ← an empty set
  loop do
    if EMPTY?(frontier) then return failure
    node ← POP(frontier)  /* chooses the shallowest node in frontier */
    add node.STATE to explored
    for each action in problem.ACTIONS(node.STATE) do
      child ← CHILD-NODE(problem, node, action)
      if child.STATE is not in explored or frontier then
        if problem.GOAL-TEST(child.STATE) then return SOLUTION(child)
        frontier ← INSERT(child, frontier)
```

Figure 3.11 Breadth-first search on a graph.

technically, breadth-first search is optimal if the path cost is a nondecreasing function of the depth of the node. The most common such scenario is that all actions have the same cost.

So far, the news about breadth-first search has been good. The news about time and space is not so good. Imagine searching a uniform tree where every state has b successors. The root of the search tree generates b nodes at the first level, each of which generates b more nodes, for a total of b^2 at the second level. Each of *these* generates b more nodes, yielding b^3 nodes at the third level, and so on. Now suppose that the solution is at depth d. In the worst case, it is the last node generated at that level. Then the total number of nodes generated is

$$b + b^2 + b^3 + \cdots + b^d = O(b^d) \ .$$

(If the algorithm were to apply the goal test to nodes when selected for expansion, rather than when generated, the whole layer of nodes at depth d would be expanded before the goal was detected and the time complexity would be $O(b^{d+1})$.)

As for space complexity: for any kind of graph search, which stores every expanded node in the *explored* set, the space complexity is always within a factor of b of the time complexity. For breadth-first graph search in particular, every node generated remains in memory. There will be $O(b^{d-1})$ nodes in the *explored* set and $O(b^d)$ nodes in the frontier,

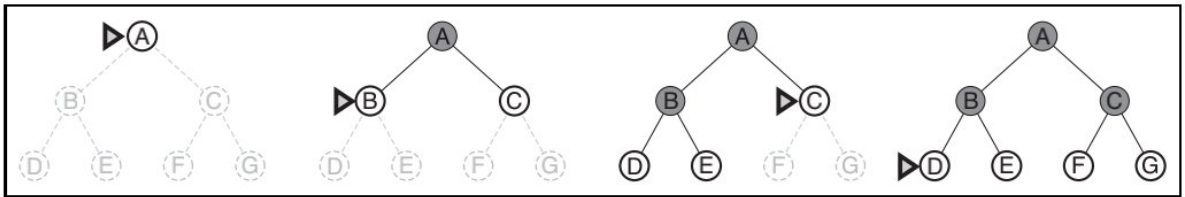


Figure 3.12 Breadth-first search on a simple binary tree. At each stage, the node to be expanded next is indicated by a marker.

so the space complexity is $O(b^d)$, i.e., it is dominated by the size of the frontier. Switching to a tree search would not save much space, and in a state space with many redundant paths, switching could cost a great deal of time.

An exponential complexity bound such as $O(b^d)$ is scary. Figure 3.13 shows why. It lists, for various values of the solution depth d, the time and memory required for a breadth-first search with branching factor $b = 10$. The table assumes that 1 million nodes can be generated per second and that a node requires 1000 bytes of storage. Many search problems fit roughly within these assumptions (give or take a factor of 100) when run on a modern personal computer.

Depth	Nodes	Time	Memory
2	110	.11 milliseconds	107 kilobytes
4	11,110	11 milliseconds	10.6 megabytes
6	10^6	1.1 seconds	1 gigabyte
8	10^8	2 minutes	103 gigabytes
10	10^{10}	3 hours	10 terabytes
12	10^{12}	13 days	1 petabyte
14	10^{14}	3.5 years	99 petabytes
16	10^{16}	350 years	10 exabytes

Figure 3.13 Time and memory requirements for breadth-first search. The numbers shown assume branching factor $b = 10$; 1 million nodes/second; 1000 bytes/node.

Two lessons can be learned from Figure 3.13. First, *the memory requirements are a bigger problem for breadth-first search than is the execution time.* One might wait 13 days for the solution to an important problem with search depth 12, but no personal computer has the petabyte of memory it would take. Fortunately, other strategies require less memory.

The second lesson is that time is still a major factor. If your problem has a solution at depth 16, then (given our assumptions) it will take about 350 years for breadth-first search (or indeed any uninformed search) to find it. In general, *exponential-complexity search problems cannot be solved by uninformed methods for any but the smallest instances.*

3.4.2 Uniform-cost search

When all step costs are equal, breadth-first search is optimal because it always expands the *shallowest* unexpanded node. By a simple extension, we can find an algorithm that is optimal with any step-cost function. Instead of expanding the shallowest node, **uniform-cost search** expands the node n with the *lowest path cost* $g(n)$. This is done by storing the frontier as a priority queue ordered by g. The algorithm is shown in Figure 3.14.

UNIFORM-COST SEARCH

In addition to the ordering of the queue by path cost, there are two other significant differences from breadth-first search. The first is that the goal test is applied to a node when it is *selected for expansion* (as in the generic graph-search algorithm shown in Figure 3.7) rather than when it is first generated. The reason is that the first goal node that is *generated*

```
function UNIFORM-COST-SEARCH(problem) returns a solution, or failure
  node ← a node with STATE = problem.INITIAL-STATE, PATH-COST = 0
  frontier ← a priority queue ordered by PATH-COST, with node as the only element
  explored ← an empty set
  loop do
    if EMPTY?(frontier) then return failure
    node ← POP(frontier)  /* chooses the lowest-cost node in frontier */
    if problem.GOAL-TEST(node.STATE) then return SOLUTION(node)
    add node.STATE to explored
    for each action in problem.ACTIONS(node.STATE) do
      child ← CHILD-NODE(problem, node, action)
      if child.STATE is not in explored or frontier then
        frontier ← INSERT(child, frontier)
      else if child.STATE is in frontier with higher PATH-COST then
        replace that frontier node with child
```

Figure 3.14 Uniform-cost search on a graph. The algorithm is identical to the general graph search algorithm in Figure 3.7, except for the use of a priority queue and the addition of an extra check in case a shorter path to a frontier state is discovered. The data structure for *frontier* needs to support efficient membership testing, so it should combine the capabilities of a priority queue and a hash table.

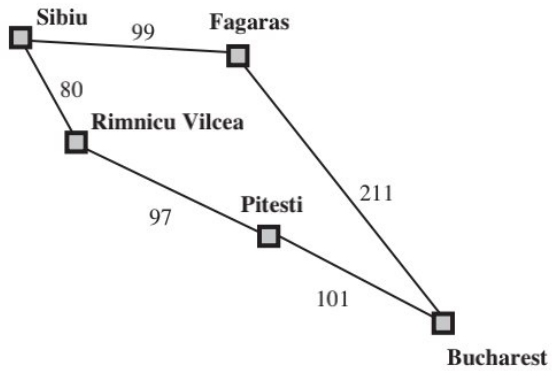


Figure 3.15 Part of the Romania state space, selected to illustrate uniform-cost search.

may be on a suboptimal path. The second difference is that a test is added in case a better path is found to a node currently on the frontier.

Both of these modifications come into play in the example shown in Figure 3.15, where the problem is to get from Sibiu to Bucharest. The successors of Sibiu are Rimnicu Vilcea and Fagaras, with costs 80 and 99, respectively. The least-cost node, Rimnicu Vilcea, is expanded next, adding Pitesti with cost $80 + 97 = 177$. The least-cost node is now Fagaras, so it is expanded, adding Bucharest with cost $99 + 211 = 310$. Now a goal node has been generated, but uniform-cost search keeps going, choosing Pitesti for expansion and adding a second path

to Bucharest with cost $80+97+101=278$. Now the algorithm checks to see if this new path is better than the old one; it is, so the old one is discarded. Bucharest, now with g-cost 278, is selected for expansion and the solution is returned.

It is easy to see that uniform-cost search is optimal in general. First, we observe that whenever uniform-cost search selects a node n for expansion, the optimal path to that node has been found. (Were this not the case, there would have to be another frontier node n' on the optimal path from the start node to n, by the graph separation property of Figure 3.9; by definition, n' would have lower g-cost than n and would have been selected first.) Then, because step costs are nonnegative, paths never get shorter as nodes are added. These two facts together imply that *uniform-cost search expands nodes in order of their optimal path cost.* Hence, the first goal node selected for expansion must be the optimal solution.

Uniform-cost search does not care about the *number* of steps a path has, but only about their total cost. Therefore, it will get stuck in an infinite loop if there is a path with an infinite sequence of zero-cost actions—for example, a sequence of $NoOp$ actions.[6] Completeness is guaranteed provided the cost of every step exceeds some small positive constant ϵ.

Uniform-cost search is guided by path costs rather than depths, so its complexity is not easily characterized in terms of b and d. Instead, let C^* be the cost of the optimal solution,[7] and assume that every action costs at least ϵ. Then the algorithm's worst-case time and space complexity is $O(b^{1+\lfloor C^*/\epsilon \rfloor})$, which can be much greater than b^d. This is because uniform-cost search can explore large trees of small steps before exploring paths involving large and perhaps useful steps. When all step costs are equal, $b^{1+\lfloor C^*/\epsilon \rfloor}$ is just b^{d+1}. When all step costs are the same, uniform-cost search is similar to breadth-first search, except that the latter stops as soon as it generates a goal, whereas uniform-cost search examines all the nodes at the goal's depth to see if one has a lower cost; thus uniform-cost search does strictly more work by expanding nodes at depth d unnecessarily.

3.4.3 Depth-first search

DEPTH-FIRST SEARCH

Depth-first search always expands the *deepest* node in the current frontier of the search tree. The progress of the search is illustrated in Figure 3.16. The search proceeds immediately to the deepest level of the search tree, where the nodes have no successors. As those nodes are expanded, they are dropped from the frontier, so then the search "backs up" to the next deepest node that still has unexplored successors.

The depth-first search algorithm is an instance of the graph-search algorithm in Figure 3.7; whereas breadth-first-search uses a FIFO queue, depth-first search uses a LIFO queue. A LIFO queue means that the most recently generated node is chosen for expansion. This must be the deepest unexpanded node because it is one deeper than its parent—which, in turn, was the deepest unexpanded node when it was selected.

As an alternative to the GRAPH-SEARCH-style implementation, it is common to implement depth-first search with a recursive function that calls itself on each of its children in turn. (A recursive depth-first algorithm incorporating a depth limit is shown in Figure 3.17.)

[6] $NoOp$, or "no operation," is the name of an assembly language instruction that does nothing.

[7] Here, and throughout the book, the "star" in C^* means an optimal value for C.

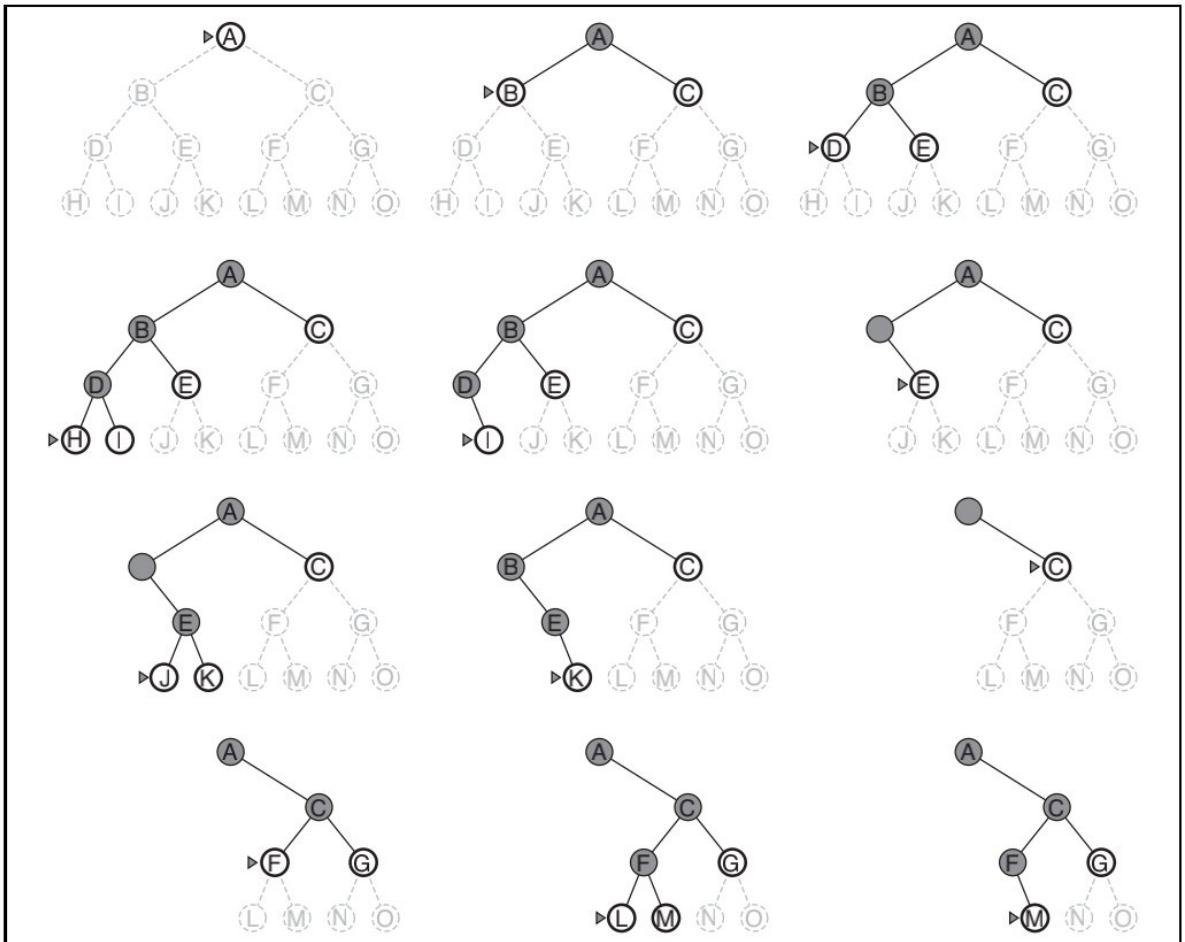


Figure 3.16 Depth-first search on a binary tree. The unexplored region is shown in light gray. Explored nodes with no descendants in the frontier are removed from memory. Nodes at depth 3 have no successors and M is the only goal node.

The properties of depth-first search depend strongly on whether the graph-search or tree-search version is used. The graph-search version, which avoids repeated states and redundant paths, is complete in finite state spaces because it will eventually expand every node. The tree-search version, on the other hand, is *not* complete—for example, in Figure 3.6 the algorithm will follow the Arad–Sibiu–Arad–Sibiu loop forever. Depth-first tree search can be modified at no extra memory cost so that it checks new states against those on the path from the root to the current node; this avoids infinite loops in finite state spaces but does not avoid the proliferation of redundant paths. In infinite state spaces, both versions fail if an infinite non-goal path is encountered. For example, in Knuth's 4 problem, depth-first search would keep applying the factorial operator forever.

For similar reasons, both versions are nonoptimal. For example, in Figure 3.16, depth-first search will explore the entire left subtree even if node C is a goal node. If node J were also a goal node, then depth-first search would return it as a solution instead of C, which would be a better solution; hence, depth-first search is not optimal.

The time complexity of depth-first graph search is bounded by the size of the state space (which may be infinite, of course). A depth-first tree search, on the other hand, may generate all of the $O(b^m)$ nodes in the search tree, where m is the maximum depth of any node; this can be much greater than the size of the state space. Note that m itself can be much larger than d (the depth of the shallowest solution) and is infinite if the tree is unbounded.

So far, depth-first search seems to have no clear advantage over breadth-first search, so why do we include it? The reason is the space complexity. For a graph search, there is no advantage, but a depth-first tree search needs to store only a single path from the root to a leaf node, along with the remaining unexpanded sibling nodes for each node on the path. Once a node has been expanded, it can be removed from memory as soon as all its descendants have been fully explored. (See Figure 3.16.) For a state space with branching factor b and maximum depth m, depth-first search requires storage of only $O(bm)$ nodes. Using the same assumptions as for Figure 3.13 and assuming that nodes at the same depth as the goal node have no successors, we find that depth-first search would require 156 kilobytes instead of 10 exabytes at depth $d = 16$, a factor of 7 trillion times less space. This has led to the adoption of depth-first tree search as the basic workhorse of many areas of AI, including constraint satisfaction (Chapter 6), propositional satisfiability (Chapter 7), and logic programming (Chapter 9). For the remainder of this section, we focus primarily on the tree-search version of depth-first search.

BACKTRACKING SEARCH

A variant of depth-first search called **backtracking search** uses still less memory. (See Chapter 6 for more details.) In backtracking, only one successor is generated at a time rather than all successors; each partially expanded node remembers which successor to generate next. In this way, only $O(m)$ memory is needed rather than $O(bm)$. Backtracking search facilitates yet another memory-saving (and time-saving) trick: the idea of generating a successor by *modifying* the current state description directly rather than copying it first. This reduces the memory requirements to just one state description and $O(m)$ actions. For this to work, we must be able to undo each modification when we go back to generate the next successor. For problems with large state descriptions, such as robotic assembly, these techniques are critical to success.

3.4.4 Depth-limited search

The embarrassing failure of depth-first search in infinite state spaces can be alleviated by supplying depth-first search with a predetermined depth limit ℓ. That is, nodes at depth ℓ are treated as if they have no successors. This approach is called **depth-limited search**. The depth limit solves the infinite-path problem. Unfortunately, it also introduces an additional source of incompleteness if we choose $\ell < d$, that is, the shallowest goal is beyond the depth limit. (This is likely when d is unknown.) Depth-limited search will also be nonoptimal if we choose $\ell > d$. Its time complexity is $O(b^\ell)$ and its space complexity is $O(b\ell)$. Depth-first search can be viewed as a special case of depth-limited search with $\ell = \infty$.

DEPTH-LIMITED SEARCH

Sometimes, depth limits can be based on knowledge of the problem. For example, on the map of Romania there are 20 cities. Therefore, we know that if there is a solution, it must be of length 19 at the longest, so $\ell = 19$ is a possible choice. But in fact if we studied the

```
function DEPTH-LIMITED-SEARCH(problem, limit) returns a solution, or failure/cutoff
  return RECURSIVE-DLS(MAKE-NODE(problem.INITIAL-STATE), problem, limit)

function RECURSIVE-DLS(node, problem, limit) returns a solution, or failure/cutoff
  if problem.GOAL-TEST(node.STATE) then return SOLUTION(node)
  else if limit = 0 then return cutoff
  else
      cutoff_occurred? ← false
      for each action in problem.ACTIONS(node.STATE) do
          child ← CHILD-NODE(problem, node, action)
          result ← RECURSIVE-DLS(child, problem, limit − 1)
          if result = cutoff then cutoff_occurred? ← true
          else if result ≠ failure then return result
      if cutoff_occurred? then return cutoff else return failure
```

Figure 3.17 A recursive implementation of depth-limited tree search.

DIAMETER

map carefully, we would discover that any city can be reached from any other city in at most 9 steps. This number, known as the **diameter** of the state space, gives us a better depth limit, which leads to a more efficient depth-limited search. For most problems, however, we will not know a good depth limit until we have solved the problem.

Depth-limited search can be implemented as a simple modification to the general tree- or graph-search algorithm. Alternatively, it can be implemented as a simple recursive algorithm as shown in Figure 3.17. Notice that depth-limited search can terminate with two kinds of failure: the standard *failure* value indicates no solution; the *cutoff* value indicates no solution within the depth limit.

3.4.5 Iterative deepening depth-first search

ITERATIVE DEEPENING SEARCH

Iterative deepening search (or iterative deepening depth-first search) is a general strategy, often used in combination with depth-first tree search, that finds the best depth limit. It does this by gradually increasing the limit—first 0, then 1, then 2, and so on—until a goal is found. This will occur when the depth limit reaches d, the depth of the shallowest goal node. The algorithm is shown in Figure 3.18. Iterative deepening combines the benefits of depth-first and breadth-first search. Like depth-first search, its memory requirements are modest: $O(bd)$ to be precise. Like breadth-first search, it is complete when the branching factor is finite and optimal when the path cost is a nondecreasing function of the depth of the node. Figure 3.19 shows four iterations of ITERATIVE-DEEPENING-SEARCH on a binary search tree, where the solution is found on the fourth iteration.

Iterative deepening search may seem wasteful because states are generated multiple times. It turns out this is not too costly. The reason is that in a search tree with the same (or nearly the same) branching factor at each level, most of the nodes are in the bottom level, so it does not matter much that the upper levels are generated multiple times. In an iterative deepening search, the nodes on the bottom level (depth d) are generated once, those on the

```
function ITERATIVE-DEEPENING-SEARCH(problem) returns a solution, or failure
    for depth = 0 to ∞ do
        result ← DEPTH-LIMITED-SEARCH(problem, depth)
        if result ≠ cutoff then return result
```

Figure 3.18 The iterative deepening search algorithm, which repeatedly applies depth-limited search with increasing limits. It terminates when a solution is found or if the depth-limited search returns *failure*, meaning that no solution exists.

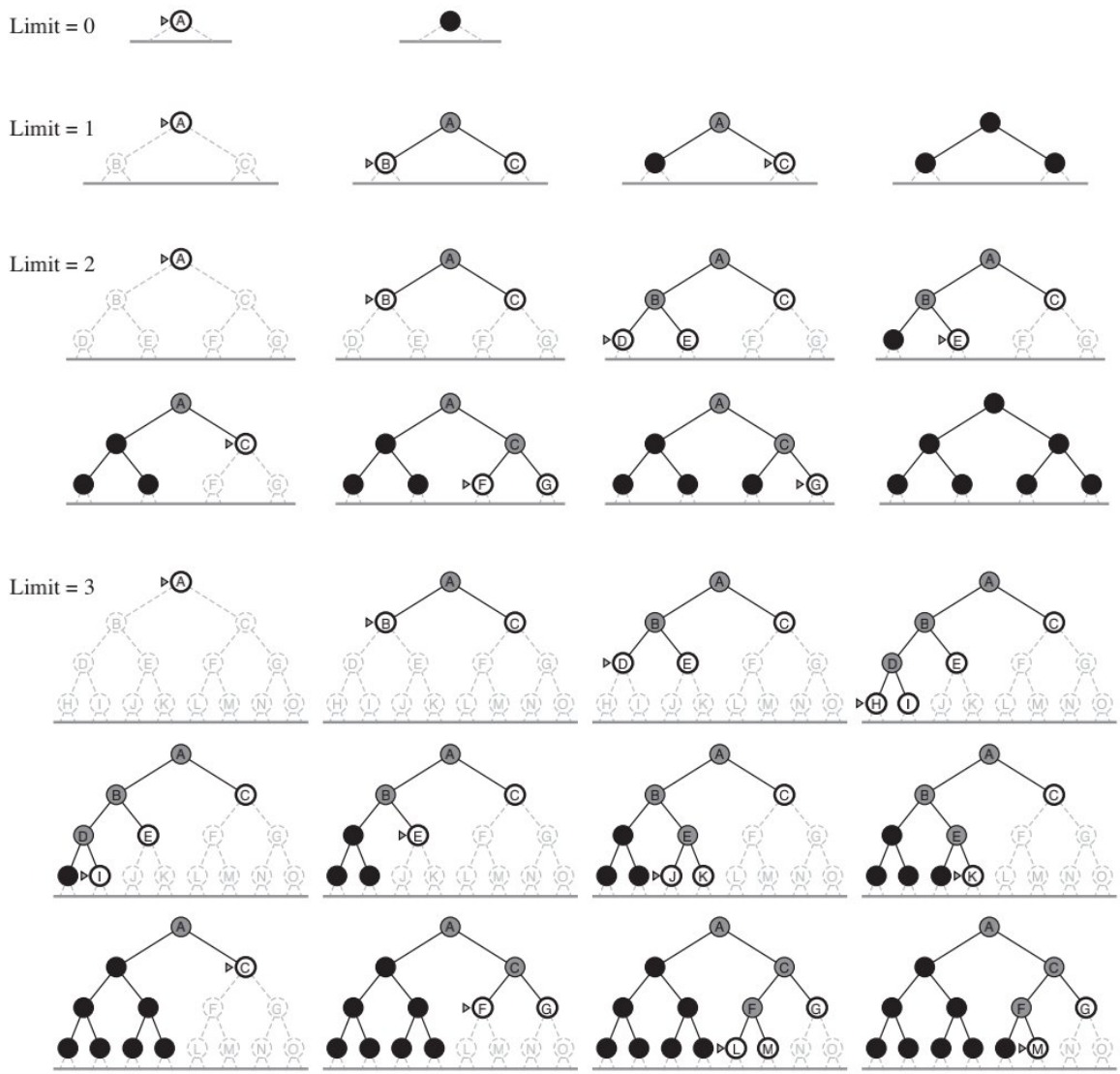


Figure 3.19 Four iterations of iterative deepening search on a binary tree.

next-to-bottom level are generated twice, and so on, up to the children of the root, which are generated d times. So the total number of nodes generated in the worst case is

$$N(\text{IDS}) = (d)b + (d-1)b^2 + \cdots + (1)b^d \ ,$$

which gives a time complexity of $O(b^d)$—asymptotically the same as breadth-first search. There is some extra cost for generating the upper levels multiple times, but it is not large. For example, if $b = 10$ and $d = 5$, the numbers are

$$\begin{aligned} N(\text{IDS}) &= 50 + 400 + 3,000 + 20,000 + 100,000 = 123,450 \\ N(\text{BFS}) &= 10 + 100 + 1,000 + 10,000 + 100,000 = 111,110 \ . \end{aligned}$$

If you are really concerned about repeating the repetition, you can use a hybrid approach that runs breadth-first search until almost all the available memory is consumed, and then runs iterative deepening from all the nodes in the frontier. *In general, iterative deepening is the preferred uninformed search method when the search space is large and the depth of the solution is not known.*

Iterative deepening search is analogous to breadth-first search in that it explores a complete layer of new nodes at each iteration before going on to the next layer. It would seem worthwhile to develop an iterative analog to uniform-cost search, inheriting the latter algorithm's optimality guarantees while avoiding its memory requirements. The idea is to use increasing path-cost limits instead of increasing depth limits. The resulting algorithm, called **iterative lengthening search**, is explored in Exercise 3.17. It turns out, unfortunately, that iterative lengthening incurs substantial overhead compared to uniform-cost search.

ITERATIVE LENGTHENING SEARCH

3.4.6 Bidirectional search

The idea behind bidirectional search is to run two simultaneous searches—one forward from the initial state and the other backward from the goal—hoping that the two searches meet in the middle (Figure 3.20). The motivation is that $b^{d/2} + b^{d/2}$ is much less than b^d, or in the figure, the area of the two small circles is less than the area of one big circle centered on the start and reaching to the goal.

Bidirectional search is implemented by replacing the goal test with a check to see whether the frontiers of the two searches intersect; if they do, a solution has been found. (It is important to realize that the first such solution found may not be optimal, even if the two searches are both breadth-first; some additional search is required to make sure there isn't another short-cut across the gap.) The check can be done when each node is generated or selected for expansion and, with a hash table, will take constant time. For example, if a problem has solution depth $d = 6$, and each direction runs breadth-first search one node at a time, then in the worst case the two searches meet when they have generated all of the nodes at depth 3. For $b = 10$, this means a total of 2,220 node generations, compared with 1,111,110 for a standard breadth-first search. Thus, the time complexity of bidirectional search using breadth-first searches in both directions is $O(b^{d/2})$. The space complexity is also $O(b^{d/2})$. We can reduce this by roughly half if one of the two searches is done by iterative deepening, but at least one of the frontiers must be kept in memory so that the intersection check can be done. This space requirement is the most significant weakness of bidirectional search.

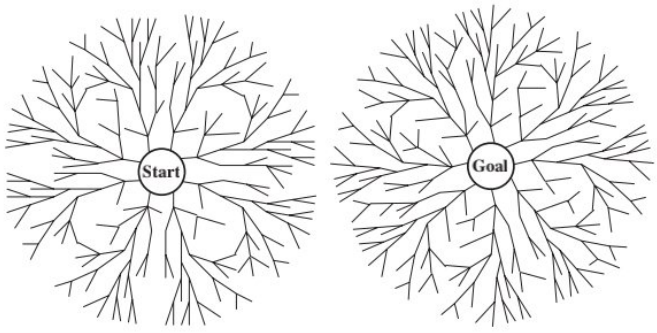


Figure 3.20 A schematic view of a bidirectional search that is about to succeed when a branch from the start node meets a branch from the goal node.

PREDECESSOR

The reduction in time complexity makes bidirectional search attractive, but how do we search backward? This is not as easy as it sounds. Let the **predecessors** of a state x be all those states that have x as a successor. Bidirectional search requires a method for computing predecessors. When all the actions in the state space are reversible, the predecessors of x are just its successors. Other cases may require substantial ingenuity.

Consider the question of what we mean by "the goal" in searching "backward from the goal." For the 8-puzzle and for finding a route in Romania, there is just one goal state, so the backward search is very much like the forward search. If there are several *explicitly listed* goal states—for example, the two dirt-free goal states in Figure 3.3—then we can construct a new dummy goal state whose immediate predecessors are all the actual goal states. But if the goal is an abstract description, such as the goal that "no queen attacks another queen" in the n-queens problem, then bidirectional search is difficult to use.

3.4.7 Comparing uninformed search strategies

Figure 3.21 compares search strategies in terms of the four evaluation criteria set forth in Section 3.3.2. This comparison is for tree-search versions. For graph searches, the main differences are that depth-first search is complete for finite state spaces and that the space and time complexities are bounded by the size of the state space.

Criterion	Breadth-First	Uniform-Cost	Depth-First	Depth-Limited	Iterative Deepening	Bidirectional (if applicable)
Complete?	Yes[a]	Yes[a,b]	No	No	Yes[a]	Yes[a,d]
Time	$O(b^d)$	$O(b^{1+\lfloor C^*/\epsilon \rfloor})$	$O(b^m)$	$O(b^\ell)$	$O(b^d)$	$O(b^{d/2})$
Space	$O(b^d)$	$O(b^{1+\lfloor C^*/\epsilon \rfloor})$	$O(bm)$	$O(b\ell)$	$O(bd)$	$O(b^{d/2})$
Optimal?	Yes[c]	Yes	No	No	Yes[c]	Yes[c,d]

Figure 3.21 Evaluation of tree-search strategies. b is the branching factor; d is the depth of the shallowest solution; m is the maximum depth of the search tree; l is the depth limit. Superscript caveats are as follows: [a] complete if b is finite; [b] complete if step costs $\geq \epsilon$ for positive ϵ; [c] optimal if step costs are all identical; [d] if both directions use breadth-first search.

3.5 INFORMED (HEURISTIC) SEARCH STRATEGIES

INFORMED SEARCH

This section shows how an **informed search** strategy—one that uses problem-specific knowledge beyond the definition of the problem itself—can find solutions more efficiently than can an uninformed strategy.

BEST-FIRST SEARCH

The general approach we consider is called **best-first search**. Best-first search is an instance of the general TREE-SEARCH or GRAPH-SEARCH algorithm in which a node is selected for expansion based on an **evaluation function**, $f(n)$. The evaluation function is construed as a cost estimate, so the node with the *lowest* evaluation is expanded first. The implementation of best-first graph search is identical to that for uniform-cost search (Figure 3.14), except for the use of f instead of g to order the priority queue.

EVALUATION FUNCTION

The choice of f determines the search strategy. (For example, as Exercise 3.21 shows, best-first tree search includes depth-first search as a special case.) Most best-first algorithms include as a component of f a **heuristic function**, denoted $h(n)$:

HEURISTIC FUNCTION

$$h(n) = \text{ estimated cost of the cheapest path from the state at node } n \text{ to a goal state.}$$

(Notice that $h(n)$ takes a *node* as input, but, unlike $g(n)$, it depends only on the *state* at that node.) For example, in Romania, one might estimate the cost of the cheapest path from Arad to Bucharest via the straight-line distance from Arad to Bucharest.

Heuristic functions are the most common form in which additional knowledge of the problem is imparted to the search algorithm. We study heuristics in more depth in Section 3.6. For now, we consider them to be arbitrary, nonnegative, problem-specific functions, with one constraint: if n is a goal node, then $h(n) = 0$. The remainder of this section covers two ways to use heuristic information to guide search.

3.5.1 Greedy best-first search

GREEDY BEST-FIRST SEARCH

Greedy best-first search[8] tries to expand the node that is closest to the goal, on the grounds that this is likely to lead to a solution quickly. Thus, it evaluates nodes by using just the heuristic function; that is, $f(n) = h(n)$.

STRAIGHT-LINE DISTANCE

Let us see how this works for route-finding problems in Romania; we use the **straight-line distance** heuristic, which we will call h_{SLD}. If the goal is Bucharest, we need to know the straight-line distances to Bucharest, which are shown in Figure 3.22. For example, $h_{SLD}(In(Arad)) = 366$. Notice that the values of h_{SLD} cannot be computed from the problem description itself. Moreover, it takes a certain amount of experience to know that h_{SLD} is correlated with actual road distances and is, therefore, a useful heuristic.

Figure 3.23 shows the progress of a greedy best-first search using h_{SLD} to find a path from Arad to Bucharest. The first node to be expanded from Arad will be Sibiu because it is closer to Bucharest than either Zerind or Timisoara. The next node to be expanded will be Fagaras because it is closest. Fagaras in turn generates Bucharest, which is the goal. For this particular problem, greedy best-first search using h_{SLD} finds a solution without ever

[8] Our first edition called this **greedy search**; other authors have called it **best-first search**. Our more general usage of the latter term follows Pearl (1984).

Arad	366	**Mehadia**	241
Bucharest	0	**Neamt**	234
Craiova	160	**Oradea**	380
Drobeta	242	**Pitesti**	100
Eforie	161	**Rimnicu Vilcea**	193
Fagaras	176	**Sibiu**	253
Giurgiu	77	**Timisoara**	329
Hirsova	151	**Urziceni**	80
Iasi	226	**Vaslui**	199
Lugoj	244	**Zerind**	374

Figure 3.22 Values of h_{SLD}—straight-line distances to Bucharest.

expanding a node that is not on the solution path; hence, its search cost is minimal. It is not optimal, however: the path via Sibiu and Fagaras to Bucharest is 32 kilometers longer than the path through Rimnicu Vilcea and Pitesti. This shows why the algorithm is called "greedy"—at each step it tries to get as close to the goal as it can.

Greedy best-first tree search is also incomplete even in a finite state space, much like depth-first search. Consider the problem of getting from Iasi to Fagaras. The heuristic suggests that Neamt be expanded first because it is closest to Fagaras, but it is a dead end. The solution is to go first to Vaslui—a step that is actually farther from the goal according to the heuristic—and then to continue to Urziceni, Bucharest, and Fagaras. The algorithm will never find this solution, however, because expanding Neamt puts Iasi back into the frontier, Iasi is closer to Fagaras than Vaslui is, and so Iasi will be expanded again, leading to an infinite loop. (The graph search version *is* complete in finite spaces, but not in infinite ones.) The worst-case time and space complexity for the tree version is $O(b^m)$, where m is the maximum depth of the search space. With a good heuristic function, however, the complexity can be reduced substantially. The amount of the reduction depends on the particular problem and on the quality of the heuristic.

3.5.2 A* search: Minimizing the total estimated solution cost

A* SEARCH

The most widely known form of best-first search is called **A* search** (pronounced "A-star search"). It evaluates nodes by combining $g(n)$, the cost to reach the node, and $h(n)$, the cost to get from the node to the goal:

$$f(n) = g(n) + h(n) \ .$$

Since $g(n)$ gives the path cost from the start node to node n, and $h(n)$ is the estimated cost of the cheapest path from n to the goal, we have

$$f(n) = \text{ estimated cost of the cheapest solution through } n \ .$$

Thus, if we are trying to find the cheapest solution, a reasonable thing to try first is the node with the lowest value of $g(n) + h(n)$. It turns out that this strategy is more than just reasonable: provided that the heuristic function $h(n)$ satisfies certain conditions, A* search is both complete and optimal. The algorithm is identical to UNIFORM-COST-SEARCH except that A* uses $g + h$ instead of g.

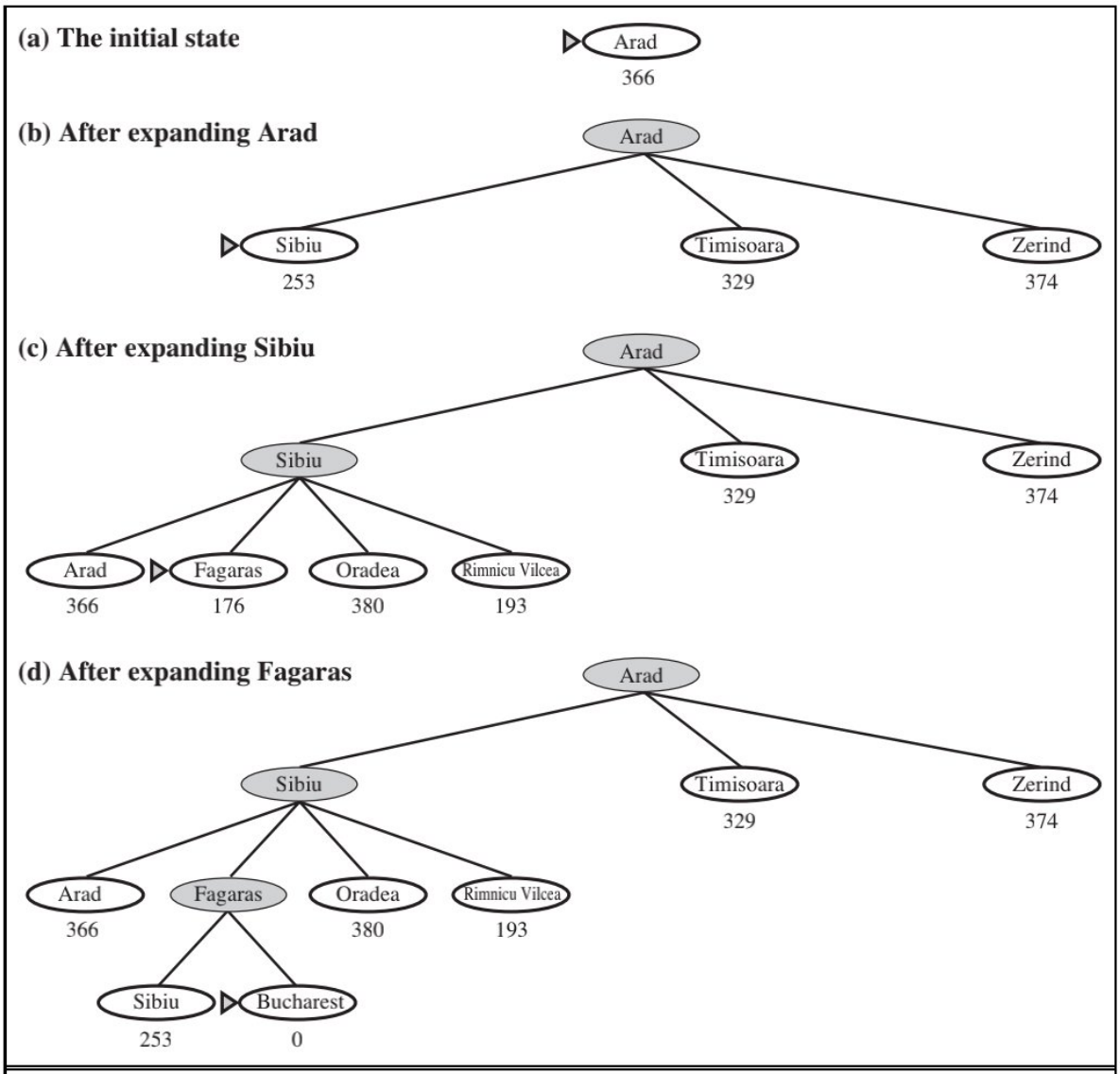


Figure 3.23 Stages in a greedy best-first tree search for Bucharest with the straight-line distance heuristic h_{SLD}. Nodes are labeled with their h-values.

Conditions for optimality: Admissibility and consistency

ADMISSIBLE HEURISTIC

The first condition we require for optimality is that $h(n)$ be an **admissible heuristic**. An admissible heuristic is one that *never overestimates* the cost to reach the goal. Because $g(n)$ is the actual cost to reach n along the current path, and $f(n) = g(n) + h(n)$, we have as an immediate consequence that $f(n)$ never overestimates the true cost of a solution along the current path through n.

Admissible heuristics are by nature optimistic because they think the cost of solving the problem is less than it actually is. An obvious example of an admissible heuristic is the straight-line distance h_{SLD} that we used in getting to Bucharest. Straight-line distance is admissible because the shortest path between any two points is a straight line, so the straight

line cannot be an overestimate. In Figure 3.24, we show the progress of an A* tree search for Bucharest. The values of g are computed from the step costs in Figure 3.2, and the values of h_{SLD} are given in Figure 3.22. Notice in particular that Bucharest first appears on the frontier at step (e), but it is not selected for expansion because its f-cost (450) is higher than that of Pitesti (417). Another way to say this is that there *might* be a solution through Pitesti whose cost is as low as 417, so the algorithm will not settle for a solution that costs 450.

CONSISTENCY
MONOTONICITY

A second, slightly stronger condition called **consistency** (or sometimes **monotonicity**) is required only for applications of A* to graph search.[9] A heuristic $h(n)$ is consistent if, for every node n and every successor n' of n generated by any action a, the estimated cost of reaching the goal from n is no greater than the step cost of getting to n' plus the estimated cost of reaching the goal from n':

$$h(n) \leq c(n, a, n') + h(n') \; .$$

TRIANGLE INEQUALITY

This is a form of the general **triangle inequality**, which stipulates that each side of a triangle cannot be longer than the sum of the other two sides. Here, the triangle is formed by n, n', and the goal G_n closest to n. For an admissible heuristic, the inequality makes perfect sense: if there were a route from n to G_n via n' that was cheaper than $h(n)$, that would violate the property that $h(n)$ is a lower bound on the cost to reach G_n.

It is fairly easy to show (Exercise 3.29) that every consistent heuristic is also admissible. Consistency is therefore a stricter requirement than admissibility, but one has to work quite hard to concoct heuristics that are admissible but not consistent. All the admissible heuristics we discuss in this chapter are also consistent. Consider, for example, h_{SLD}. We know that the general triangle inequality is satisfied when each side is measured by the straight-line distance and that the straight-line distance between n and n' is no greater than $c(n, a, n')$. Hence, h_{SLD} is a consistent heuristic.

Optimality of A*

As we mentioned earlier, A* has the following properties: *the tree-search version of A* is optimal if $h(n)$ is admissible, while the graph-search version is optimal if $h(n)$ is consistent.*

We show the second of these two claims since it is more useful. The argument essentially mirrors the argument for the optimality of uniform-cost search, with g replaced by f—just as in the A* algorithm itself.

The first step is to establish the following: *if $h(n)$ is consistent, then the values of $f(n)$ along any path are nondecreasing.* The proof follows directly from the definition of consistency. Suppose n' is a successor of n; then $g(n') = g(n) + c(n, a, n')$ for some action a, and we have

$$f(n') = g(n') + h(n') = g(n) + c(n, a, n') + h(n') \geq g(n) + h(n) = f(n) \; .$$

The next step is to prove that *whenever A* selects a node n for expansion, the optimal path to that node has been found.* Were this not the case, there would have to be another frontier node n' on the optimal path from the start node to n, by the graph separation property of

[9] With an admissible but inconsistent heuristic, A* requires some extra bookkeeping to ensure optimality.

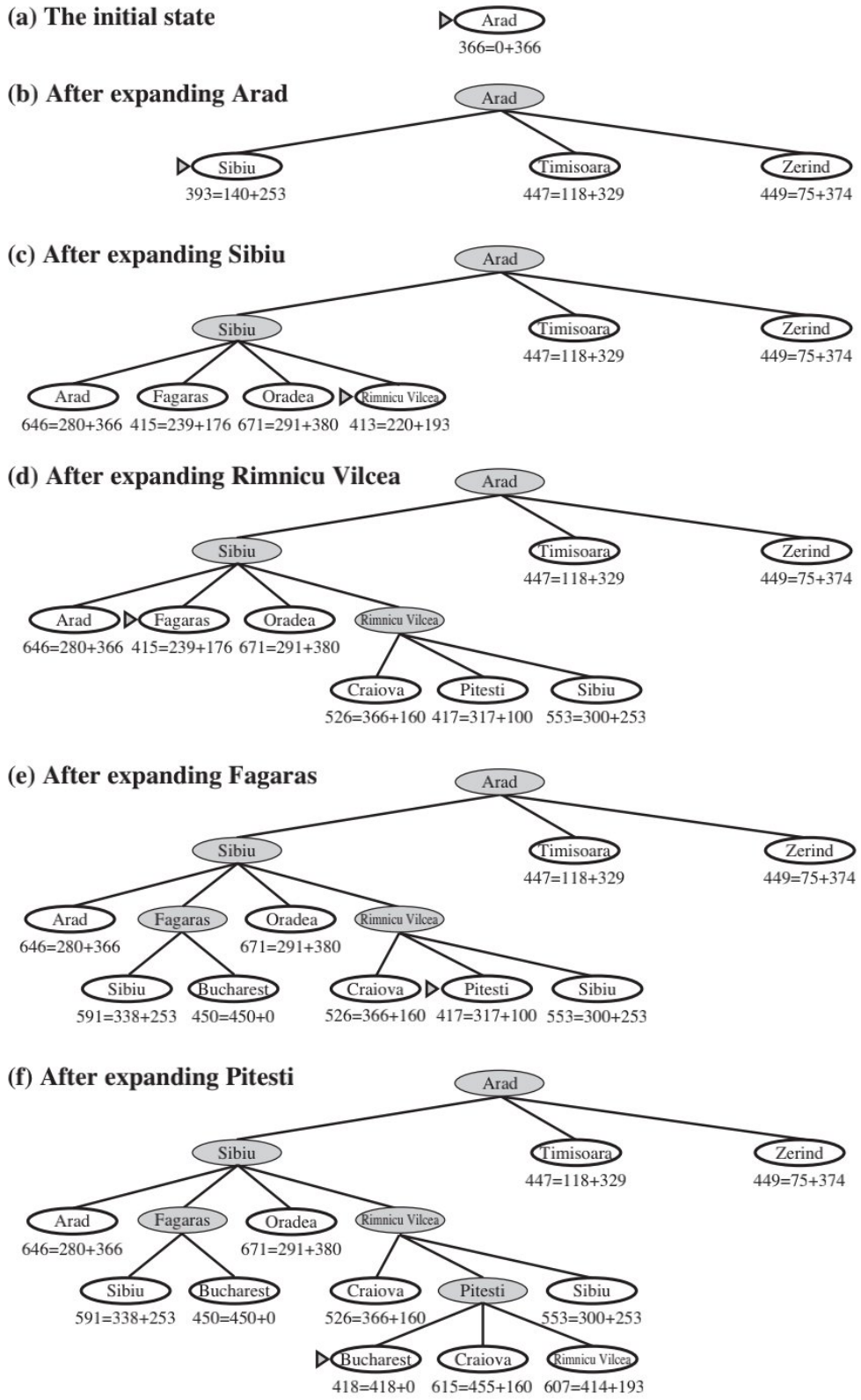


Figure 3.24 Stages in an A* search for Bucharest. Nodes are labeled with $f = g + h$. The h values are the straight-line distances to Bucharest taken from Figure 3.22.

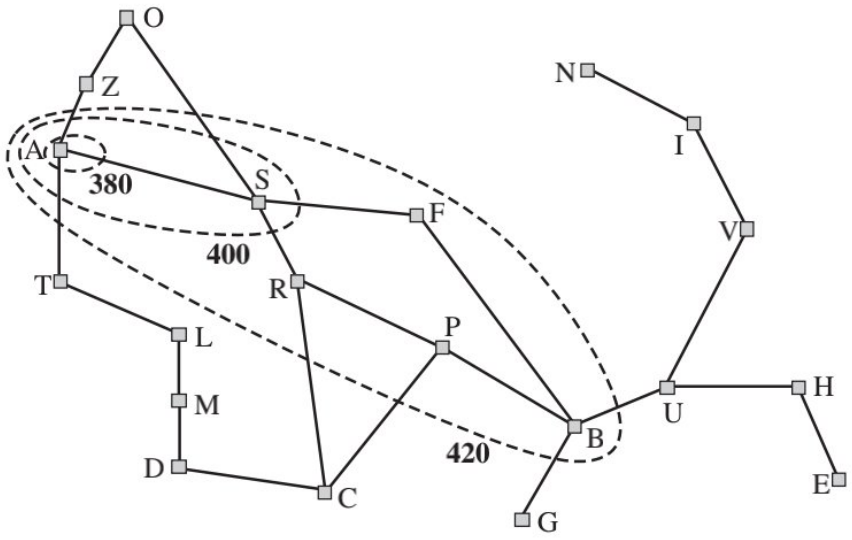


Figure 3.25 Map of Romania showing contours at $f = 380$, $f = 400$, and $f = 420$, with Arad as the start state. Nodes inside a given contour have f-costs less than or equal to the contour value.

Figure 3.9; because f is nondecreasing along any path, n' would have lower f-cost than n and would have been selected first.

From the two preceding observations, it follows that the sequence of nodes expanded by A* using GRAPH-SEARCH is in nondecreasing order of $f(n)$. Hence, the first goal node selected for expansion must be an optimal solution because f is the true cost for goal nodes (which have $h = 0$) and all later goal nodes will be at least as expensive.

CONTOUR

The fact that f-costs are nondecreasing along any path also means that we can draw **contours** in the state space, just like the contours in a topographic map. Figure 3.25 shows an example. Inside the contour labeled 400, all nodes have $f(n)$ less than or equal to 400, and so on. Then, because A* expands the frontier node of lowest f-cost, we can see that an A* search fans out from the start node, adding nodes in concentric bands of increasing f-cost.

With uniform-cost search (A* search using $h(n) = 0$), the bands will be "circular" around the start state. With more accurate heuristics, the bands will stretch toward the goal state and become more narrowly focused around the optimal path. If C^* is the cost of the optimal solution path, then we can say the following:

- A* expands all nodes with $f(n) < C^*$.
- A* might then expand some of the nodes right on the "goal contour" (where $f(n) = C^*$) before selecting a goal node.

Completeness requires that there be only finitely many nodes with cost less than or equal to C^*, a condition that is true if all step costs exceed some finite ϵ and if b is finite.

Notice that A* expands no nodes with $f(n) > C^*$—for example, Timisoara is not expanded in Figure 3.24 even though it is a child of the root. We say that the subtree below

PRUNING

Timisoara is **pruned**; because h_{SLD} is admissible, the algorithm can safely ignore this subtree while still guaranteeing optimality. The concept of pruning—eliminating possibilities from consideration without having to examine them—is important for many areas of AI.

One final observation is that among optimal algorithms of this type—algorithms that extend search paths from the root and use the same heuristic information—A* is **optimally efficient** for any given consistent heuristic. That is, no other optimal algorithm is guaranteed to expand fewer nodes than A* (except possibly through tie-breaking among nodes with $f(n) = C^*$). This is because any algorithm that *does not* expand all nodes with $f(n) < C^*$ runs the risk of missing the optimal solution.

OPTIMALLY EFFICIENT

That A* search is complete, optimal, and optimally efficient among all such algorithms is rather satisfying. Unfortunately, it does not mean that A* is the answer to all our searching needs. The catch is that, for most problems, the number of states within the goal contour search space is still exponential in the length of the solution. The details of the analysis are beyond the scope of this book, but the basic results are as follows. For problems with constant step costs, the growth in run time as a function of the optimal solution depth d is analyzed in terms of the the **absolute error** or the **relative error** of the heuristic. The absolute error is defined as $\Delta \equiv h^* - h$, where h^* is the actual cost of getting from the root to the goal, and the relative error is defined as $\epsilon \equiv (h^* - h)/h^*$.

ABSOLUTE ERROR

RELATIVE ERROR

The complexity results depend very strongly on the assumptions made about the state space. The simplest model studied is a state space that has a single goal and is essentially a tree with reversible actions. (The 8-puzzle satisfies the first and third of these assumptions.) In this case, the time complexity of A* is exponential in the maximum absolute error, that is, $O(b^{\Delta})$. For constant step costs, we can write this as $O(b^{\epsilon d})$, where d is the solution depth. For almost all heuristics in practical use, the absolute error is at least proportional to the path cost h^*, so ϵ is constant or growing and the time complexity is exponential in d. We can also see the effect of a more accurate heuristic: $O(b^{\epsilon d}) = O((b^{\epsilon})^d)$, so the effective branching factor (defined more formally in the next section) is b^{ϵ}.

When the state space has many goal states—particularly *near-optimal* goal states—the search process can be led astray from the optimal path and there is an extra cost proportional to the number of goals whose cost is within a factor ϵ of the optimal cost. Finally, in the general case of a graph, the situation is even worse. There can be exponentially many states with $f(n) < C^*$ even if the absolute error is bounded by a constant. For example, consider a version of the vacuum world where the agent can clean up any square for unit cost without even having to visit it: in that case, squares can be cleaned in any order. With N initially dirty squares, there are 2^N states where some subset has been cleaned and all of them are on an optimal solution path—and hence satisfy $f(n) < C^*$—even if the heuristic has an error of 1.

The complexity of A* often makes it impractical to insist on finding an optimal solution. One can use variants of A* that find suboptimal solutions quickly, or one can sometimes design heuristics that are more accurate but not strictly admissible. In any case, the use of a good heuristic still provides enormous savings compared to the use of an uninformed search. In Section 3.6, we look at the question of designing good heuristics.

Computation time is not, however, A*'s main drawback. Because it keeps all generated nodes in memory (as do all GRAPH-SEARCH algorithms), A* usually runs out of space long

```
function RECURSIVE-BEST-FIRST-SEARCH(problem) returns a solution, or failure
    return RBFS(problem, MAKE-NODE(problem.INITIAL-STATE), ∞)

function RBFS(problem, node, f_limit) returns a solution, or failure and a new f-cost limit
  if problem.GOAL-TEST(node.STATE) then return SOLUTION(node)
  successors ← [ ]
  for each action in problem.ACTIONS(node.STATE) do
      add CHILD-NODE(problem, node, action) into successors
  if successors is empty then return failure, ∞
  for each s in successors do /* update f with value from previous search, if any */
      s.f ← max(s.g + s.h, node.f))
  loop do
      best ← the lowest f-value node in successors
      if best.f > f_limit then return failure, best.f
      alternative ← the second-lowest f-value among successors
      result, best.f ← RBFS(problem, best, min(f_limit, alternative))
      if result ≠ failure then return result
```

Figure 3.26 The algorithm for recursive best-first search.

before it runs out of time. For this reason, A* is not practical for many large-scale problems. There are, however, algorithms that overcome the space problem without sacrificing optimality or completeness, at a small cost in execution time. We discuss these next.

3.5.3 Memory-bounded heuristic search

ITERATIVE-DEEPENING A*

The simplest way to reduce memory requirements for A* is to adapt the idea of iterative deepening to the heuristic search context, resulting in the **iterative-deepening A*** (IDA*) algorithm. The main difference between IDA* and standard iterative deepening is that the cutoff used is the f-cost ($g + h$) rather than the depth; at each iteration, the cutoff value is the smallest f-cost of any node that exceeded the cutoff on the previous iteration. IDA* is practical for many problems with unit step costs and avoids the substantial overhead associated with keeping a sorted queue of nodes. Unfortunately, it suffers from the same difficulties with real-valued costs as does the iterative version of uniform-cost search described in Exercise 3.17. This section briefly examines two other memory-bounded algorithms, called RBFS and MA*.

RECURSIVE BEST-FIRST SEARCH

Recursive best-first search (RBFS) is a simple recursive algorithm that attempts to mimic the operation of standard best-first search, but using only linear space. The algorithm is shown in Figure 3.26. Its structure is similar to that of a recursive depth-first search, but rather than continuing indefinitely down the current path, it uses the *f_limit* variable to keep track of the f-value of the best *alternative* path available from any ancestor of the current node. If the current node exceeds this limit, the recursion unwinds back to the alternative path. As the recursion unwinds, RBFS replaces the f-value of each node along the path with a **backed-up value**—the best f-value of its children. In this way, RBFS remembers the f-value of the best leaf in the forgotten subtree and can therefore decide whether it's worth

BACKED-UP VALUE

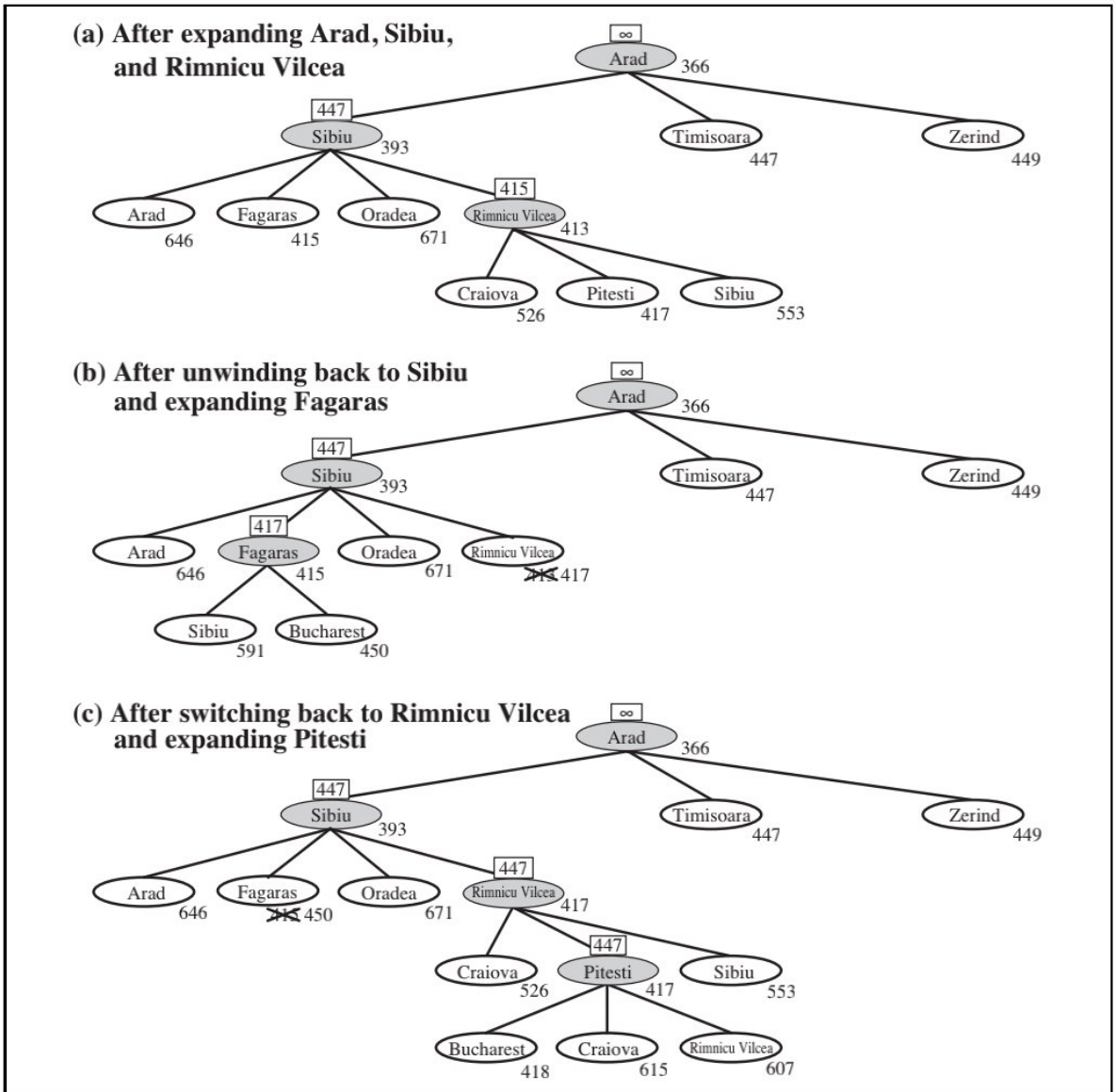


Figure 3.27 Stages in an RBFS search for the shortest route to Bucharest. The f-limit value for each recursive call is shown on top of each current node, and every node is labeled with its f-cost. (a) The path via Rimnicu Vilcea is followed until the current best leaf (Pitesti) has a value that is worse than the best alternative path (Fagaras). (b) The recursion unwinds and the best leaf value of the forgotten subtree (417) is backed up to Rimnicu Vilcea; then Fagaras is expanded, revealing a best leaf value of 450. (c) The recursion unwinds and the best leaf value of the forgotten subtree (450) is backed up to Fagaras; then Rimnicu Vilcea is expanded. This time, because the best alternative path (through Timisoara) costs at least 447, the expansion continues to Bucharest.

reexpanding the subtree at some later time. Figure 3.27 shows how RBFS reaches Bucharest.

RBFS is somewhat more efficient than IDA*, but still suffers from excessive node regeneration. In the example in Figure 3.27, RBFS follows the path via Rimnicu Vilcea, then

"changes its mind" and tries Fagaras, and then changes its mind back again. These mind changes occur because every time the current best path is extended, its f-value is likely to increase—h is usually less optimistic for nodes closer to the goal. When this happens, the second-best path might become the best path, so the search has to backtrack to follow it. Each mind change corresponds to an iteration of IDA* and could require many reexpansions of forgotten nodes to recreate the best path and extend it one more node.

Like A* tree search, RBFS is an optimal algorithm if the heuristic function $h(n)$ is admissible. Its space complexity is linear in the depth of the deepest optimal solution, but its time complexity is rather difficult to characterize: it depends both on the accuracy of the heuristic function and on how often the best path changes as nodes are expanded.

IDA* and RBFS suffer from using *too little* memory. Between iterations, IDA* retains only a single number: the current f-cost limit. RBFS retains more information in memory, but it uses only linear space: even if more memory were available, RBFS has no way to make use of it. Because they forget most of what they have done, both algorithms may end up reexpanding the same states many times over. Furthermore, they suffer the potentially exponential increase in complexity associated with redundant paths in graphs (see Section 3.3).

It seems sensible, therefore, to use all available memory. Two algorithms that do this are **MA*** (memory-bounded A*) and **SMA*** (simplified MA*). SMA* is—well—simpler, so we will describe it. SMA* proceeds just like A*, expanding the best leaf until memory is full. At this point, it cannot add a new node to the search tree without dropping an old one. SMA* always drops the *worst* leaf node—the one with the highest f-value. Like RBFS, SMA* then backs up the value of the forgotten node to its parent. In this way, the ancestor of a forgotten subtree knows the quality of the best path in that subtree. With this information, SMA* regenerates the subtree only when all other paths have been shown to look worse than the path it has forgotten. Another way of saying this is that, if all the descendants of a node n are forgotten, then we will not know which way to go from n, but we will still have an idea of how worthwhile it is to go anywhere from n.

MA*
SMA*

The complete algorithm is too complicated to reproduce here,[10] but there is one subtlety worth mentioning. We said that SMA* expands the best leaf and deletes the worst leaf. What if *all* the leaf nodes have the same f-value? To avoid selecting the same node for deletion and expansion, SMA* expands the *newest* best leaf and deletes the *oldest* worst leaf. These coincide when there is only one leaf, but in that case, the current search tree must be a single path from root to leaf that fills all of memory. If the leaf is not a goal node, then *even if it is on an optimal solution path*, that solution is not reachable with the available memory. Therefore, the node can be discarded exactly as if it had no successors.

SMA* is complete if there is any reachable solution—that is, if d, the depth of the shallowest goal node, is less than the memory size (expressed in nodes). It is optimal if any optimal solution is reachable; otherwise, it returns the best reachable solution. In practical terms, SMA* is a fairly robust choice for finding optimal solutions, particularly when the state space is a graph, step costs are not uniform, and node generation is expensive compared to the overhead of maintaining the frontier and the explored set.

[10] A rough sketch appeared in the first edition of this book.

THRASHING

On very hard problems, however, it will often be the case that SMA* is forced to switch back and forth continually among many candidate solution paths, only a small subset of which can fit in memory. (This resembles the problem of **thrashing** in disk paging systems.) Then the extra time required for repeated regeneration of the same nodes means that problems that would be practically solvable by A*, given unlimited memory, become intractable for SMA*. That is to say, *memory limitations can make a problem intractable from the point of view of computation time.* Although no current theory explains the tradeoff between time and memory, it seems that this is an inescapable problem. The only way out is to drop the optimality requirement.

3.5.4 Learning to search better

METALEVEL STATE SPACE

OBJECT-LEVEL STATE SPACE

We have presented several fixed strategies—breadth-first, greedy best-first, and so on—that have been designed by computer scientists. Could an agent *learn* how to search better? The answer is yes, and the method rests on an important concept called the **metalevel state space**. Each state in a metalevel state space captures the internal (computational) state of a program that is searching in an **object-level state space** such as Romania. For example, the internal state of the A* algorithm consists of the current search tree. Each action in the metalevel state space is a computation step that alters the internal state; for example, each computation step in A* expands a leaf node and adds its successors to the tree. Thus, Figure 3.24, which shows a sequence of larger and larger search trees, can be seen as depicting a path in the metalevel state space where each state on the path is an object-level search tree.

METALEVEL LEARNING

Now, the path in Figure 3.24 has five steps, including one step, the expansion of Fagaras, that is not especially helpful. For harder problems, there will be many such missteps, and a **metalevel learning** algorithm can learn from these experiences to avoid exploring unpromising subtrees. The techniques used for this kind of learning are described in Chapter 21. The goal of learning is to minimize the **total cost** of problem solving, trading off computational expense and path cost.

3.6 HEURISTIC FUNCTIONS

In this section, we look at heuristics for the 8-puzzle, in order to shed light on the nature of heuristics in general.

The 8-puzzle was one of the earliest heuristic search problems. As mentioned in Section 3.2, the object of the puzzle is to slide the tiles horizontally or vertically into the empty space until the configuration matches the goal configuration (Figure 3.28).

The average solution cost for a randomly generated 8-puzzle instance is about 22 steps. The branching factor is about 3. (When the empty tile is in the middle, four moves are possible; when it is in a corner, two; and when it is along an edge, three.) This means that an exhaustive tree search to depth 22 would look at about $3^{22} \approx 3.1 \times 10^{10}$ states. A graph search would cut this down by a factor of about 170,000 because only $9!/2 = 181,440$ distinct states are reachable. (See Exercise 3.4.) This is a manageable number, but

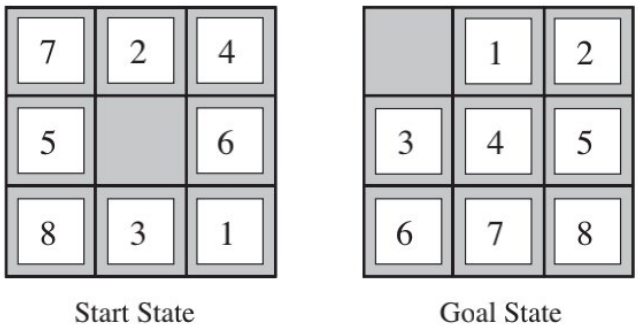


Figure 3.28 A typical instance of the 8-puzzle. The solution is 26 steps long.

the corresponding number for the 15-puzzle is roughly 10^{13}, so the next order of business is to find a good heuristic function. If we want to find the shortest solutions by using A*, we need a heuristic function that never overestimates the number of steps to the goal. There is a long history of such heuristics for the 15-puzzle; here are two commonly used candidates:

- h_1 = the number of misplaced tiles. For Figure 3.28, all of the eight tiles are out of position, so the start state would have $h_1 = 8$. h_1 is an admissible heuristic because it is clear that any tile that is out of place must be moved at least once.
- h_2 = the sum of the distances of the tiles from their goal positions. Because tiles cannot move along diagonals, the distance we will count is the sum of the horizontal and vertical distances. This is sometimes called the **city block distance** or **Manhattan distance**. h_2 is also admissible because all any move can do is move one tile one step closer to the goal. Tiles 1 to 8 in the start state give a Manhattan distance of

MANHATTAN DISTANCE

$$h_2 = 3 + 1 + 2 + 2 + 2 + 3 + 3 + 2 = 18 \ .$$

As expected, neither of these overestimates the true solution cost, which is 26.

3.6.1 The effect of heuristic accuracy on performance

EFFECTIVE BRANCHING FACTOR

One way to characterize the quality of a heuristic is the **effective branching factor** b^*. If the total number of nodes generated by A* for a particular problem is N and the solution depth is d, then b^* is the branching factor that a uniform tree of depth d would have to have in order to contain $N + 1$ nodes. Thus,

$$N + 1 = 1 + b^* + (b^*)^2 + \cdots + (b^*)^d \ .$$

For example, if A* finds a solution at depth 5 using 52 nodes, then the effective branching factor is 1.92. The effective branching factor can vary across problem instances, but usually it is fairly constant for sufficiently hard problems. (The existence of an effective branching factor follows from the result, mentioned earlier, that the number of nodes expanded by A* grows exponentially with solution depth.) Therefore, experimental measurements of b^* on a small set of problems can provide a good guide to the heuristic's overall usefulness. A well-designed heuristic would have a value of b^* close to 1, allowing fairly large problems to be solved at reasonable computational cost.

To test the heuristic functions h_1 and h_2, we generated 1200 random problems with solution lengths from 2 to 24 (100 for each even number) and solved them with iterative deepening search and with A* tree search using both h_1 and h_2. Figure 3.29 gives the average number of nodes generated by each strategy and the effective branching factor. The results suggest that h_2 is better than h_1, and is far better than using iterative deepening search. Even for small problems with $d = 12$, A* with h_2 is 50,000 times more efficient than uninformed iterative deepening search.

	Search Cost (nodes generated)			Effective Branching Factor		
d	IDS	A*(h_1)	A*(h_2)	IDS	A*(h_1)	A*(h_2)
2	10	6	6	2.45	1.79	1.79
4	112	13	12	2.87	1.48	1.45
6	680	20	18	2.73	1.34	1.30
8	6384	39	25	2.80	1.33	1.24
10	47127	93	39	2.79	1.38	1.22
12	3644035	227	73	2.78	1.42	1.24
14	–	539	113	–	1.44	1.23
16	–	1301	211	–	1.45	1.25
18	–	3056	363	–	1.46	1.26
20	–	7276	676	–	1.47	1.27
22	–	18094	1219	–	1.48	1.28
24	–	39135	1641	–	1.48	1.26

Figure 3.29 Comparison of the search costs and effective branching factors for the ITERATIVE-DEEPENING-SEARCH and A* algorithms with h_1, h_2. Data are averaged over 100 instances of the 8-puzzle for each of various solution lengths d.

One might ask whether h_2 is *always* better than h_1. The answer is "Essentially, yes." It is easy to see from the definitions of the two heuristics that, for any node n, $h_2(n) \geq h_1(n)$.

DOMINATION

We thus say that h_2 **dominates** h_1. Domination translates directly into efficiency: A* using h_2 will never expand more nodes than A* using h_1 (except possibly for some nodes with $f(n) = C^*$). The argument is simple. Recall the observation on page 97 that every node with $f(n) < C^*$ will surely be expanded. This is the same as saying that every node with $h(n) < C^* - g(n)$ will surely be expanded. But because h_2 is at least as big as h_1 for all nodes, every node that is surely expanded by A* search with h_2 will also surely be expanded with h_1, and h_1 might cause other nodes to be expanded as well. Hence, it is generally better to use a heuristic function with higher values, provided it is consistent and that the computation time for the heuristic is not too long.

3.6.2 Generating admissible heuristics from relaxed problems

We have seen that both h_1 (misplaced tiles) and h_2 (Manhattan distance) are fairly good heuristics for the 8-puzzle and that h_2 is better. How might one have come up with h_2? Is it possible for a computer to invent such a heuristic mechanically?

h_1 and h_2 are estimates of the remaining path length for the 8-puzzle, but they are also perfectly accurate path lengths for *simplified* versions of the puzzle. If the rules of the puzzle

were changed so that a tile could move anywhere instead of just to the adjacent empty square, then h_1 would give the exact number of steps in the shortest solution. Similarly, if a tile could move one square in any direction, even onto an occupied square, then h_2 would give the exact number of steps in the shortest solution. A problem with fewer restrictions on the actions is called a **relaxed problem**. The state-space graph of the relaxed problem is a *supergraph* of the original state space because the removal of restrictions creates added edges in the graph.

RELAXED PROBLEM

Because the relaxed problem adds edges to the state space, any optimal solution in the original problem is, by definition, also a solution in the relaxed problem; but the relaxed problem may have *better* solutions if the added edges provide short cuts. Hence, *the cost of an optimal solution to a relaxed problem is an admissible heuristic for the original problem.* Furthermore, because the derived heuristic is an exact cost for the relaxed problem, it must obey the triangle inequality and is therefore **consistent** (see page 95).

If a problem definition is written down in a formal language, it is possible to construct relaxed problems automatically.[11] For example, if the 8-puzzle actions are described as

> A tile can move from square A to square B if
> A is horizontally or vertically adjacent to B **and** B is blank,

we can generate three relaxed problems by removing one or both of the conditions:

(a) A tile can move from square A to square B if A is adjacent to B.
(b) A tile can move from square A to square B if B is blank.
(c) A tile can move from square A to square B.

From (a), we can derive h_2 (Manhattan distance). The reasoning is that h_2 would be the proper score if we moved each tile in turn to its destination. The heuristic derived from (b) is discussed in Exercise 3.31. From (c), we can derive h_1 (misplaced tiles) because it would be the proper score if tiles could move to their intended destination in one step. Notice that it is crucial that the relaxed problems generated by this technique can be solved essentially *without search*, because the relaxed rules allow the problem to be decomposed into eight independent subproblems. If the relaxed problem is hard to solve, then the values of the corresponding heuristic will be expensive to obtain.[12]

A program called ABSOLVER can generate heuristics automatically from problem definitions, using the "relaxed problem" method and various other techniques (Prieditis, 1993). ABSOLVER generated a new heuristic for the 8-puzzle that was better than any preexisting heuristic and found the first useful heuristic for the famous Rubik's Cube puzzle.

One problem with generating new heuristic functions is that one often fails to get a single "clearly best" heuristic. If a collection of admissible heuristics $h_1 \ldots h_m$ is available for a problem and none of them dominates any of the others, which should we choose? As it turns out, we need not make a choice. We can have the best of all worlds, by defining

$$h(n) = \max\{h_1(n), \ldots, h_m(n)\} .$$

[11] In Chapters 8 and 10, we describe formal languages suitable for this task; with formal descriptions that can be manipulated, the construction of relaxed problems can be automated. For now, we use English.

[12] Note that a perfect heuristic can be obtained simply by allowing h to run a full breadth-first search "on the sly." Thus, there is a tradeoff between accuracy and computation time for heuristic functions.

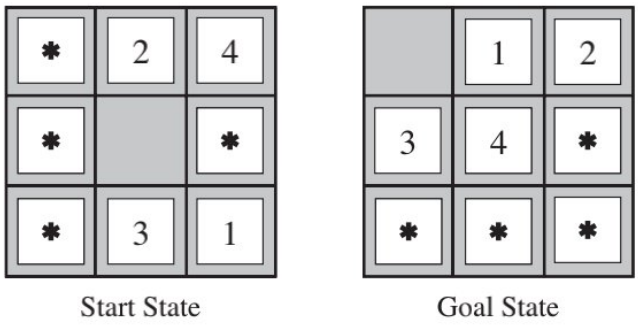


Figure 3.30 A subproblem of the 8-puzzle instance given in Figure 3.28. The task is to get tiles 1, 2, 3, and 4 into their correct positions, without worrying about what happens to the other tiles.

This composite heuristic uses whichever function is most accurate on the node in question. Because the component heuristics are admissible, h is admissible; it is also easy to prove that h is consistent. Furthermore, h dominates all of its component heuristics.

3.6.3 Generating admissible heuristics from subproblems: Pattern databases

SUBPROBLEM

Admissible heuristics can also be derived from the solution cost of a **subproblem** of a given problem. For example, Figure 3.30 shows a subproblem of the 8-puzzle instance in Figure 3.28. The subproblem involves getting tiles 1, 2, 3, 4 into their correct positions. Clearly, the cost of the optimal solution of this subproblem is a lower bound on the cost of the complete problem. It turns out to be more accurate than Manhattan distance in some cases.

PATTERN DATABASE

The idea behind **pattern databases** is to store these exact solution costs for every possible subproblem instance—in our example, every possible configuration of the four tiles and the blank. (The locations of the other four tiles are irrelevant for the purposes of solving the subproblem, but moves of those tiles do count toward the cost.) Then we compute an admissible heuristic h_{DB} for each complete state encountered during a search simply by looking up the corresponding subproblem configuration in the database. The database itself is constructed by searching back[13] from the goal and recording the cost of each new pattern encountered; the expense of this search is amortized over many subsequent problem instances.

The choice of 1-2-3-4 is fairly arbitrary; we could also construct databases for 5-6-7-8, for 2-4-6-8, and so on. Each database yields an admissible heuristic, and these heuristics can be combined, as explained earlier, by taking the maximum value. A combined heuristic of this kind is much more accurate than the Manhattan distance; the number of nodes generated when solving random 15-puzzles can be reduced by a factor of 1000.

One might wonder whether the heuristics obtained from the 1-2-3-4 database and the 5-6-7-8 could be *added*, since the two subproblems seem not to overlap. Would this still give an admissible heuristic? The answer is no, because the solutions of the 1-2-3-4 subproblem and the 5-6-7-8 subproblem for a given state will almost certainly share some moves—it is

[13] By working backward from the goal, the exact solution cost of every instance encountered is immediately available. This is an example of **dynamic programming**, which we discuss further in Chapter 17.

unlikely that 1-2-3-4 can be moved into place without touching 5-6-7-8, and vice versa. But what if we don't count those moves? That is, we record not the total cost of solving the 1-2-3-4 subproblem, but just the number of moves involving 1-2-3-4. Then it is easy to see that the sum of the two costs is still a lower bound on the cost of solving the entire problem. This is the idea behind **disjoint pattern databases**. With such databases, it is possible to solve random 15-puzzles in a few milliseconds—the number of nodes generated is reduced by a factor of 10,000 compared with the use of Manhattan distance. For 24-puzzles, a speedup of roughly a factor of a million can be obtained.

DISJOINT PATTERN DATABASES

Disjoint pattern databases work for sliding-tile puzzles because the problem can be divided up in such a way that each move affects only one subproblem—because only one tile is moved at a time. For a problem such as Rubik's Cube, this kind of subdivision is difficult because each move affects 8 or 9 of the 26 cubies. More general ways of defining additive, admissible heuristics have been proposed that do apply to Rubik's cube (Yang *et al.*, 2008), but they have not yielded a heuristic better than the best nonadditive heuristic for the problem.

3.6.4 Learning heuristics from experience

A heuristic function $h(n)$ is supposed to estimate the cost of a solution beginning from the state at node n. How could an agent construct such a function? One solution was given in the preceding sections—namely, to devise relaxed problems for which an optimal solution can be found easily. Another solution is to learn from experience. "Experience" here means solving lots of 8-puzzles, for instance. Each optimal solution to an 8-puzzle problem provides examples from which $h(n)$ can be learned. Each example consists of a state from the solution path and the actual cost of the solution from that point. From these examples, a learning algorithm can be used to construct a function $h(n)$ that can (with luck) predict solution costs for other states that arise during search. Techniques for doing just this using neural nets, decision trees, and other methods are demonstrated in Chapter 18. (The reinforcement learning methods described in Chapter 21 are also applicable.)

FEATURE

Inductive learning methods work best when supplied with **features** of a state that are relevant to predicting the state's value, rather than with just the raw state description. For example, the feature "number of misplaced tiles" might be helpful in predicting the actual distance of a state from the goal. Let's call this feature $x_1(n)$. We could take 100 randomly generated 8-puzzle configurations and gather statistics on their actual solution costs. We might find that when $x_1(n)$ is 5, the average solution cost is around 14, and so on. Given these data, the value of x_1 can be used to predict $h(n)$. Of course, we can use several features. A second feature $x_2(n)$ might be "number of pairs of adjacent tiles that are not adjacent in the goal state." How should $x_1(n)$ and $x_2(n)$ be combined to predict $h(n)$? A common approach is to use a linear combination:

$$h(n) = c_1 x_1(n) + c_2 x_2(n) \ .$$

The constants c_1 and c_2 are adjusted to give the best fit to the actual data on solution costs. One expects both c_1 and c_2 to be positive because misplaced tiles and incorrect adjacent pairs make the problem harder to solve. Notice that this heuristic does satisfy the condition that $h(n) = 0$ for goal states, but it is not necessarily admissible or consistent.

3.7 SUMMARY

This chapter has introduced methods that an agent can use to select actions in environments that are deterministic, observable, static, and completely known. In such cases, the agent can construct sequences of actions that achieve its goals; this process is called **search**.

- Before an agent can start searching for solutions, a **goal** must be identified and a well-defined **problem** must be formulated.
- A problem consists of five parts: the **initial state**, a set of **actions**, a **transition model** describing the results of those actions, a **goal test** function, and a **path cost** function. The environment of the problem is represented by a **state space**. A **path** through the state space from the initial state to a goal state is a **solution**.
- Search algorithms treat states and actions as **atomic**: they do not consider any internal structure they might possess.
- A general TREE-SEARCH algorithm considers all possible paths to find a solution, whereas a GRAPH-SEARCH algorithm avoids consideration of redundant paths.
- Search algorithms are judged on the basis of **completeness**, **optimality**, **time complexity**, and **space complexity**. Complexity depends on b, the branching factor in the state space, and d, the depth of the shallowest solution.
- **Uninformed search** methods have access only to the problem definition. The basic algorithms are as follows:
  - **Breadth-first search** expands the shallowest nodes first; it is complete, optimal for unit step costs, but has exponential space complexity.
  - **Uniform-cost search** expands the node with lowest path cost, $g(n)$, and is optimal for general step costs.
  - **Depth-first search** expands the deepest unexpanded node first. It is neither complete nor optimal, but has linear space complexity. **Depth-limited search** adds a depth bound.
  - **Iterative deepening search** calls depth-first search with increasing depth limits until a goal is found. It is complete, optimal for unit step costs, has time complexity comparable to breadth-first search, and has linear space complexity.
  - **Bidirectional search** can enormously reduce time complexity, but it is not always applicable and may require too much space.
- **Informed search** methods may have access to a **heuristic** function $h(n)$ that estimates the cost of a solution from n.
  - The generic **best-first search** algorithm selects a node for expansion according to an **evaluation function**.
  - **Greedy best-first search** expands nodes with minimal $h(n)$. It is not optimal but is often efficient.

  - **A* search** expands nodes with minimal $f(n) = g(n) + h(n)$. A* is complete and optimal, provided that $h(n)$ is admissible (for TREE-SEARCH) or consistent (for GRAPH-SEARCH). The space complexity of A* is still prohibitive.
  - **RBFS** (recursive best-first search) and **SMA*** (simplified memory-bounded A*) are robust, optimal search algorithms that use limited amounts of memory; given enough time, they can solve problems that A* cannot solve because it runs out of memory.
- The performance of heuristic search algorithms depends on the quality of the heuristic function. One can sometimes construct good heuristics by relaxing the problem definition, by storing precomputed solution costs for subproblems in a pattern database, or by learning from experience with the problem class.

BIBLIOGRAPHICAL AND HISTORICAL NOTES

The topic of state-space search originated in more or less its current form in the early years of AI. Newell and Simon's work on the Logic Theorist (1957) and GPS (1961) led to the establishment of search algorithms as the primary weapons in the armory of 1960s AI researchers and to the establishment of problem solving as the canonical AI task. Work in operations research by Richard Bellman (1957) showed the importance of additive path costs in simplifying optimization algorithms. The text on *Automated Problem Solving* by Nils Nilsson (1971) established the area on a solid theoretical footing.

Most of the state-space search problems analyzed in this chapter have a long history in the literature and are less trivial than they might seem. The missionaries and cannibals problem used in Exercise 3.9 was analyzed in detail by Amarel (1968). It had been considered earlier—in AI by Simon and Newell (1961) and in operations research by Bellman and Dreyfus (1962).

The 8-puzzle is a smaller cousin of the 15-puzzle, whose history is recounted at length by Slocum and Sonneveld (2006). It was widely believed to have been invented by the famous American game designer Sam Loyd, based on his claims to that effect from 1891 onward (Loyd, 1959). Actually it was invented by Noyes Chapman, a postmaster in Canastota, New York, in the mid-1870s. (Chapman was unable to patent his invention, as a generic patent covering sliding blocks with letters, numbers, or pictures was granted to Ernest Kinsey in 1878.) It quickly attracted the attention of the public and of mathematicians (Johnson and Story, 1879; Tait, 1880). The editors of the *American Journal of Mathematics* stated, "The '15' puzzle for the last few weeks has been prominently before the American public, and may safely be said to have engaged the attention of nine out of ten persons of both sexes and all ages and conditions of the community." Ratner and Warmuth (1986) showed that the general $n \times n$ version of the 15-puzzle belongs to the class of NP-complete problems.

The 8-queens problem was first published anonymously in the German chess magazine *Schach* in 1848; it was later attributed to one Max Bezzel. It was republished in 1850 and at that time drew the attention of the eminent mathematician Carl Friedrich Gauss, who

attempted to enumerate all possible solutions; initially he found only 72, but eventually he found the correct answer of 92, although Nauck published all 92 solutions first, in 1850. Netto (1901) generalized the problem to n queens, and Abramson and Yung (1989) found an $O(n)$ algorithm.

Each of the real-world search problems listed in the chapter has been the subject of a good deal of research effort. Methods for selecting optimal airline flights remain proprietary for the most part, but Carl de Marcken (personal communication) has shown that airline ticket pricing and restrictions have become so convoluted that the problem of selecting an optimal flight is formally *undecidable*. The traveling-salesperson problem is a standard combinatorial problem in theoretical computer science (Lawler *et al.*, 1992). Karp (1972) proved the TSP to be NP-hard, but effective heuristic approximation methods were developed (Lin and Kernighan, 1973). Arora (1998) devised a fully polynomial approximation scheme for Euclidean TSPs. VLSI layout methods are surveyed by Shahookar and Mazumder (1991), and many layout optimization papers appear in VLSI journals. Robotic navigation and assembly problems are discussed in Chapter 25.

Uninformed search algorithms for problem solving are a central topic of classical computer science (Horowitz and Sahni, 1978) and operations research (Dreyfus, 1969). Breadth-first search was formulated for solving mazes by Moore (1959). The method of **dynamic programming** (Bellman, 1957; Bellman and Dreyfus, 1962), which systematically records solutions for all subproblems of increasing lengths, can be seen as a form of breadth-first search on graphs. The two-point shortest-path algorithm of Dijkstra (1959) is the origin of uniform-cost search. These works also introduced the idea of explored and frontier sets (closed and open lists).

A version of iterative deepening designed to make efficient use of the chess clock was first used by Slate and Atkin (1977) in the CHESS 4.5 game-playing program. Martelli's algorithm B (1977) includes an iterative deepening aspect and also dominates A*'s worst-case performance with admissible but inconsistent heuristics. The iterative deepening technique came to the fore in work by Korf (1985a). Bidirectional search, which was introduced by Pohl (1971), can also be effective in some cases.

The use of heuristic information in problem solving appears in an early paper by Simon and Newell (1958), but the phrase "heuristic search" and the use of heuristic functions that estimate the distance to the goal came somewhat later (Newell and Ernst, 1965; Lin, 1965). Doran and Michie (1966) conducted extensive experimental studies of heuristic search. Although they analyzed path length and "penetrance" (the ratio of path length to the total number of nodes examined so far), they appear to have ignored the information provided by the path cost $g(n)$. The A* algorithm, incorporating the current path cost into heuristic search, was developed by Hart, Nilsson, and Raphael (1968), with some later corrections (Hart *et al.*, 1972). Dechter and Pearl (1985) demonstrated the optimal efficiency of A*.

The original A* paper introduced the consistency condition on heuristic functions. The monotone condition was introduced by Pohl (1977) as a simpler replacement, but Pearl (1984) showed that the two were equivalent.

Pohl (1977) pioneered the study of the relationship between the error in heuristic functions and the time complexity of A*. Basic results were obtained for tree search with unit step

costs and a single goal node (Pohl, 1977; Gaschnig, 1979; Huyn *et al.*, 1980; Pearl, 1984) and with multiple goal nodes (Dinh *et al.*, 2007). The "effective branching factor" was proposed by Nilsson (1971) as an empirical measure of the efficiency; it is equivalent to assuming a time cost of $O((b^*)^d)$. For tree search applied to a graph, Korf *et al.* (2001) argue that the time cost is better modeled as $O(b^{d-k})$, where k depends on the heuristic accuracy; this analysis has elicited some controversy, however. For graph search, Helmert and Röger (2008) noted that several well-known problems contained exponentially many nodes on optimal solution paths, implying exponential time complexity for A* even with constant absolute error in h.

There are many variations on the A* algorithm. Pohl (1973) proposed the use of *dynamic weighting*, which uses a weighted sum $f_w(n) = w_g g(n) + w_h h(n)$ of the current path length and the heuristic function as an evaluation function, rather than the simple sum $f(n) = g(n) + h(n)$ used in A*. The weights w_g and w_h are adjusted dynamically as the search progresses. Pohl's algorithm can be shown to be ϵ-admissible—that is, guaranteed to find solutions within a factor $1 + \epsilon$ of the optimal solution, where ϵ is a parameter supplied to the algorithm. The same property is exhibited by the A^*_ϵ algorithm (Pearl, 1984), which can select any node from the frontier provided its f-cost is within a factor $1 + \epsilon$ of the lowest-f-cost frontier node. The selection can be done so as to minimize search cost.

Bidirectional versions of A* have been investigated; a combination of bidirectional A* and known landmarks was used to efficiently find driving routes for Microsoft's online map service (Goldberg *et al.*, 2006). After caching a set of paths between landmarks, the algorithm can find an optimal path between any pair of points in a 24 million point graph of the United States, searching less than 0.1% of the graph. Others approaches to bidirectional search include a breadth-first search backward from the goal up to a fixed depth, followed by a forward IDA* search (Dillenburg and Nelson, 1994; Manzini, 1995).

A* and other state-space search algorithms are closely related to the *branch-and-bound* techniques that are widely used in operations research (Lawler and Wood, 1966). The relationships between state-space search and branch-and-bound have been investigated in depth (Kumar and Kanal, 1983; Nau *et al.*, 1984; Kumar *et al.*, 1988). Martelli and Montanari (1978) demonstrate a connection between dynamic programming (see Chapter 17) and certain types of state-space search. Kumar and Kanal (1988) attempt a "grand unification" of heuristic search, dynamic programming, and branch-and-bound techniques under the name of CDP—the "composite decision process."

Because computers in the late 1950s and early 1960s had at most a few thousand words of main memory, memory-bounded heuristic search was an early research topic. The Graph Traverser (Doran and Michie, 1966), one of the earliest search programs, commits to an operator after searching best-first up to the memory limit. IDA* (Korf, 1985a, 1985b) was the first widely used optimal, memory-bounded heuristic search algorithm, and a large number of variants have been developed. An analysis of the efficiency of IDA* and of its difficulties with real-valued heuristics appears in Patrick *et al.* (1992).

RBFS (Korf, 1993) is actually somewhat more complicated than the algorithm shown in Figure 3.26, which is closer to an independently developed algorithm called **iterative expansion** (Russell, 1992). RBFS uses a lower bound as well as the upper bound; the two algorithms behave identically with admissible heuristics, but RBFS expands nodes in best-first

ITERATIVE EXPANSION

order even with an inadmissible heuristic. The idea of keeping track of the best alternative path appeared earlier in Bratko's (1986) elegant Prolog implementation of A* and in the DTA* algorithm (Russell and Wefald, 1991). The latter work also discusses metalevel state spaces and metalevel learning.

The MA* algorithm appeared in Chakrabarti *et al.* (1989). SMA*, or Simplified MA*, emerged from an attempt to implement MA* as a comparison algorithm for IE (Russell, 1992). Kaindl and Khorsand (1994) have applied SMA* to produce a bidirectional search algorithm that is substantially faster than previous algorithms. Korf and Zhang (2000) describe a divide-and-conquer approach, and Zhou and Hansen (2002) introduce memory-bounded A* graph search and a strategy for switching to breadth-first search to increase memory-efficiency (Zhou and Hansen, 2006). Korf (1995) surveys memory-bounded search techniques.

The idea that admissible heuristics can be derived by problem relaxation appears in the seminal paper by Held and Karp (1970), who used the minimum-spanning-tree heuristic to solve the TSP. (See Exercise 3.30.)

The automation of the relaxation process was implemented successfully by Prieditis (1993), building on earlier work with Mostow (Mostow and Prieditis, 1989). Holte and Hernadvolgyi (2001) describe more recent steps towards automating the process. The use of pattern databases to derive admissible heuristics is due to Gasser (1995) and Culberson and Schaeffer (1996, 1998); disjoint pattern databases are described by Korf and Felner (2002); a similar method using symbolic patterns is due to Edelkamp (2009). Felner *et al.* (2007) show how to compress pattern databases to save space. The probabilistic interpretation of heuristics was investigated in depth by Pearl (1984) and Hansson and Mayer (1989).

By far the most comprehensive source on heuristics and heuristic search algorithms is Pearl's (1984) *Heuristics* text. This book provides especially good coverage of the wide variety of offshoots and variations of A*, including rigorous proofs of their formal properties. Kanal and Kumar (1988) present an anthology of important articles on heuristic search, and Rayward-Smith *et al.* (1996) cover approaches from Operations Research. Papers about new search algorithms—which, remarkably, continue to be discovered—appear in journals such as *Artificial Intelligence* and *Journal of the ACM*.

PARALLEL SEARCH

The topic of **parallel search** algorithms was not covered in the chapter, partly because it requires a lengthy discussion of parallel computer architectures. Parallel search became a popular topic in the 1990s in both AI and theoretical computer science (Mahanti and Daniels, 1993; Grama and Kumar, 1995; Crauser *et al.*, 1998) and is making a comeback in the era of new multicore and cluster architectures (Ralphs *et al.*, 2004; Korf and Schultze, 2005). Also of increasing importance are search algorithms for very large graphs that require disk storage (Korf, 2008).

EXERCISES

3.1 Explain why problem formulation must follow goal formulation.

3.2 Your goal is to navigate a robot out of a maze. The robot starts in the center of the maze

facing north. You can turn the robot to face north, east, south, or west. You can direct the robot to move forward a certain distance, although it will stop before hitting a wall.

a. Formulate this problem. How large is the state space?

b. In navigating a maze, the only place we need to turn is at the intersection of two or more corridors. Reformulate this problem using this observation. How large is the state space now?

c. From each point in the maze, we can move in any of the four directions until we reach a turning point, and this is the only action we need to do. Reformulate the problem using these actions. Do we need to keep track of the robot's orientation now?

d. In our initial description of the problem we already abstracted from the real world, restricting actions and removing details. List three such simplifications we made.

3.3 Suppose two friends live in different cities on a map, such as the Romania map shown in Figure 3.2. On every turn, we can simultaneously move each friend to a neighboring city on the map. The amount of time needed to move from city i to neighbor j is equal to the road distance $d(i, j)$ between the cities, but on each turn the friend that arrives first must wait until the other one arrives (and calls the first on his/her cell phone) before the next turn can begin. We want the two friends to meet as quickly as possible.

a. Write a detailed formulation for this search problem. (You will find it helpful to define some formal notation here.)

b. Let $D(i, j)$ be the straight-line distance between cities i and j. Which of the following heuristic functions are admissible? (i) $D(i, j)$; (ii) $2 \cdot D(i, j)$; (iii) $D(i, j)/2$.

c. Are there completely connected maps for which no solution exists?

d. Are there maps in which all solutions require one friend to visit the same city twice?

3.4 Show that the 8-puzzle states are divided into two disjoint sets, such that any state is reachable from any other state in the same set, while no state is reachable from any state in the other set. (*Hint:* See Berlekamp *et al.* (1982).) Devise a procedure to decide which set a given state is in, and explain why this is useful for generating random states.

3.5 Consider the n-queens problem using the "efficient" incremental formulation given on page 72. Explain why the state space has at least $\sqrt[3]{n!}$ states and estimate the largest n for which exhaustive exploration is feasible. (*Hint*: Derive a lower bound on the branching factor by considering the maximum number of squares that a queen can attack in any column.)

3.6 Give a complete problem formulation for each of the following. Choose a formulation that is precise enough to be implemented.

a. Using only four colors, you have to color a planar map in such a way that no two adjacent regions have the same color.

b. A 3-foot-tall monkey is in a room where some bananas are suspended from the 8-foot ceiling. He would like to get the bananas. The room contains two stackable, movable, climbable 3-foot-high crates.

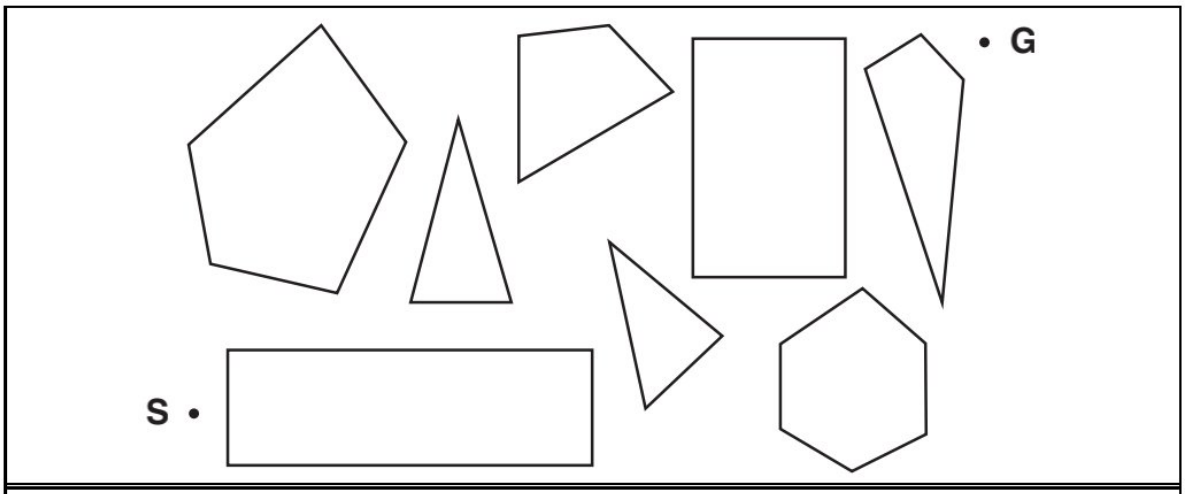
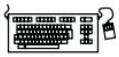


Figure 3.31 A scene with polygonal obstacles. S and G are the start and goal states.

c. You have a program that outputs the message "illegal input record" when fed a certain file of input records. You know that processing of each record is independent of the other records. You want to discover what record is illegal.

d. You have three jugs, measuring 12 gallons, 8 gallons, and 3 gallons, and a water faucet. You can fill the jugs up or empty them out from one to another or onto the ground. You need to measure out exactly one gallon.



3.7 Consider the problem of finding the shortest path between two points on a plane that has convex polygonal obstacles as shown in Figure 3.31. This is an idealization of the problem that a robot has to solve to navigate in a crowded environment.

a. Suppose the state space consists of all positions (x, y) in the plane. How many states are there? How many paths are there to the goal?

b. Explain briefly why the shortest path from one polygon vertex to any other in the scene must consist of straight-line segments joining some of the vertices of the polygons. Define a good state space now. How large is this state space?

c. Define the necessary functions to implement the search problem, including an ACTIONS function that takes a vertex as input and returns a set of vectors, each of which maps the current vertex to one of the vertices that can be reached in a straight line. (Do not forget the neighbors on the same polygon.) Use the straight-line distance for the heuristic function.

d. Apply one or more of the algorithms in this chapter to solve a range of problems in the domain, and comment on their performance.

3.8 On page 68, we said that we would not consider problems with negative path costs. In this exercise, we explore this decision in more depth.

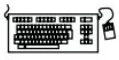
a. Suppose that actions can have arbitrarily large negative costs; explain why this possibility would force any optimal algorithm to explore the entire state space.

b. Does it help if we insist that step costs must be greater than or equal to some negative constant c? Consider both trees and graphs.

c. Suppose that a set of actions forms a loop in the state space such that executing the set in some order results in no net change to the state. If all of these actions have negative cost, what does this imply about the optimal behavior for an agent in such an environment?

d. One can easily imagine actions with high negative cost, even in domains such as route finding. For example, some stretches of road might have such beautiful scenery as to far outweigh the normal costs in terms of time and fuel. Explain, in precise terms, within the context of state-space search, why humans do not drive around scenic loops indefinitely, and explain how to define the state space and actions for route finding so that artificial agents can also avoid looping.

e. Can you think of a real domain in which step costs are such as to cause looping?



3.9 The **missionaries and cannibals** problem is usually stated as follows. Three missionaries and three cannibals are on one side of a river, along with a boat that can hold one or two people. Find a way to get everyone to the other side without ever leaving a group of missionaries in one place outnumbered by the cannibals in that place. This problem is famous in AI because it was the subject of the first paper that approached problem formulation from an analytical viewpoint (Amarel, 1968).

a. Formulate the problem precisely, making only those distinctions necessary to ensure a valid solution. Draw a diagram of the complete state space.

b. Implement and solve the problem optimally using an appropriate search algorithm. Is it a good idea to check for repeated states?

c. Why do you think people have a hard time solving this puzzle, given that the state space is so simple?

3.10 Define in your own words the following terms: state, state space, search tree, search node, goal, action, transition model, and branching factor.

3.11 What's the difference between a world state, a state description, and a search node? Why is this distinction useful?

3.12 An action such as *Go(Sibiu)* really consists of a long sequence of finer-grained actions: turn on the car, release the brake, accelerate forward, etc. Having composite actions of this kind reduces the number of steps in a solution sequence, thereby reducing the search time. Suppose we take this to the logical extreme, by making super-composite actions out of every possible sequence of *Go* actions. Then every problem instance is solved by a single super-composite action, such as *Go(Sibiu)Go(Rimnicu Vilcea)Go(Pitesti)Go(Bucharest)*. Explain how search would work in this formulation. Is this a practical approach for speeding up problem solving?

3.13 Prove that GRAPH-SEARCH satisfies the graph separation property illustrated in Figure 3.9. (*Hint*: Begin by showing that the property holds at the start, then show that if it holds before an iteration of the algorithm, it holds afterwards.) Describe a search algorithm that violates the property.

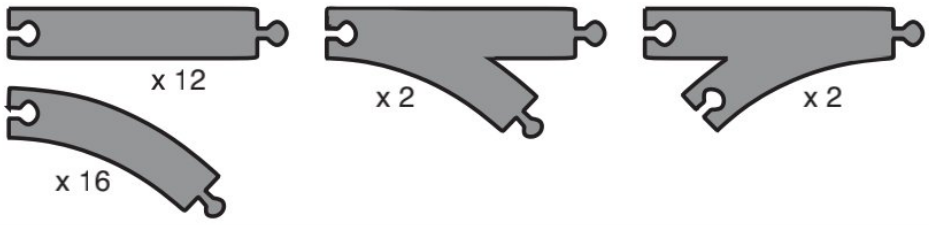


Figure 3.32 The track pieces in a wooden railway set; each is labeled with the number of copies in the set. Note that curved pieces and "fork" pieces ("switches" or "points") can be flipped over so they can curve in either direction. Each curve subtends 45 degrees.

3.14 Which of the following are true and which are false? Explain your answers.

a. Depth-first search always expands at least as many nodes as A* search with an admissible heuristic.

b. $h(n) = 0$ is an admissible heuristic for the 8-puzzle.

c. A* is of no use in robotics because percepts, states, and actions are continuous.

d. Breadth-first search is complete even if zero step costs are allowed.

e. Assume that a rook can move on a chessboard any number of squares in a straight line, vertically or horizontally, but cannot jump over other pieces. Manhattan distance is an admissible heuristic for the problem of moving the rook from square A to square B in the smallest number of moves.

3.15 Consider a state space where the start state is number 1 and each state k has two successors: numbers $2k$ and $2k + 1$.

a. Draw the portion of the state space for states 1 to 15.

b. Suppose the goal state is 11. List the order in which nodes will be visited for breadth-first search, depth-limited search with limit 3, and iterative deepening search.

c. How well would bidirectional search work on this problem? What is the branching factor in each direction of the bidirectional search?

d. Does the answer to (c) suggest a reformulation of the problem that would allow you to solve the problem of getting from state 1 to a given goal state with almost no search?

e. Call the action going from k to $2k$ Left, and the action going to $2k + 1$ Right. Can you find an algorithm that outputs the solution to this problem without any search at all?

3.16 A basic wooden railway set contains the pieces shown in Figure 3.32. The task is to connect these pieces into a railway that has no overlapping tracks and no loose ends where a train could run off onto the floor.

a. Suppose that the pieces fit together *exactly* with no slack. Give a precise formulation of the task as a search problem.

b. Identify a suitable uninformed search algorithm for this task and explain your choice.

c. Explain why removing any one of the "fork" pieces makes the problem unsolvable.

d. Give an upper bound on the total size of the state space defined by your formulation. (*Hint*: think about the maximum branching factor for the construction process and the maximum depth, ignoring the problem of overlapping pieces and loose ends. Begin by pretending that every piece is unique.)

3.17 On page 90, we mentioned **iterative lengthening search**, an iterative analog of uniform cost search. The idea is to use increasing limits on path cost. If a node is generated whose path cost exceeds the current limit, it is immediately discarded. For each new iteration, the limit is set to the lowest path cost of any node discarded in the previous iteration.

a. Show that this algorithm is optimal for general path costs.

b. Consider a uniform tree with branching factor b, solution depth d, and unit step costs. How many iterations will iterative lengthening require?

c. Now consider step costs drawn from the continuous range $[\epsilon, 1]$, where $0 < \epsilon < 1$. How many iterations are required in the worst case?

d. Implement the algorithm and apply it to instances of the 8-puzzle and traveling salesperson problems. Compare the algorithm's performance to that of uniform-cost search, and comment on your results.

3.18 Describe a state space in which iterative deepening search performs much worse than depth-first search (for example, $O(n^2)$ vs. $O(n)$).

3.19 Write a program that will take as input two Web page URLs and find a path of links from one to the other. What is an appropriate search strategy? Is bidirectional search a good idea? Could a search engine be used to implement a predecessor function?

3.20 Consider the vacuum-world problem defined in Figure 2.2.

a. Which of the algorithms defined in this chapter would be appropriate for this problem? Should the algorithm use tree search or graph search?

b. Apply your chosen algorithm to compute an optimal sequence of actions for a 3×3 world whose initial state has dirt in the three top squares and the agent in the center.

c. Construct a search agent for the vacuum world, and evaluate its performance in a set of 3×3 worlds with probability 0.2 of dirt in each square. Include the search cost as well as path cost in the performance measure, using a reasonable exchange rate.

d. Compare your best search agent with a simple randomized reflex agent that sucks if there is dirt and otherwise moves randomly.

e. Consider what would happen if the world were enlarged to $n \times n$. How does the performance of the search agent and of the reflex agent vary with n?

3.21 Prove each of the following statements, or give a counterexample:

a. Breadth-first search is a special case of uniform-cost search.

b. Depth-first search is a special case of best-first tree search.

c. Uniform-cost search is a special case of A* search.

3.22 Compare the performance of A* and RBFS on a set of randomly generated problems in the 8-puzzle (with Manhattan distance) and TSP (with MST—see Exercise 3.30) domains. Discuss your results. What happens to the performance of RBFS when a small random number is added to the heuristic values in the 8-puzzle domain?

3.23 Trace the operation of A* search applied to the problem of getting to Bucharest from Lugoj using the straight-line distance heuristic. That is, show the sequence of nodes that the algorithm will consider and the f, g, and h score for each node.

3.24 Devise a state space in which A* using GRAPH-SEARCH returns a suboptimal solution with an $h(n)$ function that is admissible but inconsistent.

HEURISTIC PATH ALGORITHM

3.25 The **heuristic path algorithm** (Pohl, 1977) is a best-first search in which the evaluation function is $f(n) = (2 - w)g(n) + wh(n)$. For what values of w is this complete? For what values is it optimal, assuming that h is admissible? What kind of search does this perform for $w = 0$, $w = 1$, and $w = 2$?

3.26 Consider the unbounded version of the regular 2D grid shown in Figure 3.9. The start state is at the origin, (0,0), and the goal state is at (x, y).

a. What is the branching factor b in this state space?
b. How many distinct states are there at depth k (for $k > 0$)?
c. What is the maximum number of nodes expanded by breadth-first tree search?
d. What is the maximum number of nodes expanded by breadth-first graph search?
e. Is $h = |u - x| + |v - y|$ an admissible heuristic for a state at (u, v)? Explain.
f. How many nodes are expanded by A* graph search using h?
g. Does h remain admissible if some links are removed?
h. Does h remain admissible if some links are added between nonadjacent states?

3.27 n vehicles occupy squares $(1, 1)$ through $(n, 1)$ (i.e., the bottom row) of an $n \times n$ grid. The vehicles must be moved to the top row but in reverse order; so the vehicle i that starts in $(i, 1)$ must end up in $(n - i + 1, n)$. On each time step, every one of the n vehicles can move one square up, down, left, or right, or stay put; but if a vehicle stays put, one other adjacent vehicle (but not more than one) can hop over it. Two vehicles cannot occupy the same square.

a. Calculate the size of the state space as a function of n.
b. Calculate the branching factor as a function of n.
c. Suppose that vehicle i is at (x_i, y_i); write a nontrivial admissible heuristic h_i for the number of moves it will require to get to its goal location $(n - i + 1, n)$, assuming no other vehicles are on the grid.
d. Which of the following heuristics are admissible for the problem of moving all n vehicles to their destinations? Explain.
(i) $\sum_{i=1}^{n} h_i$.
(ii) $\max\{h_1, \ldots, h_n\}$.
(iii) $\min\{h_1, \ldots, h_n\}$.

3.28 Invent a heuristic function for the 8-puzzle that sometimes overestimates, and show how it can lead to a suboptimal solution on a particular problem. (You can use a computer to help if you want.) Prove that if h never overestimates by more than c, A* using h returns a solution whose cost exceeds that of the optimal solution by no more than c.

3.29 Prove that if a heuristic is consistent, it must be admissible. Construct an admissible heuristic that is not consistent.

3.30 The traveling salesperson problem (TSP) can be solved with the minimum-spanning-tree (MST) heuristic, which estimates the cost of completing a tour, given that a partial tour has already been constructed. The MST cost of a set of cities is the smallest sum of the link costs of any tree that connects all the cities.

a. Show how this heuristic can be derived from a relaxed version of the TSP.

b. Show that the MST heuristic dominates straight-line distance.

c. Write a problem generator for instances of the TSP where cities are represented by random points in the unit square.

d. Find an efficient algorithm in the literature for constructing the MST, and use it with A* graph search to solve instances of the TSP.

3.31 On page 105, we defined the relaxation of the 8-puzzle in which a tile can move from square A to square B if B is blank. The exact solution of this problem defines **Gaschnig's heuristic** (Gaschnig, 1979). Explain why Gaschnig's heuristic is at least as accurate as h_1 (misplaced tiles), and show cases where it is more accurate than both h_1 and h_2 (Manhattan distance). Explain how to calculate Gaschnig's heuristic efficiently.

3.32 We gave two simple heuristics for the 8-puzzle: Manhattan distance and misplaced tiles. Several heuristics in the literature purport to improve on this—see, for example, Nilsson (1971), Mostow and Prieditis (1989), and Hansson *et al.* (1992). Test these claims by implementing the heuristics and comparing the performance of the resulting algorithms.

22 NATURAL LANGUAGE PROCESSING

In which we see how to make use of the copious knowledge that is expressed in natural language.

Homo sapiens is set apart from other species by the capacity for language. Somewhere around 100,000 years ago, humans learned how to speak, and about 7,000 years ago learned to write. Although chimpanzees, dolphins, and other animals have shown vocabularies of hundreds of signs, only humans can reliably communicate an unbounded number of qualitatively different messages on any topic using discrete signs.

Of course, there are other attributes that are uniquely human: no other species wears clothes, creates representational art, or watches three hours of television a day. But when Alan Turing proposed his Test (see Section 1.1.1), he based it on language, not art or TV. There are two main reasons why we want our computer agents to be able to process natural languages: first, to communicate with humans, a topic we take up in Chapter 23, and second, to acquire information from written language, the focus of this chapter.

KNOWLEDGE ACQUISITION

There are over a trillion pages of information on the Web, almost all of it in natural language. An agent that wants to do **knowledge acquisition** needs to understand (at least partially) the ambiguous, messy languages that humans use. We examine the problem from the point of view of specific information-seeking tasks: text classification, information retrieval, and information extraction. One common factor in addressing these tasks is the use of

LANGUAGE MODEL

language models: models that predict the probability distribution of language expressions.

22.1 LANGUAGE MODELS

LANGUAGE

Formal languages, such as the programming languages Java or Python, have precisely defined language models. A **language** can be defined as a set of strings; "`print(2 + 2)`" is a legal program in the language Python, whereas "`2)+(2 print`" is not. Since there are an infinite number of legal programs, they cannot be enumerated; instead they are specified by a

GRAMMAR

set of rules called a **grammar**. Formal languages also have rules that define the meaning or

SEMANTICS

semantics of a program; for example, the rules say that the "meaning" of "`2 + 2`" is 4, and the meaning of "`1/0`" is that an error is signaled.

Natural languages, such as English or Spanish, cannot be characterized as a definitive set of sentences. Everyone agrees that "Not to be invited is sad" is a sentence of English, but people disagree on the grammaticality of "To be not invited is sad." Therefore, it is more fruitful to define a natural language model as a probability distribution over sentences rather than a definitive set. That is, rather than asking if a string of *words* is or is not a member of the set defining the language, we instead ask for $P(S = words)$—what is the probability that a random sentence would be *words*.

AMBIGUITY

Natural languages are also **ambiguous**. "He saw her duck" can mean either that he saw a waterfowl belonging to her, or that he saw her move to evade something. Thus, again, we cannot speak of a single meaning for a sentence, but rather of a probability distribution over possible meanings.

Finally, natural languages are difficult to deal with because they are very large, and constantly changing. Thus, our language models are, at best, an approximation. We start with the simplest possible approximations and move up from there.

22.1.1 *N*-gram character models

CHARACTERS

Ultimately, a written text is composed of **characters**—letters, digits, punctuation, and spaces in English (and more exotic characters in some other languages). Thus, one of the simplest language models is a probability distribution over sequences of characters. As in Chapter 15, we write $P(c_{1:N})$ for the probability of a sequence of N characters, c_1 through c_N. In one Web collection, $P(\text{"the"}) = 0.027$ and $P(\text{"zgq"}) = 0.000000002$. A sequence of written symbols of length n is called an n-gram (from the Greek root for writing or letters), with special case "unigram" for 1-gram, "bigram" for 2-gram, and "trigram" for 3-gram. A model of the probability distribution of n-letter sequences is thus called an n**-gram model**. (But be careful: we can have n-gram models over sequences of words, syllables, or other units; not just over characters.)

N-GRAM MODEL

An n-gram model is defined as a **Markov chain** of order $n-1$. Recall from page 568 that in a Markov chain the probability of character c_i depends only on the immediately preceding characters, not on any other characters. So in a trigram model (Markov chain of order 2) we have

$$P(c_i \mid c_{1:i-1}) = P(c_i \mid c_{i-2:i-1}) \ .$$

We can define the probability of a sequence of characters $P(c_{1:N})$ under the trigram model by first factoring with the chain rule and then using the Markov assumption:

$$P(c_{1:N}) = \prod_{i=1}^{N} P(c_i \mid c_{1:i-1}) = \prod_{i=1}^{N} P(c_i \mid c_{i-2:i-1}) \ .$$

For a trigram character model in a language with 100 characters, $\mathbf{P}(C_i|C_{i-2:i-1})$ has a million entries, and can be accurately estimated by counting character sequences in a body of text of 10 million characters or more. We call a body of text a **corpus** (plural *corpora*), from the Latin word for *body*.

CORPUS

LANGUAGE IDENTIFICATION

What can we do with n-gram character models? One task for which they are well suited is **language identification**: given a text, determine what natural language it is written in. This is a relatively easy task; even with short texts such as "Hello, world" or "Wie geht es dir," it is easy to identify the first as English and the second as German. Computer systems identify languages with greater than 99% accuracy; occasionally, closely related languages, such as Swedish and Norwegian, are confused.

One approach to language identification is to first build a trigram character model of each candidate language, $P(c_i \mid c_{i-2:i-1}, \ell)$, where the variable ℓ ranges over languages. For each ℓ the model is built by counting trigrams in a corpus of that language. (About 100,000 characters of each language are needed.) That gives us a model of $\mathbf{P}(\mathit{Text} \mid \mathit{Language})$, but we want to select the most probable language given the text, so we apply Bayes' rule followed by the Markov assumption to get the most probable language:

$$\begin{aligned}\ell^* &= \operatorname*{argmax}_\ell P(\ell \mid c_{1:N}) \\ &= \operatorname*{argmax}_\ell P(\ell) P(c_{1:N} \mid \ell) \\ &= \operatorname*{argmax}_\ell P(\ell) \prod_{i=1}^{N} P(c_i \mid c_{i-2:i-1}, \ell)\end{aligned}$$

The trigram model can be learned from a corpus, but what about the prior probability $P(\ell)$? We may have some estimate of these values; for example, if we are selecting a random Web page we know that English is the most likely language and that the probability of Macedonian will be less than 1%. The exact number we select for these priors is not critical because the trigram model usually selects one language that is several orders of magnitude more probable than any other.

Other tasks for character models include spelling correction, genre classification, and named-entity recognition. Genre classification means deciding if a text is a news story, a legal document, a scientific article, etc. While many features help make this classification, counts of punctuation and other character n-gram features go a long way (Kessler *et al.*, 1997). Named-entity recognition is the task of finding names of things in a document and deciding what class they belong to. For example, in the text "Mr. Sopersteen was prescribed aciphex," we should recognize that "Mr. Sopersteen" is the name of a person and "aciphex" is the name of a drug. Character-level models are good for this task because they can associate the character sequence "ex␣" ("ex" followed by a space) with a drug name and "steen␣" with a person name, and thereby identify words that they have never seen before.

22.1.2 Smoothing *n*-gram models

The major complication of n-gram models is that the training corpus provides only an estimate of the true probability distribution. For common character sequences such as "␣th" any English corpus will give a good estimate: about 1.5% of all trigrams. On the other hand, "␣ht" is very uncommon—no dictionary words start with ht. It is likely that the sequence would have a count of zero in a training corpus of standard English. Does that mean we should assign $P(\text{"␣th"}) = 0$? If we did, then the text "The program issues an http request" would have

an English probability of zero, which seems wrong. We have a problem in generalization: we want our language models to generalize well to texts they haven't seen yet. Just because we have never seen "␣http" before does not mean that our model should claim that it is impossible. Thus, we will adjust our language model so that sequences that have a count of zero in the training corpus will be assigned a small nonzero probability (and the other counts will be adjusted downward slightly so that the probability still sums to 1). The process od adjusting the probability of low-frequency counts is called **smoothing**.

SMOOTHING

The simplest type of smoothing was suggested by Pierre-Simon Laplace in the 18th century: he said that, in the lack of further information, if a random Boolean variable X has been false in all n observations so far then the estimate for $P(X = true)$ should be $1/(n+2)$. That is, he assumes that with two more trials, one might be true and one false. Laplace smoothing (also called add-one smoothing) is a step in the right direction, but performs relatively poorly.

BACKOFF MODEL

A better approach is a **backoff model**, in which we start by estimating n-gram counts, but for any particular sequence that has a low (or zero) count, we back off to $(n-1)$-grams. **Linear interpolation smoothing** is a backoff model that combines trigram, bigram, and unigram models by linear interpolation. It defines the probability estimate as

LINEAR INTERPOLATION SMOOTHING

$$\widehat{P}(c_i|c_{i-2:i-1}) = \lambda_3 P(c_i|c_{i-2:i-1}) + \lambda_2 P(c_i|c_{i-1}) + \lambda_1 P(c_i) \ ,$$

where $\lambda_3 + \lambda_2 + \lambda_1 = 1$. The parameter values λ_i can be fixed, or they can be trained with an expectation–maximization algorithm. It is also possible to have the values of λ_i depend on the counts: if we have a high count of trigrams, then we weigh them relatively more; if only a low count, then we put more weight on the bigram and unigram models. One camp of researchers has developed ever more sophisticated smoothing models, while the other camp suggests gathering a larger corpus so that even simple smoothing models work well. Both are getting at the same goal: reducing the variance in the language model.

One complication: note that the expression $P(c_i \mid c_{i-2:i-1})$ asks for $P(c_1 \mid c_{-1:0})$ when $i = 1$, but there are no characters before c_1. We can introduce artificial characters, for example, defining c_0 to be a space character or a special "begin text" character. Or we can fall back on lower-order Markov models, in effect defining $c_{-1:0}$ to be the empty sequence and thus $P(c_1 \mid c_{-1:0}) = P(c_1)$.

22.1.3 Model evaluation

With so many possible n-gram models—unigram, bigram, trigram, interpolated smoothing with different values of λ, etc.—how do we know what model to choose? We can evaluate a model with cross-validation. Split the corpus into a training corpus and a validation corpus. Determine the parameters of the model from the training data. Then evaluate the model on the validation corpus.

The evaluation can be a task-specific metric, such as measuring accuracy on language identification. Alternatively we can have a task-independent model of language quality: calculate the probability assigned to the validation corpus by the model; the higher the probability the better. This metric is inconvenient because the probability of a large corpus will be a very small number, and floating-point underflow becomes an issue. A different way of describing the probability of a sequence is with a measure called **perplexity**, defined as

PERPLEXITY

$$Perplexity(c_{1:N}) = P(c_{1:N})^{-\frac{1}{N}} .$$

Perplexity can be thought of as the reciprocal of probability, normalized by sequence length. It can also be thought of as the weighted average branching factor of a model. Suppose there are 100 characters in our language, and our model says they are all equally likely. Then for a sequence of any length, the perplexity will be 100. If some characters are more likely than others, and the model reflects that, then the model will have a perplexity less than 100.

22.1.4 *N*-gram word models

VOCABULARY

Now we turn to n-gram models over words rather than characters. All the same mechanism applies equally to word and character models. The main difference is that the **vocabulary**—the set of symbols that make up the corpus and the model—is larger. There are only about 100 characters in most languages, and sometimes we build character models that are even more restrictive, for example by treating "A" and "a" as the same symbol or by treating all punctuation as the same symbol. But with word models we have at least tens of thousands of symbols, and sometimes millions. The wide range is because it is not clear what constitutes a word. In English a sequence of letters surrounded by spaces is a word, but in some languages, like Chinese, words are not separated by spaces, and even in English many decisions must be made to have a clear policy on word boundaries: how many words are in "ne'er-do-well"? Or in "(Tel:1-800-960-5660x123)"?

OUT OF VOCABULARY

Word n-gram models need to deal with **out of vocabulary** words. With character models, we didn't have to worry about someone inventing a new letter of the alphabet.[1] But with word models there is always the chance of a new word that was not seen in the training corpus, so we need to model that explicitly in our language model. This can be done by adding just one new word to the vocabulary: `<UNK>`, standing for the unknown word. We can estimate n-gram counts for `<UNK>` by this trick: go through the training corpus, and the first time any individual word appears it is previously unknown, so replace it with the symbol `<UNK>`. All subsequent appearances of the word remain unchanged. Then compute n-gram counts for the corpus as usual, treating `<UNK>` just like any other word. Then when an unknown word appears in a test set, we look up its probability under `<UNK>`. Sometimes multiple unknown-word symbols are used, for different classes. For example, any string of digits might be replaced with `<NUM>`, or any email address with `<EMAIL>`.

To get a feeling for what word models can do, we built unigram, bigram, and trigram models over the words in this book and then randomly sampled sequences of words from the models. The results are

Unigram: logical are as are confusion a may right tries agent goal the was . . .
Bigram: systems are very similar computational approach would be represented . . .
Trigram: planning and scheduling are integrated the success of naive bayes model is . . .

Even with this small sample, it should be clear that the unigram model is a poor approximation of either English or the content of an AI textbook, and that the bigram and trigram models are

[1] With the possible exception of the groundbreaking work of T. Geisel (1955).

much better. The models agree with this assessment: the perplexity was 891 for the unigram model, 142 for the bigram model and 91 for the trigram model.

With the basics of n-gram models—both character- and word-based—established, we can turn now to some language tasks.

22.2 TEXT CLASSIFICATION

TEXT CLASSIFICATION

We now consider in depth the task of **text classification**, also known as **categorization**: given a text of some kind, decide which of a predefined set of classes it belongs to. Language identification and genre classification are examples of text classification, as is sentiment analysis

SPAM DETECTION

(classifying a movie or product review as positive or negative) and **spam detection** (classifying an email message as spam or not-spam). Since "not-spam" is awkward, researchers have coined the term **ham** for not-spam. We can treat spam detection as a problem in supervised learning. A training set is readily available: the positive (spam) examples are in my spam folder, the negative (ham) examples are in my inbox. Here is an excerpt:

> Spam: Wholesale Fashion Watches -57% today. Designer watches for cheap ...
> Spam: You can buy ViagraFr$1.85 All Medications at unbeatable prices! ...
> Spam: WE CAN TREAT ANYTHING YOU SUFFER FROM JUST TRUST US ...
> Spam: Sta.rt earn*ing the salary yo,u d-eserve by o'btaining the prope,r crede'ntials!
>
> Ham: The practical significance of hypertree width in identifying more ...
> Ham: Abstract: We will motivate the problem of social identity clustering: ...
> Ham: Good to see you my friend. Hey Peter, It was good to hear from you. ...
> Ham: PDS implies convexity of the resulting optimization problem (Kernel Ridge ...

From this excerpt we can start to get an idea of what might be good features to include in the supervised learning model. Word n-grams such as "for cheap" and "You can buy" seem to be indicators of spam (although they would have a nonzero probability in ham as well). Character-level features also seem important: spam is more likely to be all uppercase and to have punctuation embedded in words. Apparently the spammers thought that the word bigram "you deserve" would be too indicative of spam, and thus wrote "yo,u d-eserve" instead. A character model should detect this. We could either create a full character n-gram model of spam and ham, or we could handcraft features such as "number of punctuation marks embedded in words."

Note that we have two complementary ways of talking about classification. In the language-modeling approach, we define one n-gram language model for $\mathbf{P}(Message \mid spam)$ by training on the spam folder, and one model for $\mathbf{P}(Message \mid ham)$ by training on the inbox. Then we can classify a new message with an application of Bayes' rule:

$$\underset{c \in \{spam, ham\}}{\operatorname{argmax}} P(c \mid message) = \underset{c \in \{spam, ham\}}{\operatorname{argmax}} P(message \mid c)\, P(c)\ .$$

where $P(c)$ is estimated just by counting the total number of spam and ham messages. This approach works well for spam detection, just as it did for language identification.

In the machine-learning approach we represent the message as a set of feature/value pairs and apply a classification algorithm h to the feature vector $\mathbf{X}$. We can make the language-modeling and machine-learning approaches compatible by thinking of the n-grams as features. This is easiest to see with a unigram model. The features are the words in the vocabulary: "a," "aardvark," . . ., and the values are the number of times each word appears in the message. That makes the feature vector large and sparse. If there are 100,000 words in the language model, then the feature vector has length 100,000, but for a short email message almost all the features will have count zero. This unigram representation has been called the

BAG OF WORDS

bag of words model. You can think of the model as putting the words of the training corpus in a bag and then selecting words one at a time. The notion of order of the words is lost; a unigram model gives the same probability to any permutation of a text. Higher-order n-gram models maintain some local notion of word order.

With bigrams and trigrams the number of features is squared or cubed, and we can add in other, non-n-gram features: the time the message was sent, whether a URL or an image is part of the message, an ID number for the sender of the message, the sender's number of previous spam and ham messages, and so on. The choice of features is the most important part of creating a good spam detector—more important than the choice of algorithm for processing the features. In part this is because there is a lot of training data, so if we can propose a feature, the data can accurately determine if it is good or not. It is necessary to constantly update features, because spam detection is an **adversarial task**; the spammers modify their spam in response to the spam detector's changes.

It can be expensive to run algorithms on a very large feature vector, so often a process

FEATURE SELECTION

of **feature selection** is used to keep only the features that best discriminate between spam and ham. For example, the bigram "of the" is frequent in English, and may be equally frequent in spam and ham, so there is no sense in counting it. Often the top hundred or so features do a good job of discriminating between classes.

Once we have chosen a set of features, we can apply any of the supervised learning techniques we have seen; popular ones for text categorization include k-nearest-neighbors, support vector machines, decision trees, naive Bayes, and logistic regression. All of these have been applied to spam detection, usually with accuracy in the 98%–99% range. With a carefully designed feature set, accuracy can exceed 99.9%.

22.2.1 Classification by data compression

DATA COMPRESSION

Another way to think about classification is as a problem in **data compression**. A lossless compression algorithm takes a sequence of symbols, detects repeated patterns in it, and writes a description of the sequence that is more compact than the original. For example, the text "0.142857142857142857" might be compressed to "0.[142857]*3." Compression algorithms work by building dictionaries of subsequences of the text, and then referring to entries in the dictionary. The example here had only one dictionary entry, "142857."

In effect, compression algorithms are creating a language model. The LZW algorithm in particular directly models a maximum-entropy probability distribution. To do classification by compression, we first lump together all the spam training messages and compress them as

a unit. We do the same for the ham. Then when given a new message to classify, we append it to the spam messages and compress the result. We also append it to the ham and compress that. Whichever class compresses better—adds the fewer number of additional bytes for the new message—is the predicted class. The idea is that a spam message will tend to share dictionary entries with other spam messages and thus will compress better when appended to a collection that already contains the spam dictionary.

Experiments with compression-based classification on some of the standard corpora for text classification—the 20-Newsgroups data set, the Reuters-10 Corpora, the Industry Sector corpora—indicate that whereas running off-the-shelf compression algorithms like gzip, RAR, and LZW can be quite slow, their accuracy is comparable to traditional classification algorithms. This is interesting in its own right, and also serves to point out that there is promise for algorithms that use character n-grams directly with no preprocessing of the text or feature selection: they seem to be captiring some real patterns.

22.3 INFORMATION RETRIEVAL

INFORMATION RETRIEVAL

Information retrieval is the task of finding documents that are relevant to a user's need for information. The best-known examples of information retrieval systems are search engines on the World Wide Web. A Web user can type a query such as [AI book][2] into a search engine and see a list of relevant pages. In this section, we will see how such systems are built. An information retrieval (henceforth **IR**) system can be characterized by

IR

1. **A corpus of documents.** Each system must decide what it wants to treat as a document: a paragraph, a page, or a multipage text.
2. **Queries posed in a query language**. A query specifies what the user wants to know. The query language can be just a list of words, such as [AI book]; or it can specify a phrase of words that must be adjacent, as in ["AI book"]; it can contain Boolean operators as in [AI AND book]; it can include non-Boolean operators such as [AI NEAR book] or [AI book site:www.aaai.org].
3. **A result set.** This is the subset of documents that the IR system judges to be **relevant** to the query. By *relevant*, we mean likely to be of use to the person who posed the query, for the particular information need expressed in the query.
4. **A presentation of the result set.** This can be as simple as a ranked list of document titles or as complex as a rotating color map of the result set projected onto a three-dimensional space, rendered as a two-dimensional display.

QUERY LANGUAGE

RESULT SET

RELEVANT

PRESENTATION

BOOLEAN KEYWORD MODEL

The earliest IR systems worked on a **Boolean keyword model**. Each word in the document collection is treated as a Boolean feature that is true of a document if the word occurs in the document and false if it does not. So the feature "retrieval" is true for the current chapter but false for Chapter 15. The query language is the language of Boolean expressions over

[2] We denote a search query as [*query*]. Square brackets are used rather than quotation marks so that we can distinguish the query ["two words"] from [two words].

features. A document is relevant only if the expression evaluates to true. For example, the query [information AND retrieval] is true for the current chapter and false for Chapter 15.

This model has the advantage of being simple to explain and implement. However, it has some disadvantages. First, the degree of relevance of a document is a single bit, so there is no guidance as to how to order the relevant documents for presentation. Second, Boolean expressions are unfamiliar to users who are not programmers or logicians. Users find it unintuitive that when they want to know about farming in the states of Kansas *and* Nebraska they need to issue the query [farming (Kansas OR Nebraska)]. Third, it can be hard to formulate an appropriate query, even for a skilled user. Suppose we try [information AND retrieval AND models AND optimization] and get an empty result set. We could try [information OR retrieval OR models OR optimization], but if that returns too many results, it is difficult to know what to try next.

22.3.1 IR scoring functions

BM25 SCORING FUNCTION

Most IR systems have abandoned the Boolean model and use models based on the statistics of word counts. We describe the **BM25 scoring function**, which comes from the Okapi project of Stephen Robertson and Karen Sparck Jones at London's City College, and has been used in search engines such as the open-source Lucene project.

A scoring function takes a document and a query and returns a numeric score; the most relevant documents have the highest scores. In the BM25 function, the score is a linear weighted combination of scores for each of the words that make up the query. Three factors affect the weight of a query term: First, the frequency with which a query term appears in a document (also known as TF for term frequency). For the query [farming in Kansas], documents that mention "farming" frequently will have higher scores. Second, the inverse document frequency of the term, or IDF. The word "in" appears in almost every document, so it has a high document frequency, and thus a low inverse document frequency, and thus it is not as important to the query as "farming" or "Kansas." Third, the length of the document. A million-word document will probably mention all the query words, but may not actually be about the query. A short document that mentions all the words is a much better candidate.

The BM25 function takes all three of these into account. We assume we have created an index of the N documents in the corpus so that we can look up $TF(q_i, d_j)$, the count of the number of times word q_i appears in document d_j. We also assume a table of document frequency counts, $DF(q_i)$, that gives the number of documents that contain the word q_i. Then, given a document d_j and a query consisting of the words $q_{1:N}$, we have

$$BM25(d_j, q_{1:N}) = \sum_{i=1}^{N} IDF(q_i) \cdot \frac{TF(q_i, d_j) \cdot (k+1)}{TF(q_i, d_j) + k \cdot (1 - b + b \cdot \frac{|d_j|}{L})} ,$$

where $|d_j|$ is the length of document d_j in words, and L is the average document length in the corpus: $L = \sum_i |d_i|/N$. We have two parameters, k and b, that can be tuned by cross-validation; typical values are $k = 2.0$ and $b = 0.75$. $IDF(q_i)$ is the inverse document

frequency of word q_i, given by

$$IDF(q_i) = \log \frac{N - DF(q_i) + 0.5}{DF(q_i) + 0.5} .$$

Of course, it would be impractical to apply the BM25 scoring function to every document in the corpus. Instead, systems create an **index** ahead of time that lists, for each vocabulary word, the documents that contain the word. This is called the **hit list** for the word. Then when given a query, we intersect the hit lists of the query words and only score the documents in the intersection.

INDEX

HIT LIST

22.3.2 IR system evaluation

How do we know whether an IR system is performing well? We undertake an experiment in which the system is given a set of queries and the result sets are scored with respect to human relevance judgments. Traditionally, there have been two measures used in the scoring: recall and precision. We explain them with the help of an example. Imagine that an IR system has returned a result set for a single query, for which we know which documents are and are not relevant, out of a corpus of 100 documents. The document counts in each category are given in the following table:

	In result set	Not in result set
Relevant	30	20
Not relevant	10	40

PRECISION

Precision measures the proportion of documents in the result set that are actually relevant. In our example, the precision is $30/(30 + 10) = .75$. The false positive rate is $1 - .75 = .25$.

RECALL

Recall measures the proportion of all the relevant documents in the collection that are in the result set. In our example, recall is $30/(30 + 20) = .60$. The false negative rate is $1 - .60 = .40$. In a very large document collection, such as the World Wide Web, recall is difficult to compute, because there is no easy way to examine every page on the Web for relevance. All we can do is either estimate recall by sampling or ignore recall completely and just judge precision. In the case of a Web search engine, there may be thousands of documents in the result set, so it makes more sense to measure precision for several different sizes, such as "P@10" (precision in the top 10 results) or "P@50," rather than to estimate precision in the entire result set.

It is possible to trade off precision against recall by varying the size of the result set returned. In the extreme, a system that returns every document in the document collection is guaranteed a recall of 100%, but will have low precision. Alternately, a system could return a single document and have low recall, but a decent chance at 100% precision. A summary of both measures is the F_1 score, a single number that is the harmonic mean of precision and recall, $2PR/(P + R)$.

22.3.3 IR refinements

There are many possible refinements to the system described here, and indeed Web search engines are continually updating their algorithms as they discover new approaches and as the Web grows and changes.

One common refinement is a better model of the effect of document length on relevance. Singhal *et al.* (1996) observed that simple document length normalization schemes tend to favor short documents too much and long documents not enough. They propose a *pivoted* document length normalization scheme; the idea is that the pivot is the document length at which the old-style normalization is correct; documents shorter than that get a boost and longer ones get a penalty.

The BM25 scoring function uses a word model that treats all words as completely independent, but we know that some words are correlated: "couch" is closely related to both "couches" and "sofa." Many IR systems attempt to account for these correlations.

For example, if the query is [couch], it would be a shame to exclude from the result set those documents that mention "COUCH" or "couches" but not "couch." Most IR systems do **case folding** of "COUCH" to "couch," and some use a **stemming** algorithm to reduce "couches" to the stem form "couch," both in the query and the documents. This typically yields a small increase in recall (on the order of 2% for English). However, it can harm precision. For example, stemming "stocking" to "stock" will tend to decrease precision for queries about either foot coverings or financial instruments, although it could improve recall for queries about warehousing. Stemming algorithms based on rules (e.g., remove "-ing") cannot avoid this problem, but algorithms based on dictionaries (don't remove "-ing" if the word is already listed in the dictionary) can. While stemming has a small effect in English, it is more important in other languages. In German, for example, it is not uncommon to see words like "Lebensversicherungsgesellschaftsangestellter" (life insurance company employee). Languages such as Finnish, Turkish, Inuit, and Yupik have recursive morphological rules that in principle generate words of unbounded length.

CASE FOLDING

STEMMING

SYNONYM

The next step is to recognize **synonyms**, such as "sofa" for "couch." As with stemming, this has the potential for small gains in recall, but can hurt precision. A user who gives the query [Tim Couch] wants to see results about the football player, not sofas. The problem is that "languages abhor absolute synonyms just as nature abhors a vacuum" (Cruse, 1986). That is, anytime there are two words that mean the same thing, speakers of the language conspire to evolve the meanings to remove the confusion. Related words that are not synonyms also play an important role in ranking—terms like "leather", "wooden," or "modern" can serve to confirm that the document really is about "couch." Synonyms and related words can be found in dictionaries or by looking for correlations in documents or in queries—if we find that many users who ask the query [new sofa] follow it up with the query [new couch], we can in the future alter [new sofa] to be [new sofa OR new couch].

METADATA

LINKS

As a final refinement, IR can be improved by considering **metadata**—data outside of the text of the document. Examples include human-supplied keywords and publication data. On the Web, hypertext **links** between documents are a crucial source of information.

22.3.4 The PageRank algorithm

PAGERANK

PageRank[3] was one of the two original ideas that set Google's search apart from other Web search engines when it was introduced in 1997. (The other innovation was the use of anchor

[3] The name stands both for Web pages and for coinventor Larry Page (Brin and Page, 1998).

```
function HITS(query) returns pages with hub and authority numbers
  pages ← EXPAND-PAGES(RELEVANT-PAGES(query))
  for each p in pages do
    p.AUTHORITY ← 1
    p.HUB ← 1
  repeat until convergence do
    for each p in pages do
      p.AUTHORITY ← Σ_i INLINK_i(p).HUB
      p.HUB ← Σ_i OUTLINK_i(p).AUTHORITY
    NORMALIZE(pages)
  return pages
```

Figure 22.1 The HITS algorithm for computing hubs and authorities with respect to a query. RELEVANT-PAGES fetches the pages that match the query, and EXPAND-PAGES adds in every page that links to or is linked from one of the relevant pages. NORMALIZE divides each page's score by the sum of the squares of all pages' scores (separately for both the authority and hubs scores).

text—the underlined text in a hyperlink—to index a page, even though the anchor text was on a *different* page than the one being indexed.) PageRank was invented to solve the problem of the tyranny of TF scores: if the query is [IBM], how do we make sure that IBM's home page, `ibm.com`, is the first result, even if another page mentions the term "IBM" more frequently? The idea is that `ibm.com` has many in-links (links to the page), so it should be ranked higher: each in-link is a vote for the quality of the linked-to page. But if we only counted in-links, then it would be possible for a Web spammer to create a network of pages and have them all point to a page of his choosing, increasing the score of that page. Therefore, the PageRank algorithm is designed to weight links from high-quality sites more heavily. What is a high-quality site? One that is linked to by other high-quality sites. The definition is recursive, but we will see that the recursion bottoms out properly. The PageRank for a page p is defined as:

$$PR(p) = \frac{1-d}{N} + d\sum_i \frac{PR(in_i)}{C(in_i)} ,$$

where $PR(p)$ is the PageRank of page p, N is the total number of pages in the corpus, in_i are the pages that link in to p, and $C(in_i)$ is the count of the total number of out-links on page in_i. The constant d is a damping factor. It can be understood through the **random surfer model**: imagine a Web surfer who starts at some random page and begins exploring. With probability d (we'll assume $d = 0.85$) the surfer clicks on one of the links on the page (choosing uniformly among them), and with probability $1 - d$ she gets bored with the page and restarts on a random page anywhere on the Web. The PageRank of page p is then the probability that the random surfer will be at page p at any point in time. PageRank can be computed by an iterative procedure: start with all pages having $PR(p) = 1$, and iterate the algorithm, updating ranks until they converge.

RANDOM SURFER MODEL

22.3.5 The HITS algorithm

The Hyperlink-Induced Topic Search algorithm, also known as "Hubs and Authorities" or HITS, is another influential link-analysis algorithm (see Figure 22.1). HITS differs from PageRank in several ways. First, it is a query-dependent measure: it rates pages with respect to a query. That means that it must be computed anew for each query—a computational burden that most search engines have elected not to take on. Given a query, HITS first finds a set of pages that are relevant to the query. It does that by intersecting hit lists of query words, and then adding pages in the link neighborhood of these pages—pages that link to or are linked from one of the pages in the original relevant set.

AUTHORITY

HUB

Each page in this set is considered an **authority** on the query to the degree that other pages in the relevant set point to it. A page is considered a **hub** to the degree that it points to other authoritative pages in the relevant set. Just as with PageRank, we don't want to merely count the number of links; we want to give more value to the high-quality hubs and authorities. Thus, as with PageRank, we iterate a process that updates the authority score of a page to be the sum of the hub scores of the pages that point to it, and the hub score to be the sum of the authority scores of the pages it points to. If we then normalize the scores and repeat k times, the process will converge.

Both PageRank and HITS played important roles in developing our understanding of Web information retrieval. These algorithms and their extensions are used in ranking billions of queries daily as search engines steadily develop better ways of extracting yet finer signals of search relevance.

22.3.6 Question answering

QUESTION ANSWERING

Information retrieval is the task of finding documents that are relevant to a query, where the query may be a question, or just a topic area or concept. **Question answering** is a somewhat different task, in which the query really is a question, and the answer is not a ranked list of documents but rather a short response—a sentence, or even just a phrase. There have been question-answering NLP (natural language processing) systems since the 1960s, but only since 2001 have such systems used Web information retrieval to radically increase their breadth of coverage.

The ASKMSR system (Banko *et al.*, 2002) is a typical Web-based question-answering system. It is based on the intuition that most questions will be answered many times on the Web, so question answering should be thought of as a problem in precision, not recall. We don't have to deal with all the different ways that an answer might be phrased—we only have to find one of them. For example, consider the query [Who killed Abraham Lincoln?] Suppose a system had to answer that question with access only to a single encyclopedia, whose entry on Lincoln said

> John Wilkes Booth altered history with a bullet. He will forever be known as the man who ended Abraham Lincoln's life.

To use this passage to answer the question, the system would have to know that ending a life can be a killing, that "He" refers to Booth, and several other linguistic and semantic facts.

ASKMSR does not attempt this kind of sophistication—it knows nothing about pronoun reference, or about killing, or any other verb. It does know 15 different kinds of questions, and how they can be rewritten as queries to a search engine. It knows that [Who killed Abraham Lincoln] can be rewritten as the query [* killed Abraham Lincoln] and as [Abraham Lincoln was killed by *]. It issues these rewritten queries and examines the results that come back—not the full Web pages, just the short summaries of text that appear near the query terms. The results are broken into 1-, 2-, and 3-grams and tallied for frequency in the result sets and for weight: an n-gram that came back from a very specific query rewrite (such as the exact phrase match query ["Abraham Lincoln was killed by *"]) would get more weight than one from a general query rewrite, such as [Abraham OR Lincoln OR killed]. We would expect that "John Wilkes Booth" would be among the highly ranked n-grams retrieved, but so would "Abraham Lincoln" and "the assassination of" and "Ford's Theatre."

Once the n-grams are scored, they are filtered by expected type. If the original query starts with "who," then we filter on names of people; for "how many" we filter on numbers, for "when," on a date or time. There is also a filter that says the answer should not be part of the question; together these should allow us to return "John Wilkes Booth" (and not "Abraham Lincoln") as the highest-scoring response.

In some cases the answer will be longer than three words; since the components responses only go up to 3-grams, a longer response would have to be pieced together from shorter pieces. For example, in a system that used only bigrams, the answer "John Wilkes Booth" could be pieced together from high-scoring pieces "John Wilkes" and "Wilkes Booth."

At the Text Retrieval Evaluation Conference (TREC), ASKMSR was rated as one of the top systems, beating out competitors with the ability to do far more complex language understanding. ASKMSR relies upon the breadth of the content on the Web rather than on its own depth of understanding. It won't be able to handle complex inference patterns like associating "who killed" with "ended the life of." But it knows that the Web is so vast that it can afford to ignore passages like that and wait for a simple passage it can handle.

22.4 INFORMATION EXTRACTION

INFORMATION EXTRACTION

Information extraction is the process of acquiring knowledge by skimming a text and looking for occurrences of a particular class of object and for relationships among objects. A typical task is to extract instances of addresses from Web pages, with database fields for street, city, state, and zip code; or instances of storms from weather reports, with fields for temperature, wind speed, and precipitation. In a limited domain, this can be done with high accuracy. As the domain gets more general, more complex linguistic models and more complex learning techniques are necessary. We will see in Chapter 23 how to define complex language models of the phrase structure (noun phrases and verb phrases) of English. But so far there are no complete models of this kind, so for the limited needs of information extraction, we define limited models that approximate the full English model, and concentrate on just the parts that are needed for the task at hand. The models we describe in this sec-

tion are approximations in the same way that the simple 1-CNF logical model in Figure 7.21 (page 271) is an approximations of the full, wiggly, logical model.

In this section we describe six different approaches to information extraction, in order of increasing complexity on several dimensions: deterministic to stochastic, domain-specific to general, hand-crafted to learned, and small-scale to large-scale.

22.4.1 Finite-state automata for information extraction

ATTRIBUTE-BASED EXTRACTION

The simplest type of information extraction system is an **attribute-based extraction** system that assumes that the entire text refers to a single object and the task is to extract attributes of that object. For example, we mentioned in Section 12.7 the problem of extracting from the text "IBM ThinkBook 970. Our price: $399.00" the set of attributes {Manufacturer=IBM, Model=ThinkBook970, Price=$399.00}. We can address this problem by defining a **template** (also known as a pattern) for each attribute we would like to extract. The template is defined by a finite state automaton, the simplest example of which is the **regular expression**, or regex. Regular expressions are used in Unix commands such as grep, in programming languages such as Perl, and in word processors such as Microsoft Word. The details vary slightly from one tool to another and so are best learned from the appropriate manual, but here we show how to build up a regular expression template for prices in dollars:

TEMPLATE

REGULAR EXPRESSION

`[0-9]`	matches any digit from 0 to 9
`[0-9]+`	matches one or more digits
`[.][0-9][0-9]`	matches a period followed by two digits
`([.][0-9][0-9])?`	matches a period followed by two digits, or nothing
`[$][0-9]+([.][0-9][0-9])?`	matches $249.99 or $1.23 or $1000000 or ...

Templates are often defined with three parts: a prefix regex, a target regex, and a postfix regex. For prices, the target regex is as above, the prefix would look for strings such as "price:" and the postfix could be empty. The idea is that some clues about an attribute come from the attribute value itself and some come from the surrounding text.

If a regular expression for an attribute matches the text exactly once, then we can pull out the portion of the text that is the value of the attribute. If there is no match, all we can do is give a default value or leave the attribute missing; but if there are several matches, we need a process to choose among them. One strategy is to have several templates for each attribute, ordered by priority. So, for example, the top-priority template for price might look for the prefix "our price:"; if that is not found, we look for the prefix "price:" and if that is not found, the empty prefix. Another strategy is to take all the matches and find some way to choose among them. For example, we could take the lowest price that is within 50% of the highest price. That will select $78.00 as the target from the text "List price $99.00, special sale price $78.00, shipping $3.00."

RELATIONAL EXTRACTION

One step up from attribute-based extraction systems are **relational extraction** systems, which deal with multiple objects and the relations among them. Thus, when these systems see the text "$249.99," they need to determine not just that it is a price, but also which object has that price. A typical relational-based extraction system is FASTUS, which handles news stories about corporate mergers and acquisitions. It can read the story

> Bridgestone Sports Co. said Friday it has set up a joint venture in Taiwan with a local concern and a Japanese trading house to produce golf clubs to be shipped to Japan.

and extract the relations:

$$e \in JointVentures \wedge Product(e, \text{“}golf\ clubs\text{”}) \wedge Date(e, \text{“}Friday\text{”}) \\ \wedge Member(e, \text{“}Bridgestone\ Sports\ Co\text{”}) \wedge Member(e, \text{“}a\ local\ concern\text{”}) \\ \wedge Member(e, \text{“}a\ Japanese\ trading\ house\text{”}) \ .$$

CASCADED FINITE-STATE TRANSDUCERS

A relational extraction system can be built as a series of **cascaded finite-state transducers**. That is, the system consists of a series of small, efficient finite-state automata (FSAs), where each automaton receives text as input, transduces the text into a different format, and passes it along to the next automaton. FASTUS consists of five stages:

1. Tokenization
2. Complex-word handling
3. Basic-group handling
4. Complex-phrase handling
5. Structure merging

FASTUS's first stage is **tokenization**, which segments the stream of characters into tokens (words, numbers, and punctuation). For English, tokenization can be fairly simple; just separating characters at white space or punctuation does a fairly good job. Some tokenizers also deal with markup languages such as HTML, SGML, and XML.

The second stage handles **complex words**, including collocations such as "set up" and "joint venture," as well as proper names such as "Bridgestone Sports Co." These are recognized by a combination of lexical entries and finite-state grammar rules. For example, a company name might be recognized by the rule

> CapitalizedWord+ ("Company" | "Co" | "Inc" | "Ltd")

The third stage handles **basic groups**, meaning noun groups and verb groups. The idea is to chunk these into units that will be managed by the later stages. We will see how to write a complex description of noun and verb phrases in Chapter 23, but here we have simple rules that only approximate the complexity of English, but have the advantage of being representable by finite state automata. The example sentence would emerge from this stage as the following sequence of tagged groups:

```
1 NG: Bridgestone Sports Co.      10 NG: a local concern
2 VG: said                        11 CJ: and
3 NG: Friday                      12 NG: a Japanese trading house
4 NG: it                          13 VG: to produce
5 VG: had set up                  14 NG: golf clubs
6 NG: a joint venture             15 VG: to be shipped
7 PR: in                          16 PR: to
8 NG: Taiwan                      17 NG: Japan
9 PR: with
```

Here NG means noun group, VG is verb group, PR is preposition, and CJ is conjunction.

The fourth stage combines the basic groups into **complex phrases**. Again, the aim is to have rules that are finite-state and thus can be processed quickly, and that result in unambiguous (or nearly unambiguous) output phrases. One type of combination rule deals with domain-specific events. For example, the rule

Company+ SetUp JointVenture ("with" Company+)?

captures one way to describe the formation of a joint venture. This stage is the first one in the cascade where the output is placed into a database template as well as being placed in the output stream. The final stage **merges structures** that were built up in the previous step. If the next sentence says "The joint venture will start production in January," then this step will notice that there are two references to a joint venture, and that they should be merged into one. This is an instance of the **identity uncertainty problem** discussed in Section 14.6.3.

In general, finite-state template-based information extraction works well for a restricted domain in which it is possible to predetermine what subjects will be discussed, and how they will be mentioned. The cascaded transducer model helps modularize the necessary knowledge, easing construction of the system. These systems work especially well when they are reverse-engineering text that has been generated by a program. For example, a shopping site on the Web is generated by a program that takes database entries and formats them into Web pages; a template-based extractor then recovers the original database. Finite-state information extraction is less successful at recovering information in highly variable format, such as text written by humans on a variety of subjects.

22.4.2 Probabilistic models for information extraction

When information extraction must be attempted from noisy or varied input, simple finite-state approaches fare poorly. It is too hard to get all the rules and their priorities right; it is better to use a probabilistic model rather than a rule-based model. The simplest probabilistic model for sequences with hidden state is the hidden Markov model, or HMM.

Recall from Section 15.3 that an HMM models a progression through a sequence of hidden states, $\mathbf{x}_t$, with an observation $\mathbf{e}_t$ at each step. To apply HMMs to information extraction, we can either build one big HMM for all the attributes or build a separate HMM for each attribute. We'll do the second. The observations are the words of the text, and the hidden states are whether we are in the target, prefix, or postfix part of the attribute template, or in the background (not part of a template). For example, here is a brief text and the most probable (Viterbi) path for that text for two HMMs, one trained to recognize the speaker in a talk announcement, and one trained to recognize dates. The "-" indicates a background state:

Text:	There	will	be	a	seminar	by	Dr.	Andrew	McCallum	on	Friday
Speaker:	-	-	-	-	PRE	PRE	TARGET	TARGET	TARGET	POST	-
Date:	-	-	-	-	-	-	-	-	-	PRE	TARGET

HMMs have two big advantages over FSAs for extraction. First, HMMs are probabilistic, and thus tolerant to noise. In a regular expression, if a single expected character is missing, the regex fails to match; with HMMs there is graceful degradation with missing characters/words, and we get a probability indicating the degree of match, not just a Boolean match/fail. Second,

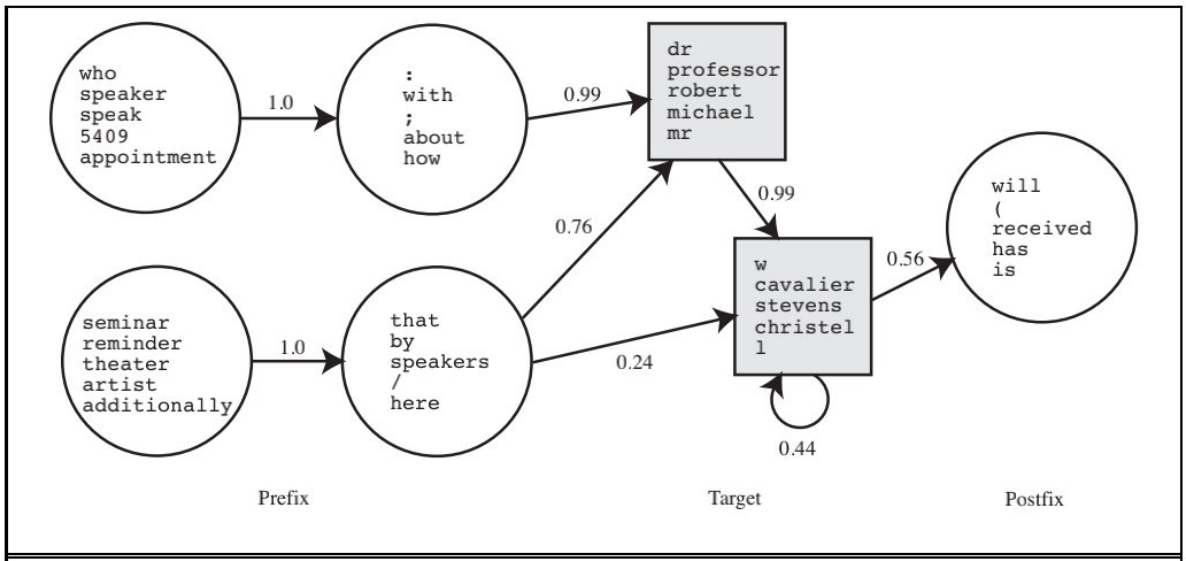


Figure 22.2 Hidden Markov model for the **speaker** of a talk announcement. The two square states are the target (note the second target state has a self-loop, so the target can match a string of any length), the four circles to the left are the prefix, and the one on the right is the postfix. For each state, only a few of the high-probability words are shown. From Freitag and McCallum (2000).

HMMs can be trained from data; they don't require laborious engineering of templates, and thus they can more easily be kept up to date as text changes over time.

Note that we have assumed a certain level of structure in our HMM templates: they all consist of one or more target states, and any prefix states must precede the targets, postfix states most follow the targets, and other states must be background. This structure makes it easier to learn HMMs from examples. With a partially specified structure, the forward–backward algorithm can be used to learn both the transition probabilities $\mathbf{P}(\mathbf{X}_t \mid \mathbf{X}_{t-1})$ between states and the observation model, $\mathbf{P}(\mathbf{E}_t \mid \mathbf{X}_t)$, which says how likely each word is in each state. For example, the word "Friday" would have high probability in one or more of the target states of the date HMM, and lower probability elsewhere.

With sufficient training data, the HMM automatically learns a structure of dates that we find intuitive: the date HMM might have one target state in which the high-probability words are "Monday," "Tuesday," etc., and which has a high-probability transition to a target state with words "Jan", "January," "Feb," etc. Figure 22.2 shows the HMM for the speaker of a talk announcement, as learned from data. The prefix covers expressions such as "Speaker:" and "seminar by," and the target has one state that covers titles and first names and another state that covers initials and last names.

Once the HMMs have been learned, we can apply them to a text, using the Viterbi algorithm to find the most likely path through the HMM states. One approach is to apply each attribute HMM separately; in this case you would expect most of the HMMs to spend most of their time in background states. This is appropriate when the extraction is sparse—when the number of extracted words is small compared to the length of the text.

The other approach is to combine all the individual attributes into one big HMM, which would then find a path that wanders through different target attributes, first finding a speaker target, then a date target, etc. Separate HMMs are better when we expect just one of each attribute in a text and one big HMM is better when the texts are more free-form and dense with attributes. With either approach, in the end we have a collection of target attribute observations, and have to decide what to do with them. If every expected attribute has one target filler then the decision is easy: we have an instance of the desired relation. If there are multiple fillers, we need to decide which to choose, as we discussed with template-based systems. HMMs have the advantage of supplying probability numbers that can help make the choice. If some targets are missing, we need to decide if this is an instance of the desired relation at all, or if the targets found are false positives. A machine learning algorithm can be trained to make this choice.

22.4.3 Conditional random fields for information extraction

One issue with HMMs for the information extraction task is that they model a lot of probabilities that we don't really need. An HMM is a generative model; it models the full joint probability of observations and hidden states, and thus can be used to generate samples. That is, we can use the HMM model not only to parse a text and recover the speaker and date, but also to generate a random instance of a text containing a speaker and a date. Since we're not interested in that task, it is natural to ask whether we might be better off with a model that doesn't bother modeling that possibility. All we need in order to understand a text is a **discriminative model**, one that models the conditional probability of the hidden attributes given the observations (the text). Given a text $\mathbf{e}_{1:N}$, the conditional model finds the hidden state sequence $\mathbf{X}_{1:N}$ that maximizes $P(\mathbf{X}_{1:N} \mid \mathbf{e}_{1:N})$.

CONDITIONAL RANDOM FIELD

LINEAR-CHAIN CONDITIONAL RANDOM FIELD

Modeling this directly gives us some freedom. We don't need the independence assumptions of the Markov model—we can have an $\mathbf{x}_t$ that is dependent on $\mathbf{x}_1$. A framework for this type of model is the **conditional random field**, or CRF, which models a conditional probability distribution of a set of target variables given a set of observed variables. Like Bayesian networks, CRFs can represent many different structures of dependencies among the variables. One common structure is the **linear-chain conditional random field** for representing Markov dependencies among variables in a temporal sequence. Thus, HMMs are the temporal version of naive Bayes models, and linear-chain CRFs are the temporal version of logistic regression, where the predicted target is an entire state sequence rather than a single binary variable.

Let $\mathbf{e}_{1:N}$ be the observations (e.g., words in a document), and $\mathbf{x}_{1:N}$ be the sequence of hidden states (e.g., the prefix, target, and postfix states). A linear-chain conditional random field defines a conditional probability distribution:

$$\mathbf{P}(\mathbf{x}_{1:N}|\mathbf{e}_{1:N}) = \alpha\, e^{\left[\sum_{i=1}^{N} F(\mathbf{x}_{i-1},\mathbf{x}_i,\mathbf{e},i)\right]} ,$$

where α is a normalization factor (to make sure the probabilities sum to 1), and F is a feature function defined as the weighted sum of a collection of k component feature functions:

$$F(\mathbf{x}_{i-1},\mathbf{x}_i,\mathbf{e},i) = \sum_k \lambda_k\, f_k(\mathbf{x}_{i-1},\mathbf{x}_i,\mathbf{e},i) .$$

The λ_k parameter values are learned with a MAP (maximum a posteriori) estimation procedure that maximizes the conditional likelihood of the training data. The feature functions are the key components of a CRF. The function f_k has access to a pair of adjacent states, $\mathbf{x}_{i-1}$ and $\mathbf{x}_i$, but also the entire observation (word) sequence $\mathbf{e}$, and the current position in the temporal sequence, i. This gives us a lot of flexibility in defining features. We can define a simple feature function, for example one that produces a value of 1 if the current word is ANDREW and the current state is SPEAKER:

$$f_1(\mathbf{x}_{i-1}, \mathbf{x}_i, \mathbf{e}, i) = \begin{cases} 1 & \text{if } \mathbf{x}_i = \text{ SPEAKER and } \mathbf{e}_i = \text{ ANDREW} \\ 0 & \text{otherwise} \end{cases}$$

How are features like these used? It depends on their corresponding weights. If $\lambda_1 > 0$, then whenever f_1 is true, it increases the probability of the hidden state sequence $\mathbf{x}_{1:N}$. This is another way of saying "the CRF model should prefer the target state SPEAKER for the word ANDREW." If on the other hand $\lambda_1 < 0$, the CRF model will try to avoid this association, and if $\lambda_1 = 0$, this feature is ignored. Parameter values can be set manually or can be learned from data. Now consider a second feature function:

$$f_2(\mathbf{x}_{i-1}, \mathbf{x}_i, \mathbf{e}, i) = \begin{cases} 1 & \text{if } \mathbf{x}_i = \text{ SPEAKER and } \mathbf{e}_{i+1} = \text{ SAID} \\ 0 & \text{otherwise} \end{cases}$$

This feature is true if the current state is SPEAKER and the next word is "said." One would therefore expect a positive λ_2 value to go with the feature. More interestingly, note that both f_1 and f_2 can hold at the same time for a sentence like "Andrew said ...." In this case, the two features overlap each other and both boost the belief in $\mathbf{x}_1 =$ SPEAKER. Because of the independence assumption, HMMs cannot use overlapping features; CRFs can. Furthermore, a feature in a CRF can use any part of the sequence $\mathbf{e}_{1:N}$. Features can also be defined over transitions between states. The features we defined here were binary, but in general, a feature function can be any real-valued function. For domains where we have some knowledge about the types of features we would like to include, the CRF formalism gives us a great deal of flexibility in defining them. This flexibility can lead to accuracies that are higher than with less flexible models such as HMMs.

22.4.4 Ontology extraction from large corpora

So far we have thought of information extraction as finding a specific set of relations (e.g., speaker, time, location) in a specific text (e.g., a talk announcement). A different application of extraction technology is building a large knowledge base or ontology of facts from a corpus. This is different in three ways: First it is open-ended—we want to acquire facts about all types of domains, not just one specific domain. Second, with a large corpus, this task is dominated by precision, not recall—just as with question answering on the Web (Section 22.3.6). Third, the results can be statistical aggregates gathered from multiple sources, rather than being extracted from one specific text.

For example, Hearst (1992) looked at the problem of learning an ontology of concept categories and subcategories from a large corpus. (In 1992, a large corpus was a 1000-page encyclopedia; today it would be a 100-million-page Web corpus.) The work concentrated on templates that are very general (not tied to a specific domain) and have high precision (are

almost always correct when they match) but low recall (do not always match). Here is one of the most productive templates:

NP **such as** NP (**,** NP)* (**,**)? ((**and** | **or**) NP)? .

Here the bold words and commas must appear literally in the text, but the parentheses are for grouping, the asterisk means *repetition of zero or more*, and the question mark means *optional*. NP is a variable standing for a noun phrase; Chapter 23 describes how to identify noun phrases; for now just assume that we know some words are nouns and other words (such as verbs) that we can reliably assume are not part of a simple noun phrase. This template matches the texts "diseases such as rabies affect your dog" and "supports network protocols such as DNS," concluding that rabies is a disease and DNS is a network protocol. Similar templates can be constructed with the key words "including," "especially," and "or other." Of course these templates will fail to match many relevant passages, like "Rabies is a disease." That is intentional. The "NP is a NP" template does indeed sometimes denote a subcategory relation, but it often means something else, as in "There is a God" or "She is a little tired." With a large corpus we can afford to be picky; to use only the high-precision templates. We'll miss many statements of a subcategory relationship, but most likely we'll find a paraphrase of the statement somewhere else in the corpus in a form we can use.

22.4.5 Automated template construction

The *subcategory* relation is so fundamental that is worthwhile to handcraft a few templates to help identify instances of it occurring in natural language text. But what about the thousands of other relations in the world? There aren't enough AI grad students in the world to create and debug templates for all of them. Fortunately, it is possible to *learn* templates from a few examples, then use the templates to learn more examples, from which more templates can be learned, and so on. In one of the first experiments of this kind, Brin (1999) started with a data set of just five examples:

("Isaac Asimov", "The Robots of Dawn")
("David Brin", "Startide Rising")
("James Gleick", "Chaos—Making a New Science")
("Charles Dickens", "Great Expectations")
("William Shakespeare", "The Comedy of Errors")

Clearly these are examples of the author–title relation, but the learning system had no knowledge of authors or titles. The words in these examples were used in a search over a Web corpus, resulting in 199 matches. Each match is defined as a tuple of seven strings,

(*Author, Title, Order, Prefix, Middle, Postfix, URL*) ,

where *Order* is true if the author came first and false if the title came first, *Middle* is the characters between the author and title, *Prefix* is the 10 characters before the match, *Suffix* is the 10 characters after the match, and *URL* is the Web address where the match was made.

Given a set of matches, a simple template-generation scheme can find templates to explain the matches. The language of templates was designed to have a close mapping to the matches themselves, to be amenable to automated learning, and to emphasize high precision

(possibly at the risk of lower recall). Each template has the same seven components as a match. The $Author$ and $Title$ are regexes consisting of any characters (but beginning and ending in letters) and constrained to have a length from half the minimum length of the examples to twice the maximum length. The prefix, middle, and postfix are restricted to literal strings, not regexes. The middle is the easiest to learn: each distinct middle string in the set of matches is a distinct candidate template. For each such candidate, the template's *Prefix* is then defined as the longest common suffix of all the prefixes in the matches, and the *Postfix* is defined as the longest common prefix of all the postfixes in the matches. If either of these is of length zero, then the template is rejected. The *URL* of the template is defined as the longest prefix of the URLs in the matches.

In the experiment run by Brin, the first 199 matches generated three templates. The most productive template was

<LI><B> *Title* </B> by *Author* (
URL: www.sff.net/locus/c

The three templates were then used to retrieve 4047 more (author, title) examples. The examples were then used to generate more templates, and so on, eventually yielding over 15,000 titles. Given a good set of templates, the system can collect a good set of examples. Given a good set of examples, the system can build a good set of templates.

The biggest weakness in this approach is the sensitivity to noise. If one of the first few templates is incorrect, errors can propagate quickly. One way to limit this problem is to not accept a new example unless it is verified by multiple templates, and not accept a new template unless it discovers multiple examples that are also found by other templates.

22.4.6 Machine reading

Automated template construction is a big step up from handcrafted template construction, but it still requires a handful of labeled examples of each relation to get started. To build a large ontology with many thousands of relations, even that amount of work would be onerous; we would like to have an extraction system with *no* human input of any kind—a system that could read on its own and build up its own database. Such a system would be relation-independent; would work for any relation. In practice, these systems work on *all* relations in parallel, because of the I/O demands of large corpora. They behave less like a traditional information-extraction system that is targeted at a few relations and more like a human reader who learns from the text itself; because of this the field has been called **machine reading**.

MACHINE READING

A representative machine-reading system is TEXTRUNNER (Banko and Etzioni, 2008). TEXTRUNNER uses cotraining to boost its performance, but it needs something to bootstrap from. In the case of Hearst (1992), specific patterns (e.g., *such as*) provided the bootstrap, and for Brin (1998), it was a set of five author–title pairs. For TEXTRUNNER, the original inspiration was a taxonomy of eight very general syntactic templates, as shown in Figure 22.3. It was felt that a small number of templates like this could cover most of the ways that relationships are expressed in English. The actual bootsrapping starts from a set of labelled examples that are extracted from the Penn Treebank, a corpus of parsed sentences. For example, from the parse of the sentence "Einstein received the Nobel Prize in 1921," TEXTRUNNER is able

to extract the relation ("Einstein," "received," "Nobel Prize").

Given a set of labeled examples of this type, TEXTRUNNER trains a linear-chain CRF to extract further examples from unlabeled text. The features in the CRF include function words like "to" and "of" and "the," but not nouns and verbs (and not noun phrases or verb phrases). Because TEXTRUNNER is domain-independent, it cannot rely on predefined lists of nouns and verbs.

Type	Template	Example	Frequency
Verb	NP_1 *Verb* NP_2	X established Y	38%
Noun–Prep	NP_1 *NP Prep* NP_2	X settlement with Y	23%
Verb–Prep	NP_1 *Verb Prep* NP_2	X moved to Y	16%
Infinitive	NP_1 **to** *Verb* NP_2	X plans to acquire Y	9%
Modifier	NP_1 *Verb* NP_2 *Noun*	X is Y winner	5%
Noun-Coordinate	NP_1 (**,** | **and** | **-** | **:**) NP_2 *NP*	X-Y deal	2%
Verb-Coordinate	NP_1 (**,**| **and**) NP_2 *Verb*	X, Y merge	1%
Appositive	NP_1 *NP* (**:**| **,**)? NP_2	X hometown : Y	1%

Figure 22.3 Eight general templates that cover about 95% of the ways that relations are expressed in English.

TEXTRUNNER achieves a precision of 88% and recall of 45% (F_1 of 60%) on a large Web corpus. TEXTRUNNER has extracted hundreds of millions of facts from a corpus of a half-billion Web pages. For example, even though it has no predefined medical knowledge, it has extracted over 2000 answers to the query [what kills bacteria]; correct answers include antibiotics, ozone, chlorine, Cipro, and broccoli sprouts. Questionable answers include "water," which came from the sentence "Boiling water for at least 10 minutes will kill bacteria." It would be better to attribute this to "boiling water" rather than just "water."

With the techniques outlined in this chapter and continual new inventions, we are starting to get closer to the goal of machine reading.

22.5 SUMMARY

The main points of this chapter are as follows:

- Probabilistic language models based on n-grams recover a surprising amount of information about a language. They can perform well on such diverse tasks as language identification, spelling correction, genre classification, and named-entity recognition.
- These language models can have millions of features, so feature selection and preprocessing of the data to reduce noise is important.
- **Text classification** can be done with naive Bayes n-gram models or with any of the classification algorithms we have previously discussed. Classification can also be seen as a problem in data compression.

- **Information retrieval** systems use a very simple language model based on bags of words, yet still manage to perform well in terms of **recall** and **precision** on very large corpora of text. On Web corpora, link-analysis algorithms improve performance.
- **Question answering** can be handled by an approach based on information retrieval, for questions that have multiple answers in the corpus. When more answers are available in the corpus, we can use techniques that emphasize precision rather than recall.
- **Information-extraction** systems use a more complex model that includes limited notions of syntax and semantics in the form of templates. They can be built from finite-state automata, HMMs, or conditional random fields, and can be learned from examples.
- In building a statistical language system, it is best to devise a model that can make good use of available **data**, even if the model seems overly simplistic.

BIBLIOGRAPHICAL AND HISTORICAL NOTES

N-gram letter models for language modeling were proposed by Markov (1913). Claude Shannon (Shannon and Weaver, 1949) was the first to generate n-gram word models of English. Chomsky (1956, 1957) pointed out the limitations of finite-state models compared with context-free models, concluding, "Probabilistic models give no particular insight into some of the basic problems of syntactic structure." This is true, but probabilistic models *do* provide insight into some *other* basic problems—problems that context-free models ignore. Chomsky's remarks had the unfortunate effect of scaring many people away from statistical models for two decades, until these models reemerged for use in speech recognition (Jelinek, 1976).

Kessler *et al.* (1997) show how to apply character n-gram models to genre classification, and Klein *et al.* (2003) describe named-entity recognition with character models. Franz and Brants (2006) describe the Google n-gram corpus of 13 million unique words from a trillion words of Web text; it is now publicly available. The **bag of words** model gets its name from a passage from linguist Zellig Harris (1954), "language is not merely a bag of words but a tool with particular properties." Norvig (2009) gives some examples of tasks that can be accomplished with n-gram models.

Add-one smoothing, first suggested by Pierre-Simon Laplace (1816), was formalized by Jeffreys (1948), and interpolation smoothing is due to Jelinek and Mercer (1980), who used it for speech recognition. Other techniques include Witten–Bell smoothing (1991), Good–Turing smoothing (Church and Gale, 1991) and Kneser–Ney smoothing (1995). Chen and Goodman (1996) and Goodman (2001) survey smoothing techniques.

Simple n-gram letter and word models are not the only possible probabilistic models. Blei *et al.* (2001) describe a probabilistic text model called **latent Dirichlet allocation** that views a document as a mixture of topics, each with its own distribution of words. This model can be seen as an extension and rationalization of the **latent semantic indexing** model of (Deerwester *et al.*, 1990) (see also Papadimitriou *et al.* (1998)) and is also related to the multiple-cause mixture model of (Sahami *et al.*, 1996).

Manning and Schütze (1999) and Sebastiani (2002) survey text-classification techniques. Joachims (2001) uses statistical learning theory and support vector machines to give a theoretical analysis of when classification will be successful. Apté *et al.* (1994) report an accuracy of 96% in classifying Reuters news articles into the "Earnings" category. Koller and Sahami (1997) report accuracy up to 95% with a naive Bayes classifier, and up to 98.6% with a Bayes classifier that accounts for some dependencies among features. Lewis (1998) surveys forty years of application of naive Bayes techniques to text classification and retrieval. Schapire and Singer (2000) show that simple linear classifiers can often achieve accuracy almost as good as more complex models and are more efficient to evaluate. Nigam *et al.* (2000) show how to use the EM algorithm to label unlabeled documents, thus learning a better classification model. Witten *et al.* (1999) describe compression algorithms for classification, and show the deep connection between the LZW compression algorithm and maximum-entropy language models.

Many of the n-gram model techniques are also used in bioinformatics problems. Biostatistics and probabilistic NLP are coming closer together, as each deals with long, structured sequences chosen from an alphabet of constituents.

The field of **information retrieval** is experiencing a regrowth in interest, sparked by the wide usage of Internet searching. Robertson (1977) gives an early overview and introduces the probability ranking principle. Croft *et al.* (2009) and Manning *et al.* (2008) are the first textbooks to cover Web-based search as well as traditional IR. Hearst (2009) covers user interfaces for Web search. The TREC conference, organized by the U.S. government's National Institute of Standards and Technology (NIST), hosts an annual competition for IR systems and publishes proceedings with results. In the first seven years of the competition, performance roughly doubled.

The most popular model for IR is the **vector space model** (Salton *et al.*, 1975). Salton's work dominated the early years of the field. There are two alternative probabilistic models, one due to Ponte and Croft (1998) and one by Maron and Kuhns (1960) and Robertson and Sparck Jones (1976). Lafferty and Zhai (2001) show that the models are based on the same joint probability distribution, but that the choice of model has implications for training the parameters. Craswell *et al.* (2005) describe the BM25 scoring function and Svore and Burges (2009) describe how BM25 can be improved with a machine learning approach that incorporates click data—examples of past search queies and the results that were clicked on.

Brin and Page (1998) describe the PageRank algorithm and the implementation of a Web search engine. Kleinberg (1999) describes the HITS algorithm. Silverstein *et al.* (1998) investigate a log of a billion Web searches. The journal *Information Retrieval* and the proceedings of the annual *SIGIR* conference cover recent developments in the field.

Early information extraction programs include GUS (Bobrow *et al.*, 1977) and FRUMP (DeJong, 1982). Recent information extraction has been pushed forward by the annual Message Understand Conferences (MUC), sponsored by the U.S. government. The FASTUS finite-state system was done by Hobbs *et al.* (1997). It was based in part on the idea from Pereira and Wright (1991) of using FSAs as approximations to phrase-structure grammars. Surveys of template-based systems are given by Roche and Schabes (1997), Appelt (1999),

and Muslea (1999). Large databases of facts were extracted by Craven *et al.* (2000), Pasca *et al.* (2006), Mitchell (2007), and Durme and Pasca (2008).

Freitag and McCallum (2000) discuss HMMs for Information Extraction. CRFs were introduced by Lafferty *et al.* (2001); an example of their use for information extraction is described in (McCallum, 2003) and a tutorial with practical guidance is given by (Sutton and McCallum, 2007). Sarawagi (2007) gives a comprehensive survey.

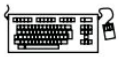
Banko *et al.* (2002) present the ASKMSR question-answering system; a similar system is due to Kwok *et al.* (2001). Pasca and Harabagiu (2001) discuss a contest-winning question-answering system. Two early influential approaches to automated knowledge engineering were by Riloff (1993), who showed that an automatically constructed dictionary performed almost as well as a carefully handcrafted domain-specific dictionary, and by Yarowsky (1995), who showed that the task of word sense classification (see page 756) could be accomplished through unsupervised training on a corpus of unlabeled text with accuracy as good as supervised methods.

The idea of simultaneously extracting templates and examples from a handful of labeled examples was developed independently and simultaneously by Blum and Mitchell (1998), who called it **cotraining** and by Brin (1998), who called it DIPRE (Dual Iterative Pattern Relation Extraction). You can see why the term *cotraining* has stuck. Similar early work, under the name of bootstrapping, was done by Jones *et al.* (1999). The method was advanced by the QXTRACT (Agichtein and Gravano, 2003) and KNOWITALL (Etzioni *et al.*, 2005) systems. Machine reading was introduced by Mitchell (2005) and Etzioni *et al.* (2006) and is the focus of the TEXTRUNNER project (Banko *et al.*, 2007; Banko and Etzioni, 2008).

This chapter has focused on natural language text, but it is also possible to do information extraction based on the physical structure or layout of text rather than on the linguistic structure. HTML lists and tables in both HTML and relational databases are home to data that can be extracted and consolidated (Hurst, 2000; Pinto *et al.*, 2003; Cafarella *et al.*, 2008).

The Association for Computational Linguistics (ACL) holds regular conferences and publishes the journal *Computational Linguistics*. There is also an International Conference on Computational Linguistics (COLING). The textbook by Manning and Schütze (1999) covers statistical language processing, while Jurafsky and Martin (2008) give a comprehensive introduction to speech and natural language processing.

EXERCISES



22.1 This exercise explores the quality of the n-gram model of language. Find or create a monolingual corpus of 100,000 words or more. Segment it into words, and compute the frequency of each word. How many distinct words are there? Also count frequencies of bigrams (two consecutive words) and trigrams (three consecutive words). Now use those frequencies to generate language: from the unigram, bigram, and trigram models, in turn, generate a 100-word text by making random choices according to the frequency counts. Compare the three generated texts with actual language. Finally, calculate the perplexity of each model.

22.2 Write a program to do **segmentation** of words without spaces. Given a string, such as the URL "thelongestlistofthelongeststuffatthelongestdomainnameatlonglast.com," return a list of component words: ["the," "longest," "list," ...]. This task is useful for parsing URLs, for spelling correction when words runtogether, and for languages such as Chinese that do not have spaces between words. It can be solved with a unigram or bigram word model and a dynamic programming algorithm similar to the Viterbi algorithm.

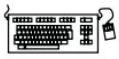
22.3 (Adapted from Jurafsky and Martin (2000).) In this exercise you will develop a classifier for authorship: given a text, the classifier predicts which of two candidate authors wrote the text. Obtain samples of text from two different authors. Separate them into training and test sets. Now train a language model on the training set. You can choose what features to use; n-grams of words or letters are the easiest, but you can add additional features that you think may help. Then compute the probability of the text under each language model and chose the most probable model. Assess the accuracy of this technique. How does accuracy change as you alter the set of features? This subfield of linguistics is called **stylometry**; its successes include the identification of the author of the disputed *Federalist Papers* (Mosteller and Wallace, 1964) and some disputed works of Shakespeare (Hope, 1994). Khmelev and Tweedie (2001) produce good results with a simple letter bigram model.

STYLOMETRY

22.4 This exercise concerns the classification of spam email. Create a corpus of spam email and one of non-spam mail. Examine each corpus and decide what features appear to be useful for classification: unigram words? bigrams? message length, sender, time of arrival? Then train a classification algorithm (decision tree, naive Bayes, SVM, logistic regression, or some other algorithm of your choosing) on a training set and report its accuracy on a test set.

22.5 Create a test set of ten queries, and pose them to three major Web search engines. Evaluate each one for precision at 1, 3, and 10 documents. Can you explain the differences between engines?

22.6 Try to ascertain which of the search engines from the previous exercise are using case folding, stemming, synonyms, and spelling correction.



22.7 Write a regular expression or a short program to extract company names. Test it on a corpus of business news articles. Report your recall and precision.

22.8 Consider the problem of trying to evaluate the quality of an IR system that returns a ranked list of answers (like most Web search engines). The appropriate measure of quality depends on the presumed model of what the searcher is trying to achieve, and what strategy she employs. For each of the following models, propose a corresponding numeric measure.

a. The searcher will look at the first twenty answers returned, with the objective of getting as much relevant information as possible.

b. The searcher needs only one relevant document, and will go down the list until she finds the first one.

c. The searcher has a fairly narrow query and is able to examine all the answers retrieved. She wants to be sure that she has seen everything in the document collection that is

relevant to her query. (E.g., a lawyer wants to be sure that she has found *all* relevant precedents, and is willing to spend considerable resources on that.)

d. The searcher needs just one document relevant to the query, and can afford to pay a research assistant for an hour's work looking through the results. The assistant can look through 100 retrieved documents in an hour. The assistant will charge the searcher for the full hour regardless of whether he finds it immediately or at the end of the hour.

e. The searcher will look through all the answers. Examining a document has cost $\$A$; finding a relevant document has value $\$B$; failing to find a relevant document has cost $\$C$ for each relevant document not found.

f. The searcher wants to collect as many relevant documents as possible, but needs steady encouragement. She looks through the documents in order. If the documents she has looked at so far are mostly good, she will continue; otherwise, she will stop.

Chapter 1. Introduction - Machine Learning and Statistical Science

Machine learning has definitely been one of the most talked about fields in recent years, and for good reason. Every day new applications and models are discovered, and researchers around the world announce impressive advances in the quality of results on a daily basis.

Each day, many new practitioners decide to take courses and search for introductory materials so they can employ these newly available techniques that will improve their applications. But in many cases, the whole corpus of machine learning, as normally explained in the literature, requires a good understanding of mathematical concepts as a prerequisite, thus imposing a high bar for programmers who typically have good algorithmic skills but are less familiar with higher mathematical concepts.

This first chapter will be a general introduction to the field, covering the main study areas of machine learning, and will offer an overview of the basic statistics, probability, and calculus, accompanied by source code examples in a way that allows you to experiment with the provided formulas and parameters.

In this first chapter, you will learn the following topics:

- What is machine learning?
- Machine learning areas
- Elements of statistics and probability
- Elements of calculus

The world around us provides huge amounts of data. At a basic level, we are continually acquiring and learning from text, image, sound, and other types of information surrounding us. The availability of data, then, is the first step in the process of acquiring the skills to perform a task.

A myriad of computing devices around the world collect and store an overwhelming amount of information that is image-, video-, and text-based. So, the raw material for learning is clearly abundant, and it's available in a format that a computer can deal with.

That's the starting point for the rise of the discipline discussed in this book: the study of techniques and methods allowing computers to learn from data without being explicitly programmed.

A more formal definition of machine learning, from *Tom Mitchell*, is as follows:

> *"A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E."*

This definition is complete, and reinstates the elements that play a role in every machine learning project: the task to perform, the successive experiments, and a clear and appropriate performance measure. In simpler words, we have a program that improves how it performs a task based on experience and guided by a certain criterion.

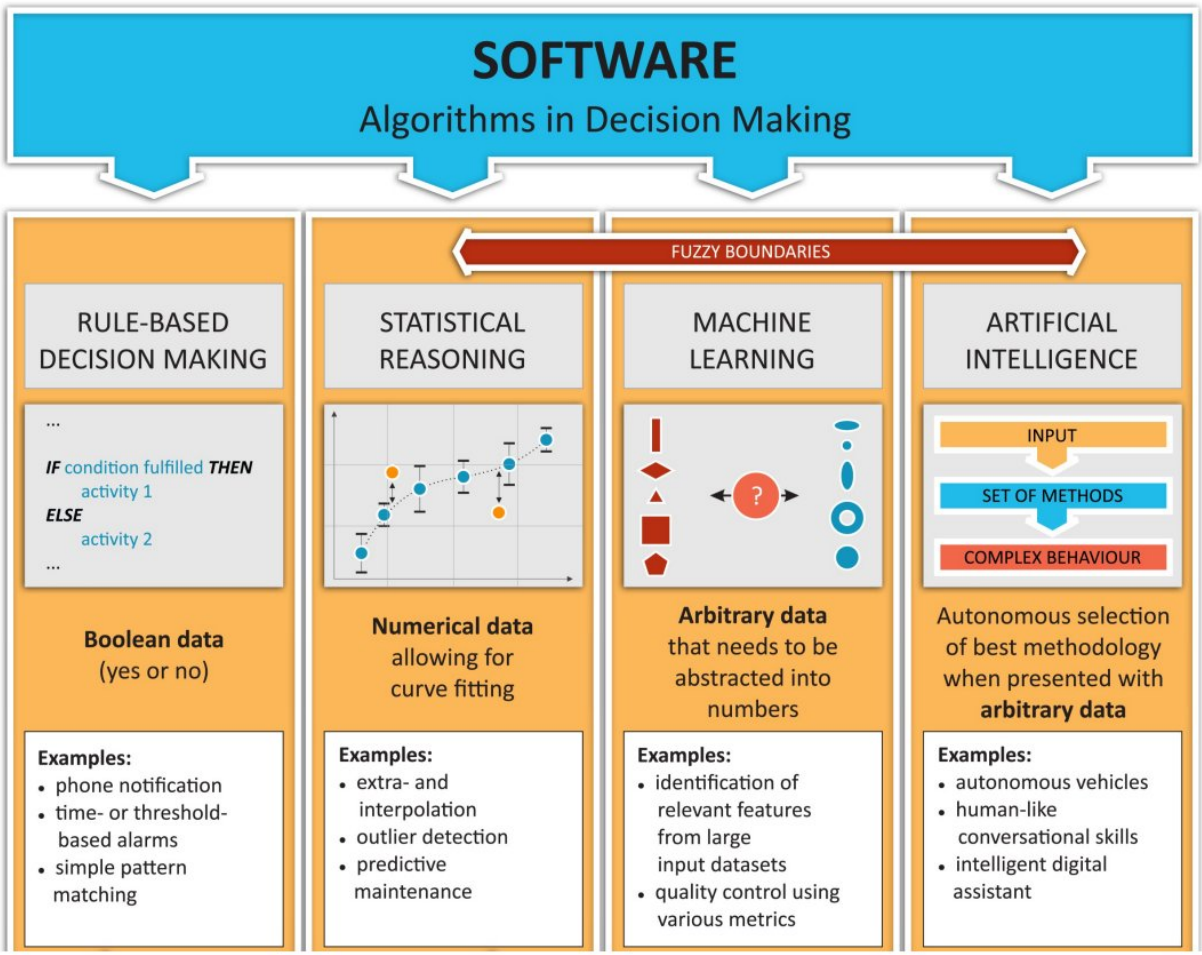
Machine learning in the bigger picture

Machine learning as a discipline is not an isolated field—it is framed inside a wider domain, **Artificial Intelligence** (**AI**). But as you can guess, machine learning didn't appear from the void. As a discipline it has its predecessors, and it has been evolving in stages of increasing complexity in the following four clearly differentiated steps:

1. The first model of machine learning involved rule-based decisions and a simple level of data-based algorithms that includes in itself, and as a prerequisite, all the possible ramifications and decision rules, implying that all the possible options will be hardcoded into the model beforehand by an expert in the field. This structure was implemented in the majority of applications developed since the first programming languages appeared in 1950. The main data type and function being handled by this kind of algorithm is the Boolean, as it exclusively dealt with yes or no decisions.

2. During the second developmental stage of statistical reasoning, we started to let the probabilistic characteristics of the data have a say, in addition to the previous choices set up in advance. This better reflects the fuzzy nature of real-world problems, where outliers are common and where it is more important to take into account the nondeterministic tendencies of the data than the rigid approach of fixed questions. This discipline adds to the mix of mathematical tools elements of **Bayesian probability theory**. Methods pertaining to this category include curve fitting (usually of linear or polynomial), which has the common property of working with numerical data.
3. The machine learning stage is the realm in which we are going to be working throughout this book, and it involves more complex tasks than the simplest Bayesian elements of the previous stage. The most outstanding feature of machine learning algorithms is that they can generalize models from data but the models are capable of generating their own feature selectors, which aren't limited by a rigid target function, as they are generated and defined as the training process evolves. Another differentiator of this kind of model is that they can take a large variety of data types as input, such as speech, images, video, text, and other data susceptible to being represented as vectors.
4. AI is the last step in the scale of abstraction capabilities that, in a way, include all previous algorithm types, but with one key difference: AI algorithms are able to apply the learned knowledge to solve tasks that had never been considered during training. The types of data with which this algorithm works are even more generic than the types of data supported by machine learning, and they should be able, by definition, to transfer problem-solving capabilities from one data type to another, without a complete retraining of the model. In this way, we could develop an algorithm for object detection in black and white images and the model could abstract the knowledge to apply the model to color images.

In the following diagram, we represent these four stages of development towards real AI applications:

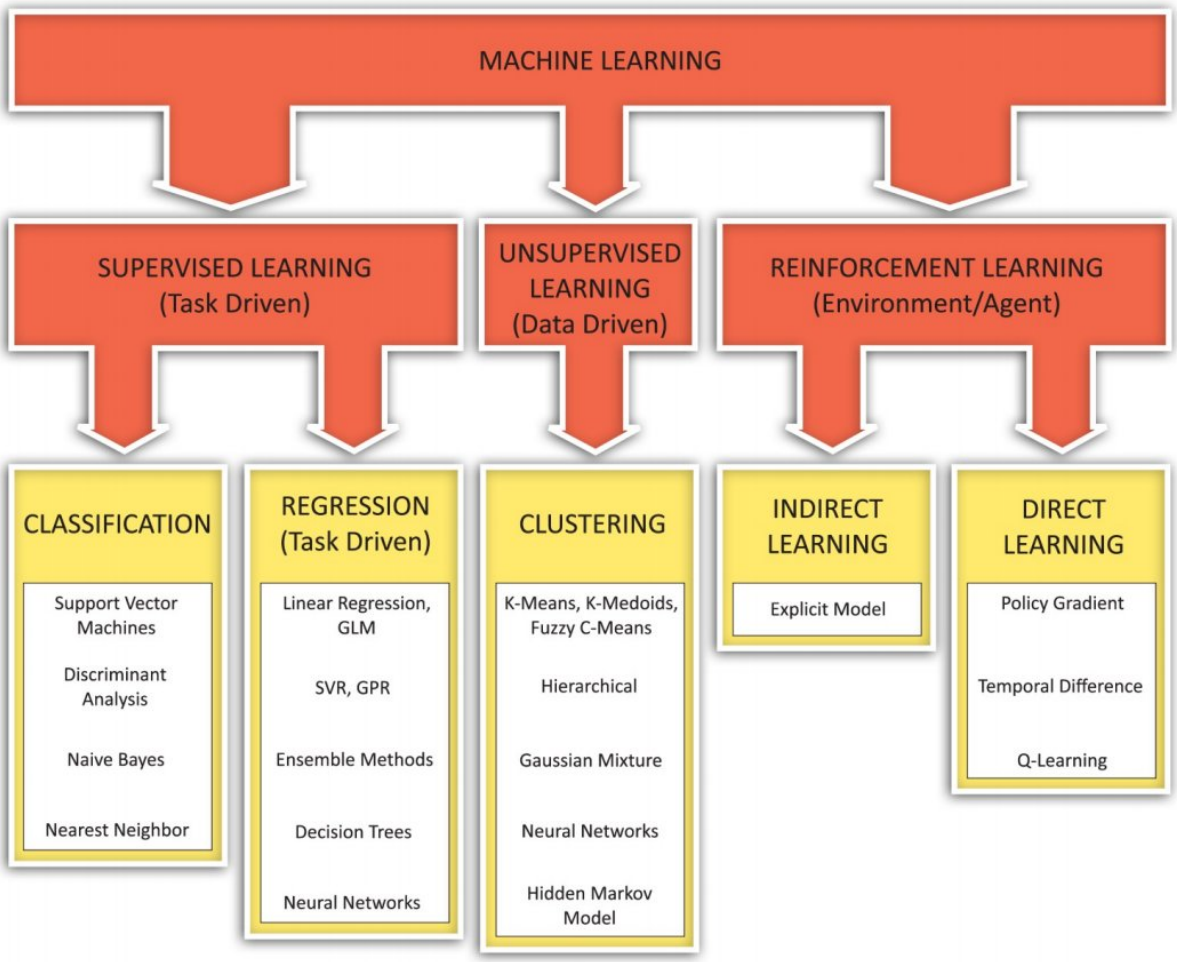


Types of machine learning

Let's try to dissect the different types of machine learning project, starting from the grade of previous knowledge from the point of view of the implementer. The project can be of the following types:

- **Supervised learning**: In this type of learning, we are given a sample set of real data, accompanied by the result the model should give us after applying it. In statistical terms, we have the outcome of all the training set experiments.
- **Unsupervised learning:** This type of learning provides only the sample data from the problem domain, but the task of grouping similar data and applying a category has no previous information from which it can be inferred.
- **Reinforcement learning:** This type of learning doesn't have a labeled sample set and has a different number of participating elements, which include an agent, an environment, and learning an optimum policy or set of steps, maximizing a goal-oriented approach by using rewards or penalties (the result of each attempt).

Take a look at the following diagram:



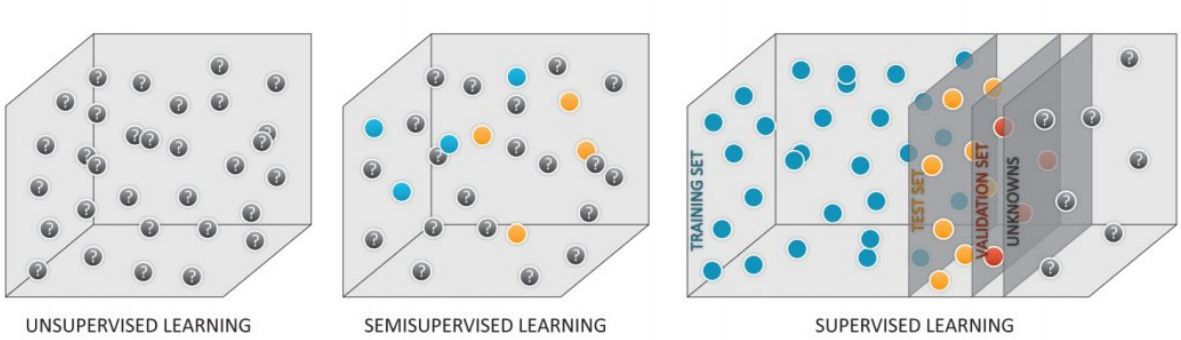
Main areas of Machine Learning

Grades of supervision

The learning process supports gradual steps in the realm of supervision:

- Unsupervised Learning doesn't have previous knowledge of the class or value of any sample, it should infer it automatically.
- Semi-Supervised Learning, needs a seed of known samples, and the model infers the remaining samples class or value from that seed.
- Supervised Learning: This approach normally includes a set of known samples, called training set, another set used to validate the model's generalization, and a third one, called test set, which is used after the training process to have an independent number of samples outside of the training set, and warranty independence of testing.

In the following diagram, depicts the mentioned approaches:



Graphical depiction of the training techniques for Unsupervised, Semi-Supervised and Supervised Learning

Supervised learning strategies - regression versus classification

This type of learning has the following two main types of problem to solve:

- **Regression problem**: This type of problem accepts samples from the problem domain and, after training the model, minimizes the error by comparing the output with the real answers, which allows the prediction of the right answer when given a new unknown sample
- **Classification problem**: This type of problem uses samples from the domain to assign a label or group to new unknown samples

Unsupervised problem solving–clustering

The vast majority of unsupervised problem solving consist of grouping items by looking at similarities or the value of shared features of the observed items, because there is no certain information about the *apriori* classes. This type of technique is called clustering.

Outside of these main problem types, there is a mix of both, which is called semi-supervised problem solving, in which we can train a labeled set of elements and also use inference to assign information to unlabeled data during training time. To assign data to unknown entities, three main criteria are used—smoothness (points close to each other are of the same class), cluster (data tends to form clusters, a special case of smoothness), and manifold (data pertains to a manifold of much lower dimensionality than the original domain).

1 Introduction

1.1 What is Machine Learning

Machine learning is a subfield of computer science that is concerned with building algorithms which, to be useful, rely on a collection of examples of some phenomenon. These examples can come from nature, be handcrafted by humans or generated by another algorithm.

Machine learning can also be defined as the process of solving a practical problem by 1) gathering a dataset, and 2) algorithmically building a statistical model based on that dataset. That statistical model is assumed to be used somehow to solve the practical problem.

To save keystrokes, I use the terms "learning" and "machine learning" interchangeably.

1.2 Types of Learning

Learning can be supervised, semi-supervised, unsupervised and reinforcement.

1.2.1 Supervised Learning

In **supervised learning**[1], the **dataset** is the collection of **labeled examples** $\{(\mathbf{x}_i, y_i)\}_{i=1}^{N}$. Each element $\mathbf{x}_i$ among N is called a **feature vector**. A feature vector is a vector in which each dimension $j = 1, \ldots, D$ contains a value that describes the example somehow. That value is called a **feature** and is denoted as $x^{(j)}$. For instance, if each example $\mathbf{x}$ in our collection represents a person, then the first feature, $x^{(1)}$, could contain height in cm, the second feature, $x^{(2)}$, could contain weight in kg, $x^{(3)}$ could contain gender, and so on. For all examples in the dataset, the feature at position j in the feature vector always contains the same kind of information. It means that if $x_i^{(2)}$ contains weight in kg in some example $\mathbf{x}_i$, then $x_k^{(2)}$ will also contain weight in kg in every example $\mathbf{x}_k$, $k = 1, \ldots, N$. The **label** y_i can be either an element belonging to a finite set of **classes** $\{1, 2, \ldots, C\}$, or a real number, or a more complex structure, like a vector, a matrix, a tree, or a graph. Unless otherwise stated, in this book y_i is either one of a finite set of classes or a real number. You can see a class as a category to which an example belongs. For instance, if your examples are email messages and your problem is spam detection, then you have two classes $\{spam, not\_spam\}$.

The goal of a **supervised learning algorithm** is to use the dataset to produce a **model** that takes a feature vector $\mathbf{x}$ as input and outputs information that allows deducing the label for this feature vector. For instance, the model created using the dataset of people could take as input a feature vector describing a person and output a probability that the person has cancer.

[1] In this book, if a term is **in bold**, that means that this term can be found in the index at the end of the book.

1.2.2 Unsupervised Learning

In **unsupervised learning**, the dataset is a collection of **unlabeled examples** $\{\mathbf{x}_i\}_{i=1}^{N}$. Again, $\mathbf{x}$ is a feature vector, and the goal of an **unsupervised learning algorithm** is to create a **model** that takes a feature vector $\mathbf{x}$ as input and either transforms it into another vector or into a value that can be used to solve a practical problem. For example, in **clustering**, the model returns the id of the cluster for each feature vector in the dataset. In **dimensionality reduction**, the output of the model is a feature vector that has fewer features than the input $\mathbf{x}$; in **outlier detection**, the output is a real number that indicates how $\mathbf{x}$ is different from a "typical" example in the dataset.

1.2.3 Semi-Supervised Learning

In **semi-supervised learning**, the dataset contains both labeled and unlabeled examples. Usually, the quantity of unlabeled examples is much higher than the number of labeled examples. The goal of a **semi-supervised learning algorithm** is the same as the goal of the supervised learning algorithm. The hope here is that using many unlabeled examples can help the learning algorithm to find (we might say "produce" or "compute") a better model[2].

1.2.4 Reinforcement Learning

Reinforcement learning is a subfield of machine learning where the machine "lives" in an environment and is capable of perceiving the **state** of that environment as a vector of features. The machine can execute **actions** in every state. Different actions bring different **rewards** and could also move the machine to another state of the environment. The goal of a reinforcement learning algorithm is to learn a **policy**. A policy is a function f (similar to the model in supervised learning) that takes the feature vector of a state as input and outputs an optimal action to execute in that state. The action is optimal if it maximizes the **expected average reward**.

Reinforcement learning solves a particular kind of problems where decision making is sequential, and the goal is long-term, such as game playing, robotics, resource management, or logistics. In this book, I put emphasis on one-shot decision making where input examples are independent of one another and the predictions made in the past. I leave reinforcement learning out of the scope of this book.

[2]It could look counter-intuitive that learning could benefit from adding more unlabeled examples. It seems like we add more uncertainty to the problem. However, when you add unlabeled examples, you add more information about your problem: a larger sample reflects better the probability distribution the data we labeled came from. Theoretically, a learning algorithm should be able to leverage this additional information.

1.3 How Supervised Learning Works

In this section, I briefly explain how supervised learning works so that you have the picture of the whole process before we go into detail. I decided to use supervised learning as an example because it's the type of machine learning most frequently used in practice.

The supervised learning process starts with gathering the data. The data for supervised learning is a collection of pairs (input, output). Input could be anything, for example, email messages, pictures, or sensor measurements. Outputs are usually real numbers, or labels (e.g. "spam", "not_spam", "cat", "dog", "mouse", etc). In some cases, outputs are vectors (e.g., four coordinates of the rectangle around a person on the picture), sequences (e.g. ["adjective", "adjective", "noun"] for the input "big beautiful car"), or have some other structure.

Let's say the problem that you want to solve using supervised learning is spam detection. You gather the data, for example, 10,000 email messages, each with a label either "spam" or "not_spam" (you could add those labels manually or pay someone to do that for us). Now, you have to convert each email message into a feature vector.

The data analyst decides, based on their experience, how to convert a real-world entity, such as an email message, into a feature vector. One common way to convert a text into a feature vector, called **bag of words**, is to take a dictionary of English words (let's say it contains 20,000 alphabetically sorted words) and stipulate that in our feature vector:

- the first feature is equal to 1 if the email message contains the word "a"; otherwise, this feature is 0;
- the second feature is equal to 1 if the email message contains the word "aaron"; otherwise, this feature equals 0;
- ...
- the feature at position 20,000 is equal to 1 if the email message contains the word "zulu"; otherwise, this feature is equal to 0.

You repeat the above procedure for every email message in our collection, which gives us 10,000 feature vectors (each vector having the dimensionality of 20,000) and a label ("spam"/"not_spam").

Now you have a machine-readable input data, but the output labels are still in the form of human-readable text. Some learning algorithms require transforming labels into numbers. For example, some algorithms require numbers like 0 (to represent the label "not_spam") and 1 (to represent the label "spam"). The algorithm I use to illustrate supervised learning is called **Support Vector Machine** (SVM). This algorithm requires that the positive label (in our case it's "spam") has the numeric value of +1 (one), and the negative label ("not_spam") has the value of −1 (minus one).

At this point, you have a **dataset** and a **learning algorithm**, so you are ready to apply the learning algorithm to the dataset to get the **model**.

SVM sees every feature vector as a point in a high-dimensional space (in our case, space

is 20,000-dimensional). The algorithm puts all feature vectors on an imaginary 20,000-dimensional plot and draws an imaginary 20,000-dimensional line (a *hyperplane*) that separates examples with positive labels from examples with negative labels. In machine learning, the boundary separating the examples of different classes is called the **decision boundary**.

The equation of the hyperplane is given by two **parameters**, a real-valued vector $\mathbf{w}$ of the same dimensionality as our input feature vector $\mathbf{x}$, and a real number b like this:

$$\mathbf{wx} - b = 0,$$

where the expression $\mathbf{wx}$ means $w^{(1)}x^{(1)} + w^{(2)}x^{(2)} + \ldots + w^{(D)}x^{(D)}$, and D is the number of dimensions of the feature vector $\mathbf{x}$.

(If some equations aren't clear to you right now, in Chapter 2 we revisit the math and statistical concepts necessary to understand them. For the moment, try to get an intuition of what's happening here. It all becomes more clear after you read the next chapter.)

Now, the predicted label for some input feature vector $\mathbf{x}$ is given like this:

$$y = \text{sign}(\mathbf{wx} - b),$$

where sign is a mathematical operator that takes any value as input and returns $+1$ if the input is a positive number or -1 if the input is a negative number.

The goal of the learning algorithm — SVM in this case — is to leverage the dataset and find the optimal values $\mathbf{w}^*$ and b^* for parameters $\mathbf{w}$ and b. Once the learning algorithm identifies these optimal values, the **model** $f(\mathbf{x})$ is then defined as:

$$f(\mathbf{x}) = \text{sign}(\mathbf{w}^*\mathbf{x} - b^*)$$

Therefore, to predict whether an email message is spam or not spam using an SVM model, you have to take a text of the message, convert it into a feature vector, then multiply this vector by $\mathbf{w}^*$, subtract b^* and take the sign of the result. This will give us the prediction ($+1$ means "spam", -1 means "not_spam").

Now, how does the machine find $\mathbf{w}^*$ and b^*? It solves an optimization problem. Machines are good at optimizing functions under constraints.

So what are the constraints we want to satisfy here? First of all, we want the model to predict the labels of our 10,000 examples correctly. Remember that each example $i = 1, \ldots, 10000$ is given by a pair $(\mathbf{x}_i, y_i)$, where $\mathbf{x}_i$ is the feature vector of example i and y_i is its label that takes values either -1 or $+1$. So the constraints are naturally:

- $\mathbf{wx}_i - b \geq 1$ if $y_i = +1$, and
- $\mathbf{wx}_i - b \leq -1$ if $y_i = -1$

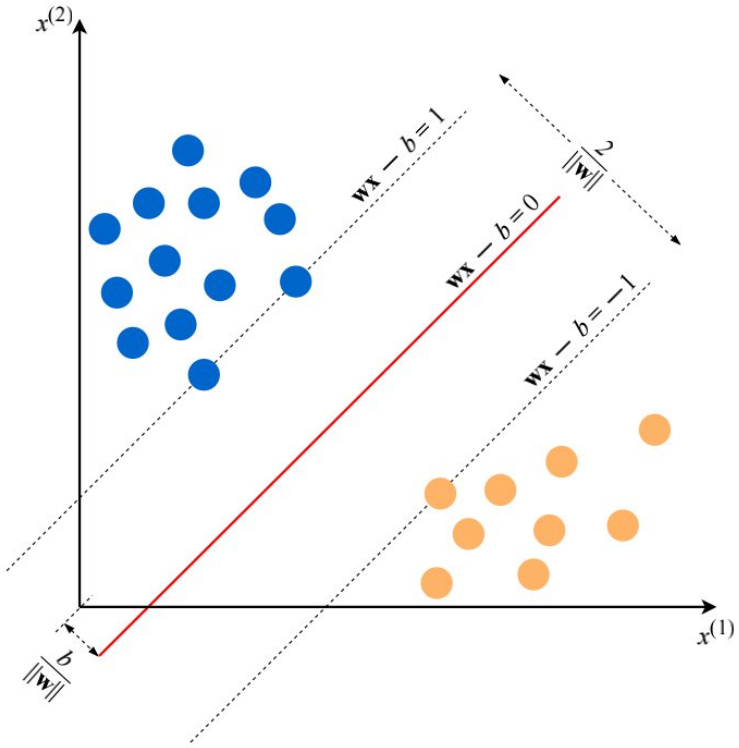


Figure 1: An example of an SVM model for two-dimensional feature vectors.

We would also prefer that the hyperplane separates positive examples from negative ones with the largest **margin**. The margin is the distance between the closest examples of two classes, as defined by the decision boundary. A large margin contributes to a better **generalization**, that is how well the model will classify new examples in the future. To achieve that, we need to minimize the Euclidean norm of $\mathbf{w}$ denoted by $\|\mathbf{w}\|$ and given by $\sqrt{\sum_{j=1}^{D}(w^{(j)})^2}$.

So, the optimization problem that we want the machine to solve looks like this:

Minimize $\|\mathbf{w}\|$ *subject to* $y_i(\mathbf{wx}_i - b) \geq 1$ *for* $i = 1, \ldots, N$. The expression $y_i(\mathbf{wx}_i - b) \geq 1$ is just a compact way to write the above two constraints.

The solution of this optimization problem, given by $\mathbf{w}^*$ and b^*, is called the **statistical model**, or, simply, the **model**. The process of building the model is called **training**.

For two-dimensional feature vectors, the problem and the solution can be visualized as shown in fig. 1. The blue and orange circles represent, respectively, positive and negative examples, and the line given by $\mathbf{wx} - b = 0$ is the decision boundary.

Why, by minimizing the norm of $\mathbf{w}$, do we find the highest margin between the two classes? Geometrically, the equations $\mathbf{wx} - b = 1$ and $\mathbf{wx} - b = -1$ define two parallel hyperplanes, as you see in fig. 1. The distance between these hyperplanes is given by $\frac{2}{\|\mathbf{w}\|}$, so the smaller

the norm $\|\mathbf{w}\|$, the larger the distance between these two hyperplanes.

That's how Support Vector Machines work. This particular version of the algorithm builds the so-called *linear model*. It's called linear because the decision boundary is a straight line (or a plane, or a hyperplane). SVM can also incorporate **kernels** that can make the decision boundary arbitrarily non-linear. In some cases, it could be impossible to perfectly separate the two groups of points because of noise in the data, errors of labeling, or **outliers** (examples very different from a "typical" example in the dataset). Another version of SVM can also incorporate a penalty hyperparameter for misclassification of training examples of specific classes. We study the SVM algorithm in more detail in Chapter 3.

At this point, you should retain the following: any classification learning algorithm that builds a model implicitly or explicitly creates a decision boundary. The decision boundary can be straight, or curved, or it can have a complex form, or it can be a superposition of some geometrical figures. The form of the decision boundary determines the **accuracy** of the model (that is the ratio of examples whose labels are predicted correctly). The form of the decision boundary, the way it is algorithmically or mathematically computed based on the training data, differentiates one learning algorithm from another.

In practice, there are two other essential differentiators of learning algorithms to consider: speed of model building and prediction processing time. In many practical cases, you would prefer a learning algorithm that builds a less accurate model fast. Additionally, you might prefer a less accurate model that is much quicker at making predictions.

1.4 Why the Model Works on New Data

Why is a machine-learned model capable of predicting correctly the labels of new, previously unseen examples? To understand that, look at the plot in fig. 1. If two classes are separable from one another by a decision boundary, then, obviously, examples that belong to each class are located in two different subspaces which the decision boundary creates.

If the examples used for training were selected randomly, independently of one another, and following the same procedure, then, statistically, it is *more likely* that the new negative example will be located on the plot somewhere not too far from other negative examples. The same concerns the new positive example: it will *likely* come from the surroundings of other positive examples. In such a case, our decision boundary will still, *with high probability*, separate well new positive and negative examples from one another. For other, *less likely situations*, our model will make errors, but because such situations are less likely, the number of errors will likely be smaller than the number of correct predictions.

Intuitively, the larger is the set of training examples, the more unlikely that the new examples will be dissimilar to (and lie on the plot far from) the examples used for training. To minimize the probability of making errors on new examples, the SVM algorithm, by looking for the largest margin, explicitly tries to draw the decision boundary in such a way that it lies as far as possible from examples of both classes.

The Economist Intelligence Unit

An Economist Intelligence Unit briefing paper

ARTIFICIAL INTELLIGENCE IN THE REAL WORLD

The business case takes shape

Sponsored by

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Contents

1 Testing the waters

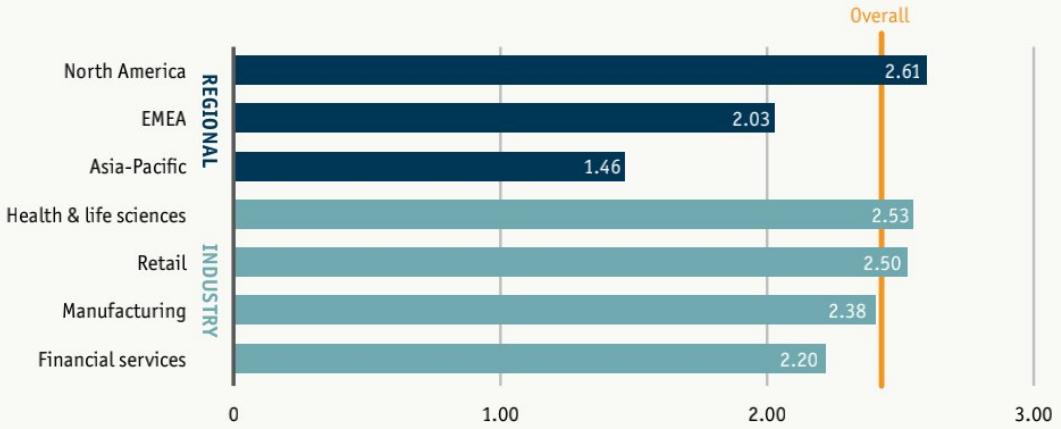
When new families of technology grab the headlines, business leaders often get anxious. "Is this just another round of tech hype?", they may ask themselves, "Or is this one for real?" Judging by the results of our research, executives in several industries are taking AI seriously.

> "We're exploring AI applications in various parts of UBS. We're taking a stepwise approach, putting in the building blocks—the control frameworks, the technology, centres of expertise—and making sure we have use cases to help us flesh out our thinking across all our businesses."
>
> Chris Gelvin, chief operating officer, Group COO functions, UBS

One taking it seriously is Paul Clarke, chief technology officer at Ocado, a UK-based online grocer. "AI has to be the centre of everything we do now. I am sending that message to all of the technology teams in Ocado. Previously the message would have been 'Collect all data and make sure everything is measurable.' The new message is 'Collect the data and make sure everything is architected for AI from day one.'"

Few companies are currently as resolute about AI as Ocado, but many are testing the waters. Most of those in the survey are at early stages of work with it. Just over one-third of respondents' companies are experimenting with AI technologies in 1-2 areas of operation. About one-tenth have begun to utilise AI in a limited fashion. A small number (2.5%) even say their firms have deployed AI widely in their operations. And exploratory research is under way for another third of respondents.

Figure 1: The US and the healthcare sector lead the way in AI application
AI implementation score: regional vs. industry comparison
(Scale: 1=nascent, 2=exploratory, 3=experimental, 4=applied, 5=deployed)



The AI business index

Expressed in an index, the AI implementation score across all the firms represented in our survey is 2.40 on a 1-5 scale, where 1=nascent, 2=exploratory, 3=experimental, 4=applied and 5=deployed. This signifies a transition for many firms from exploratory research to active experimentation.

The index score is highest in North America (2.61), confirmation that work with AI is considerably more advanced there than elsewhere (figure 1). This is not surprising given the dominant role of US laboratories and universities over the years in basic AI research, and the plethora of Silicon Valley and other start-ups taking it forward into practical applications. Nearly one-fifth of North American firms in the survey have begun to use AI technologies actively in their business.

Regional comparison

The EMEA score of 2.03 suggests that firms in that region are at the early stage of exploratory work, while a 1.46 score indicates that business use of AI in Asia-Pacific is at a nascent stage (figure 1).

Ralf Herbrich, director of machine learning at Amazon, an online retailer, believes the US lead is also partly due to its high excitement levels for consumer technology. However, he notes that Europe has taken the lead in areas of AI such as natural language processing for multi-lingual settings. And at least one forecaster predicts that Asia-Pacific will experience faster growth of AI technologies than other regions between 2016 and 2020.[3]

Industry comparison

The highest sectoral score (figure 1) belongs to health and life sciences (2.53), followed closely by retail (2.50). The health sector's lead is no surprise to several of the experts we interviewed for this study. Both Jerry Kaplan, a visiting lecturer at Stanford University in California, and James Hendler, director of the Institute for Data Exploration and Applications at Rensselaer Polytechnic Institute in Troy, New York, believe that in the medium term healthcare provision holds brighter prospects for AI application than other fields.

For Mr Kaplan (author of Humans need not apply: A guide to wealth and work in the age of artificial intelligence), AI's potential in healthcare is predicated on the enormous volumes of patient data and medical research that the industry has accumulated. "The broad availability of data on outcomes, procedures, clinical trials, expenditures and other areas mean that the use of machine learning techniques can offer very unique and useful insights."

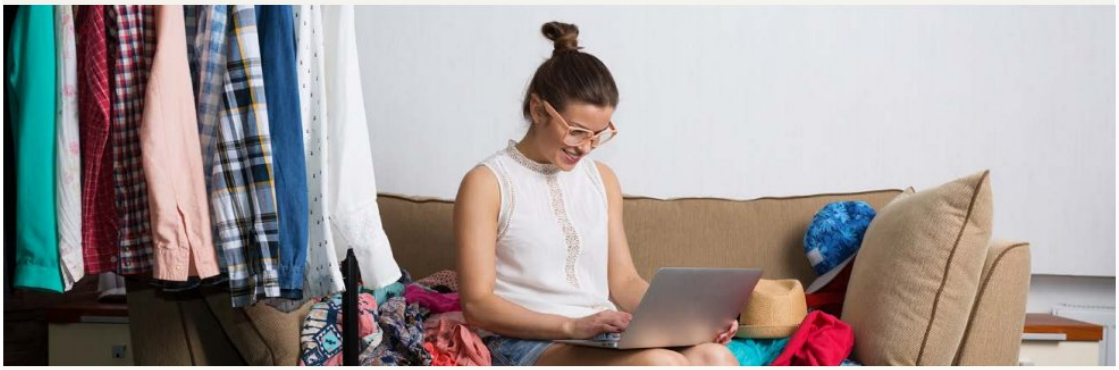
Gathering momentum

The pace of AI implementation is likely to quicken everywhere. Three-quarters of survey respondents anticipate AI to be "actively implemented" in their part of the business within the next three years. Another 3% say this is already the case in their firms. The pace will remain the quickest in North America (active implementation in 84% of firms); amongst sectors more retail respondents (84%) say this than others.

John Straw, an AI venture capitalist, believes the retail industry will be experiencing significant change from AI as early as three years from now. He expects, for example, to see AI-driven chatbots performing much of retailers' customer service and sales information functions within that time frame. High Street stores, he believes, will not disappear but will largely take on the role of showrooms, where a combination of AI and virtual reality technologies will help customers view and experience products before they buy.

3 Research and Markets, Artificial Intelligence (AI) Market by Technology (Machine Learning, Natural Language Processing (NLP), Image Processing, And Speech Recognition), Application & Geography—Global Forecast to 2020 (April 2016).

Case study 1: Algorithms for your evening wear



Stitch Fix, an online personalised clothing retailer, has machine learning in its DNA, according to Eric Colson, its chief algorithms officer. Founded in 2011 in San Francisco, its business model from the start has been predicated on the marriage of personal stylists, detailed customer-provided data and powerful algorithms. Machine learning techniques are increasingly being used to refine the algorithms and augment—rather than replace, says Mr Colson—the work of its personal stylists and, ultimately, its customers' satisfaction with the clothing they purchase.

At the heart of things is the company's "styling algorithm", which selects clothes for the customer once he or she completes a detailed online questionnaire about size measurements, colours and other preferences. It is performed, according to Mr Colson, by both machines and humans. "An algorithm is just a set of instructions. And all the steps in the instructions are performed by different types of processors. Some are better suited to machines; others to humans."

A machine learning component, he says, more precisely learns what the customer's 'true' size is. There are no standards for sizing across apparel brands. Stitch Fix uses feedback received from customers after trying on the clothing to determine how each brand actually fits. The algorithm is able to learn about each customer's individual preferences and how each piece of merchandise fits on various types of customers. "That's a machine task, involving millions of calculations," says Mr Colson. "You can't ask a human to perform that."

Customers, however, often include deeply personal notes in their questionnaire responses, and they expect a human to respond, explains Mr Colson. An example: "A woman's husband is returning from a six-month tour of military duty overseas, and she wants an outfit for a very special date night. Only the personal stylist, a human, knows what that means to the customer. They can empathise." For the algorithms to perform well, he says, "you need the right resource to do each of those tasks. The machines are one and humans are another."

The company recently launched a "computer vision" algorithm which enables machines to use images to learn a customer's style. "Sometimes it's easier for a customer to articulate preferences with a picture than in words," explains Mr Colson. "Our customers make us Pinterest pinboards of things they like, and we—both our human stylists and our machines—ingest them. Then we can find out what to the customer is edgy or bohemian chic."

2 Hopes and expectations

Given the novelty and still futuristic perceptions of AI popularised in the media, why are many companies moving so decisively to develop AI capabilities? In time-honoured business fashion, it is a combination of fear and hope. Competitive pressures are spurring companies on, and there is a sense of urgency amongst many industry managers about not falling behind. Over one-third of survey respondents, for example, believe AI will enable technology companies to enter and disrupt their industry.

44% of executives say delaying AI implementation will make their business vulnerable to new, disruptive tech start-ups

Figure 2: AI is bad news for slow movers
Delaying AI implementation will make business vulnerable to start-ups (% of respondents)

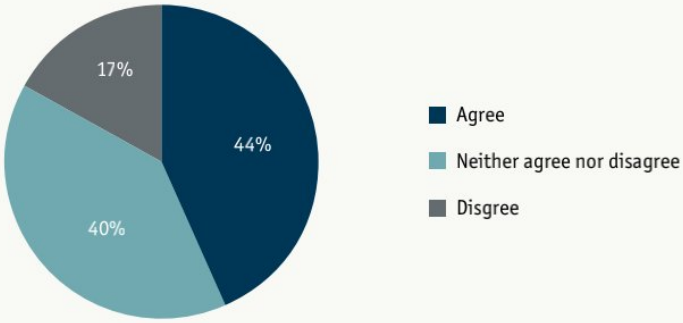
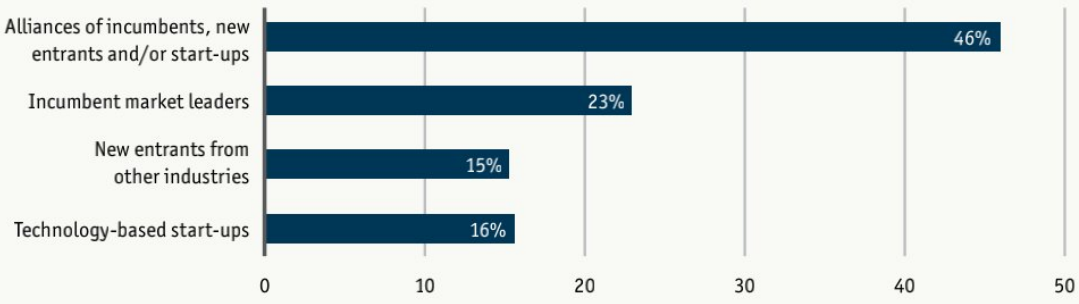


Figure 3: AI could revolutionise technology start-ups
Market players that are most likely to bring about the greatest change in your industry (% of respondents)



Even more (44%) say that delaying AI implementation will make their own business vulnerable to such technology-based raiders (figure 2). Almost half (46%) believe it will be start-ups rather than incumbents who shake their markets up the most (figure 3).

The shape of returns to come

Along with the fear of disruption comes the hope of handsome returns. The business expectations run high, although not necessarily in relation to financial results (at least in the short term).

Many respondents expect AI to have a positive impact on their key performance metrics over the next five years, such as revenue, operating efficiency and quality of decision-making (figure 4). For most companies, though, AI's greater impact is likely to be felt in the area of user experience. John Straw believes the use of AI technologies will, for example, lead to more productive and efficient customer service interaction (notwithstanding the current imperfections of chatbots). But the bigger reward is what services (and products) companies can provide based on analysis of the data they are gathering from customers.

"Ultimately it starts with improving the customer experience," says Chris Gelvin, chief operating officer for Group COO functions at UBS, a Swiss bank. "Customers will notice the faster responses, reduced error rates and new insights we're able to provide. We will also obtain some nice benefits of increased control, better insights for ourselves, and better ways to become more effective and efficient. If you attack this as a cost play, you'd be limiting the possibilities that these technologies have to offer."

AI's potential for improving the user experience is readily visible in the healthcare sector, where users are both patients and practitioners. Mr LeCun of Facebook includes healthcare amongst the sectors likely to experience a sizeable impact from AI technologies in the next 3-5 years. "The impact will go beyond medical image analysis to such areas as genomics, predictive models that can predict the course of development of an illness and suggest a plan for treatment."

Matthew Howard, European lead of IBM Watson Health, adds that AI systems can do this at unprecedented scale. "If in performing a literature review you need to look through 25 scientific papers and you want to extract a series of data points from them, that is quite a labour intensive exercise. You really want to be doing the high value-added analysis. AI techniques will help do that much faster and with a reduced risk of missing anything. But you also increase the scale of what you can feed into it. So instead of looking at 25 papers you can look at 10,000."

Mobile apps which help individuals to monitor diet and fitness levels, and recommend courses of action to improve them, are now commonplace, numbering in the thousands. A more recent phenomenon is apps that diagnose users' maladies. One such service is provided by Your.MD, a London-based firm; the AI-based software behind the app analyses user-provided and public health service data not only to diagnose an individual's ailment but to suggest non-prescription medicines or home procedures that could relieve the symptoms [see "Creating a new healthcare market with AI"].

Artificially intelligent decisions

There are few clearer examples of AI's cognitive power than in equity trading, where investment firms are beginning to deploy powerful machine learning algorithms that make frequent and sizeable portfolio decisions. Large fund managers

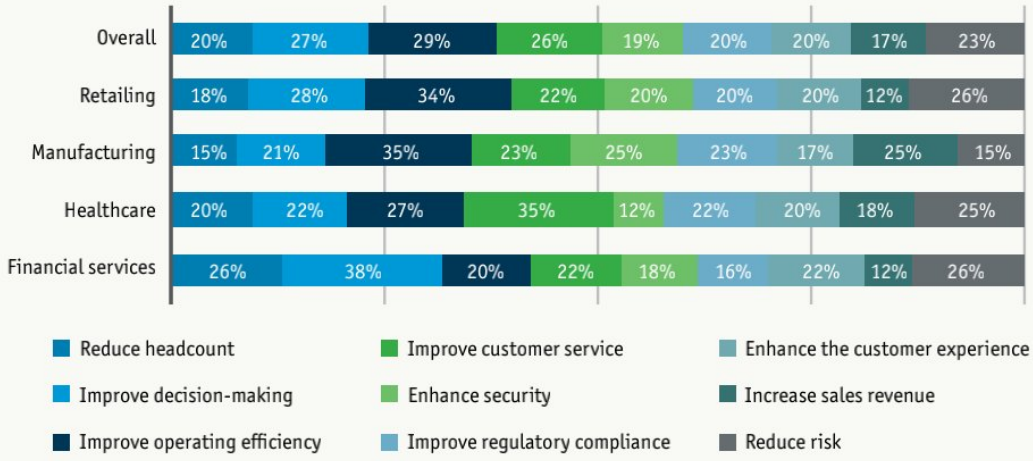
Case study 2: Creating a new healthcare market with AI

In the UK, a common complaint about the National Health Service (NHS)—from staff as well as the public—is that general practitioners (GPs) and primary care surgeries are overburdened. Some GPs and support staff grumble about visitor overload and excessive bureaucracy, while in London and other big cities, waiting times for GP appointments stretch ever longer. Matteo Berlucchi, chief executive of Your.MD, a digital healthcare firm, offers an explanation: "The reason there are so many problems with primary care is that there is no 'pre-primary care'. There is no shield or gateway which filters people from when they're not well to primary care." Too often, he believes, people see a GP when they don't really need to.

Your.MD, a firm founded in Norway of which Mr Berlucchi is chief executive, has created a mobile app which uses AI techniques to provide users with personalised advice about their medical complaints. Along with personal factors, the app records the user's symptoms and matches these with a 'map' of clinical data about illnesses compiled from public sources with the help of contributing doctors. According to Mr Berlucchi, Your.MD engages about 30 doctors to conduct research on symptoms, conditions and treatments and to "teach" the AI system. Additional information is gathered through crowdsourcing on web forums. The more data it ingests from multiple sources and the more interactions it has with users, he says, the more accurate its diagnoses become.

For Mr Berlucchi and Your.MD, the opportunity is to create a new, "pre-primary care" market which does not exist today. Far from displacing humans in healthcare provision, he says, such systems will ease the existing burdens of medical staff and help improve their work. "We think initial screening of non-acute conditions could be done digitally," he says, "thereby giving doctors more time with patients that would benefit from a consultation." The benefit to users, he says, is providing them with information and suggestions for relieving their symptoms without having to wait for a GP appointment.

Figure 4: AI will improve operational efficiency, decision making and customer service
Main benefits from introducing AI to business (% of respondents)



such as Blackrock and Bridgewater, as well as small players such as Aidyia, have been quietly testing AI trading strategies for three or more years. Mr Goertzel emphasises that AI trading systems like Aidyia's are much more about accuracy of investment decisions than about their speed.

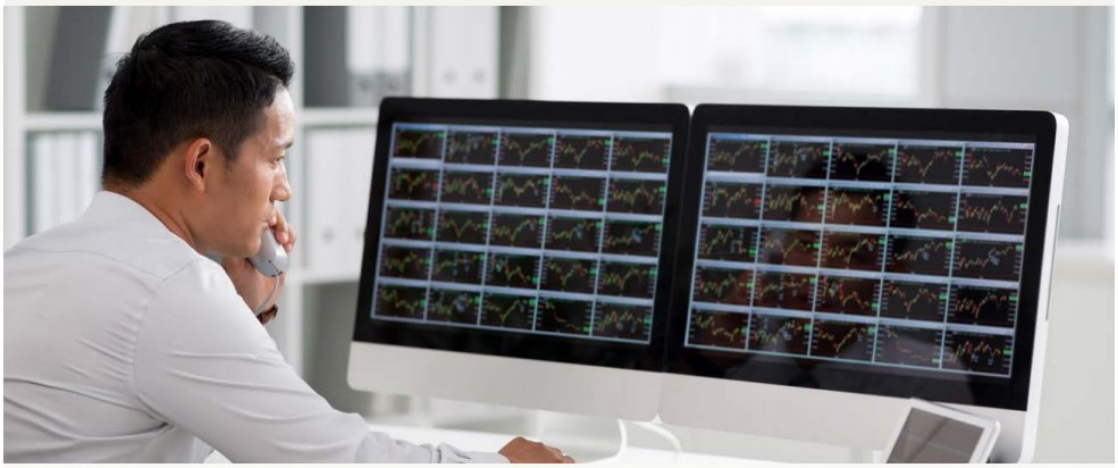
The same will be true in retail investing, where "robo-advisers" today make automated online recommendations to individual investors about individual trades or wider portfolio decisions. Robo-advice has thus far been generated for clients using pre-programmed algorithms. Financial management firms are now beginning to apply AI techniques to robo-advice delivery; when fully integrated, the machine-generated recommendations will be based on a wider-scale and more in-depth analysis of market and environmental data (including social media sentiment) as well as each individual's past investment behaviour and preferences. The algorithms will, moreover, evolve and adapt themselves as situations and data change.

Banks are similarly planning to upgrade their automated services provided to customers with the help of AI. The UK's Royal Bank of Scotland, for example, will employ AI-powered robo-advisers to provide investment advice to its wealth-management customers. Switzerland's UBS is doing the same. In part they are responding to the challenge laid down by successful robo-adviser start-ups, such as UK-based Nutmeg and Wealthfront in the US.

In the healthcare field, Mr Howard cites another reason why AI systems should improve decision-making. "Unlike humans, AI-based machines are unbiased. For example, once it is appropriately trained, an AI system may give a senior leader a very unbiased, unblinkered view of the information and possible options, and the individual can then decide on what actions to take."

Customer experience may be a high priority, but the goal of improving efficiency is, of course, never far from a good CEO's or CFO's mind. It is integral to the AI business case for most organisations considering it,

Case study 3: AI in financial markets: risk agent or risk minimiser?



Equity trading is no stranger to algorithm-based automation, but the results have not always been as anticipated. High-frequency trading (HFT), for example, accounted for a large share of trading volumes in the US and other major markets between 2008 and 2013, but since then its popularity amongst trading firms has tailed off, mainly due to declining margins from such activity. However, HFT is also widely believed to have caused or contributed to several bouts of extreme market volatility (notably the 2010 "Flash Crash" in the US).

AI-powered trading is vastly different, says Ben Goertzel, chief scientist of Aidyia, a small Hong Kong-based hedge fund which has been trading in the US using machine learning techniques since early 2016. Both its, and HFT systems are fully automated, but the similarities end there. "What we're doing is not about speed at all," he explains, but the ability to identify patterns humans could not be expected to see when analysing vast amounts of data. "It's about the accuracy of investment decisions rather than about speed." He adds that some decisions made by its system may be a few weeks or more in the making, as it needs to view time series of data in order to identify patterns. Seen from this vantage point, AI systems' greater accuracy and deliberation should help to reduce the risks of market volatility rather than heighten them.

Others see a different type of risk involved with AI systems. For Gerrit van Wingerden, who manages the Japan office of Tora Trading Services, it's the risk of the unknown. He explains: "Before when you had an algorithm that was coded using human rules, you would know exactly how the algorithm works. Now it's more of a black box; you're throwing data at it, the algorithm comes up with an approach that might deliver great results, but you really don't know necessarily what the algorithm is doing."

This is all the more reason, says Mr van Wingerden, why humans need to remain involved in the process, setting the risk parameters. Even then, he warns, financial regulators, not to mention risk managers, are wary about the potential fall-out should a company's trading algorithms go awry.

Case study 4: Ocado's "flying swarms of intelligent robots"

Logistics and digital technology both lie at the heart of the business model of Ocado, an online-only grocery retailer based in the UK. Working with academic and other partners, Ocado has in recent years been developing and piloting different types of warehouse systems that incorporate AI elements, according to its chief technology officer, Paul Clarke. One is a humanoid robot, dubbed "Second Hands", which is designed to assist maintenance engineers as they fix mechanical problems at its own (and ultimately its customers') facilities. What will make Second Hands different to earlier factory-floor robots, says Mr Clarke, is its ability to "learn on the job, applying lessons gained from its work with its human colleagues to other situations".

Should another technology programme meet its objectives, Second Hands will be far from the only AI-powered robot operating in Ocado's warehouses. A fully automated facility soon to open in Hampshire will, according to Mr Clarke, "have swarms of thousands of robots flying around that are controlled by a very sophisticated, machine-learning-based traffic control system." He likens the warehouse to a chessboard: "Imagine rooks moving down rows or columns. The 'chessboard' actually overlays stacks of storage bins; a rook, or robot, can pick up a bin from the top of a stack and either move it to another stack or bring it outside of that grid. There, different machines pick items from it and other bins and place them in a customer order." Human involvement with the flying robots will be minimal, says Mr Clarke.

AI also figures prominently in other Ocado initiatives. These include the robotic picking of groceries—"much more complex than picking up components in a production line", according to Mr Clarke, requiring intelligent vision systems and dexterous handling. Another is autonomous guided vehicles (AGVs), such as drones and driverless cars.

As beneficial as such initiatives are expected to be for Ocado's efficiency and competitiveness, its management has even grander plans—to become a platform provider. The company wants to make its AI, robotics and other technologies available to other retailers looking to make the shift to online without having to invest in their own technology. "We want to offer the same shortcut to moving online to large bricks-and-mortar grocery retailers around the world," says Mr Clarke.

and the chief benefit that manufacturers and retailers in particular hope to gain.

Markus Lorenz, Munich-based partner of the Boston Consulting Group (BCG), believes that the gains in manufacturing will be won less on the production floor, where (human-programmed) robots have been a presence for many years, and more in areas such as predictive maintenance of machinery and in product design. When it comes to the latter, he says, AI will help designers learn how better to produce and assemble a new product. "What will be the product's wear and tear properties? How can it be best assembled? How can it be best serviced? That's a massive amount of data that an engineer or designer cannot credibly own. But an AI system will provide all that information and inform the designer of the trade-offs that need to be made."

Ralf Herbrich of Amazon describes the advantage AI brings to large-scale stock handling: "In the past a stock manager may have been able to manage a portfolio of 1,000 different products during a day. Now, a person can probably manage 100,000 different products, thanks to the past accuracy of the patterns identified by the algorithms. Some are still erroneous, but with the help of scientists and engineers, this can probably be pushed to a million products per person. That helps an individual to reach a much higher level of efficiency, because the easy-to-predict patterns and decisions are taken care of by algorithms."

Jared Teo, senior program officer with the Health Innovation Fund, California Health Care Foundation, also sees big potential for efficiency gains in healthcare. Improvements in workflow and operations, for example, will boost hospitals' operational efficiency by helping staff make better choices around resource allocation. AI systems, he says, can take data about weather patterns and local events and make predictions about emergency room traffic, allowing the hospital to staff more efficiently.

3 Industry perspectives on the AI impact

The AI impact on business functions will play out differently in the different sectors. In financial services firms, AI's impact is expected to be felt most strongly in the area of customer interaction (figure 5); in manufacturing firms—product development (figure 5).

Respondents from health and life sciences firms, meanwhile, anticipate the AI impact will be greatest in management decision-making (figure 5). Retail executives believe the effects will be equally tangible across transport and logistics, pricing and promotion, supplier interaction, and management decision-making (figure 5).

Figure 5: Industry comparison of AI impact on business functions
Functions on which AI will have the greatest impact in the next 5 years (% of respondents)

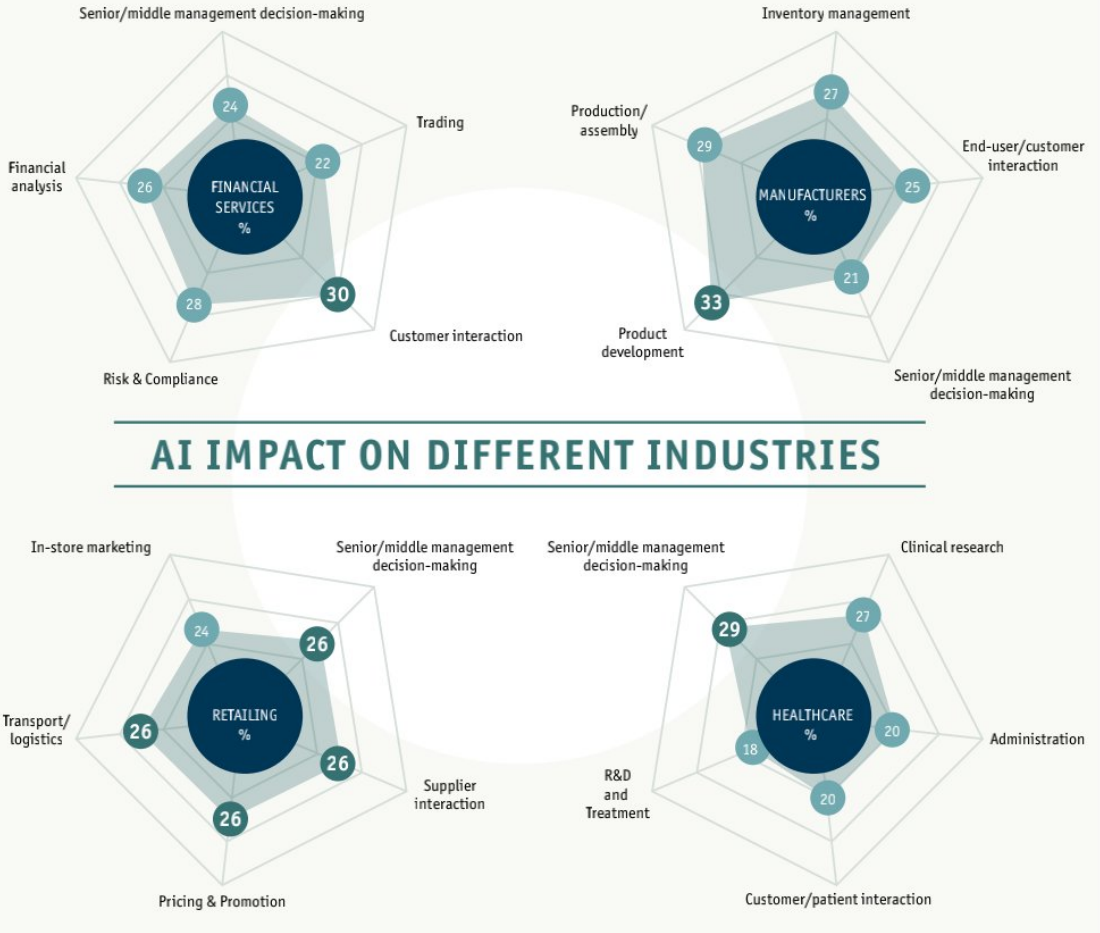
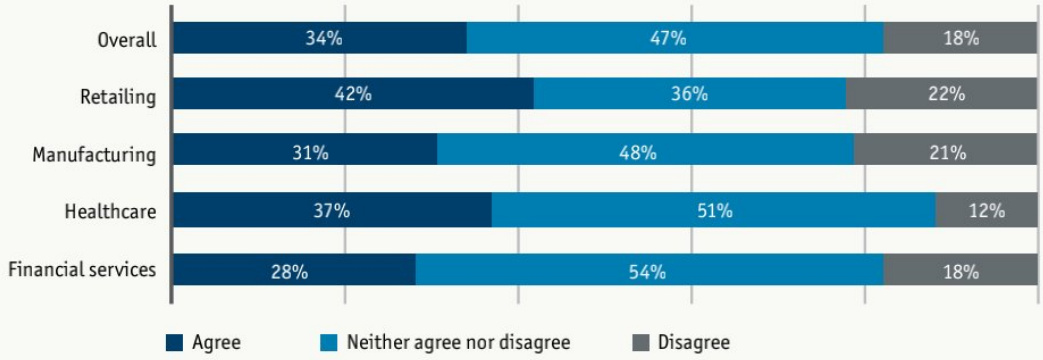


Figure 6: Executives in retail industry are wary of AI
AI poses more risks than opportunities (% of respondents)

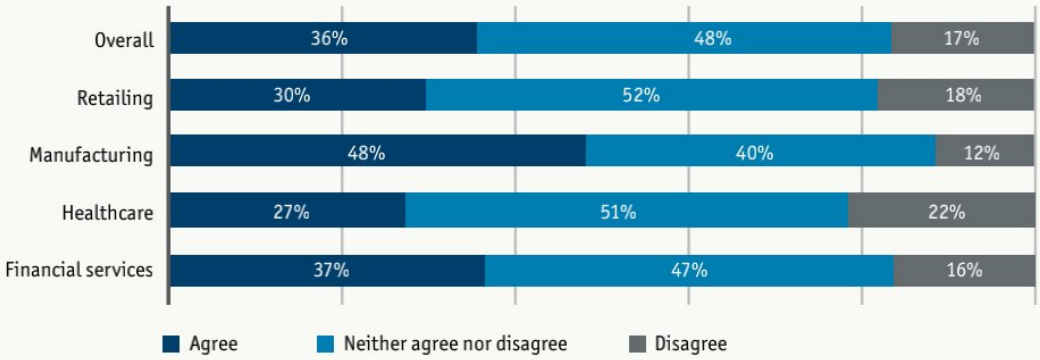


Retailers express greater concern than peers from other industries with the risks that AI poses to businesses (figure 6).

Manufacturers are particularly wary of AI-driven disruption to their industry from technology entrants (figure 7).

Operating efficiency is the primary area where manufacturers and retailers hope to see gains from AI implementation, whereas healthcare and life sciences firms place the greatest hope on customer (patient) service gains. For financial service providers, better decision-making is the chief reward (figure 4).

Figure 7: Executives in manufacturing think AI is a threat to their industry
AI will enable disruptive technology entrants (% of respondents)



4 Rising to the challenges

Past dawns of emerging business technology have often been followed by executive disappointment once the implementation challenges they posed became clear. The executives in our survey appear reasonably level-headed about AI from the outset, however. Asked about the impact AI will have on their organisation over the next five years, half (49%) believe it will be moderate, and another 20% expect little or no impact at all.

One reason for the sober thinking may be that, for many non-technology managers, AI remains a futuristic concept. Building a business case for investment in AI projects is not straightforward when senior management lack a clear understanding of AI and machine learning and the concepts behind them (a complaint of over 30% of survey respondents).

30% of surveyed executives admit that senior management lacks sufficient understanding of AI which makes building a business case for AI challenging

Even for those managers knowledgeable about AI, the business case is complicated by the immaturity of the technologies and their business application. Ocado's Mr Clarke emphasises that much remains unclear about AI, and for some companies it will raise more questions than answers. "If you're not going to build platforms and applications yourself like we do, who will? Standards are still missing in many product areas, as are guidelines around privacy and security. Many pieces of the puzzle are missing."

Cost and data

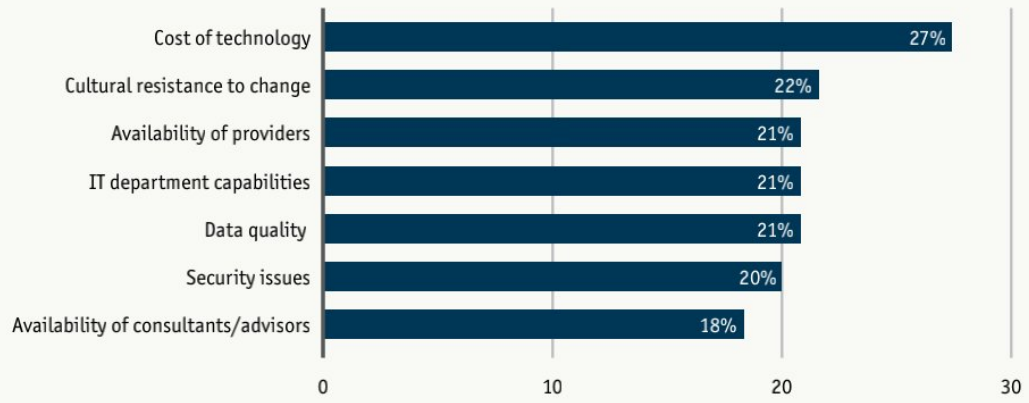
Businesses will not be able to answer most of these questions themselves, but they can do more to address the practical challenges of implementing AI technologies. Top of this list for respondents—and by some distance for manufacturers—is cost (figure 8).

Mr Clarke agrees that AI-powered robotics used in warehouses or production floors involve large adoption costs. Small companies can manage these by using third-party cloud platforms. Developers at smaller businesses can also take advantage of the open-source AI platforms that big technology companies have recently made available. Gerrit van Wingerden, managing director of Japan Tora Trading Services, reports that smaller firms like his are utilising such platforms to good effect. "You can do the training much more quickly than you could internally, and the rates are affordable. Plus, you don't really have to worry about the software because it's fairly easy to use the platform. Now many more firms can use these algorithms."

The data-crunching power underpinning AI and predictive analytics involve two types of costs, believes Amazon's Mr Herbrich. One is the cost of training, referred to above. The other he calls the "cost of predictions", which scale differently. "These are the hardware and energy costs that are run up with every single computation and prediction. As we think about deploying AI technology worldwide, per individual, the prediction costs will scale with every use."

AI's effectiveness rests on its ability to analyse and learn from large volumes of data. It goes without

Figure 8: Executives cite technology cost as the biggest obstacle for AI
Practical challanges to implementing AI in business (% of respondents)



saying that the learning and the predictions will only be as good as the quality of the data. Matteo Berlucchi believes this presents enormous challenges for the healthcare industry: "Countries' healthcare systems are typically fragmented and based on old models. Only a few hospitals embrace data collection in the correct way. Data quality and quantity is a challenge for most companies in the industry, especially start-ups."

Mr LeCun agrees: "The obstacle to AI implementation in healthcare is not technological but access to data. Research is hampered by difficulties in accessing large medical data sets, for legal or other reasons. It's particularly tough for start-ups in the field; larger players already have access to such data."

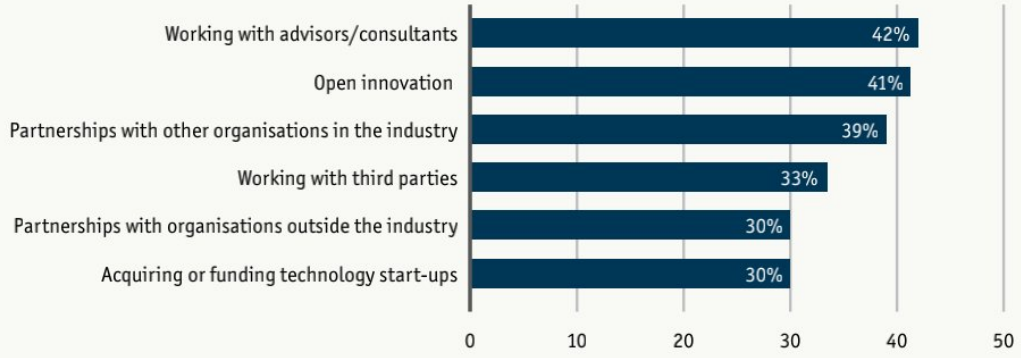
Cleaning your data is Mr Herbrich's chief recommendation for companies embarking on AI projects. "The most important thing any company must do is start collecting clean data. If you don't have clean data—identities about your product, your vendors, your customers, other information that is accessible—you will not have the input to generate accurate predictions. Noisy data, where identities are re-used, or records are missing, is hard to correct. It is better to have no data."

40% of North American firms and 38% of manufacturers say they are acquiring or funding technology start-ups

Culture skirmishes

Cultural resistance to change—also high on the list of practical challenges provided by respondents—will be a tougher nut to crack for many companies. Ben Goertzel deems this the biggest implementation challenge that the financial sector will face with AI. "It's very cross-disciplinary at this point to get AI to work really well in the finance domain.... It will take a while for finance industry companies to build up the cultural and intellectual assets where you have finance people who know enough about machine learning and machine learning people who know enough about finance, and they can work together productively to get these applications to work." He observes that this

Figure 9: External collaboration and openness are key to AI implementation
Companies explore different ways to develop AI capability (% of respondents)



is easier done in a start-up than, say, a large bank. "Start-ups can bring together people from different backgrounds and let them work together freely. Banks, though, are rigidly structured and not always agile. It often takes them years or decades to change each time a paradigm shift comes along."

Business leaders are all too familiar with internal resistance to technology-led change. When it comes to developing AI capabilities, relatively few are relying on internal assets alone. Large numbers in the survey, particularly in North America and Asia-Pacific, say their firms are looking to crowdsourcing and other forms of open innovation to develop AI applications (figure 9). Many others are partnering with other organisations inside and outside their sector. Almost one-third (40% of North American firms and 38% of manufacturers) are acquiring or funding technology start-ups. Such partnerships often allow companies to sidestep entrenched silos in order to implement new processes or services based on new technologies.

Case study 5: AI visions for manufacturing

According to Per Vegard Nerseth, managing director of the robotics business unit at ABB, an industrial engineering company, there are no standardised manufacturing robots today that have real AI or machine learning capabilities. They are very much part of his "factory of the future", however. Tomorrow's intelligent robots, he expects, will master the extremely complex (for robots) processes of assembly. Using cameras, for example, the robot will observe the steps the human engineer is taking to assemble a car or a mobile device. Machine learning will enable the robot to repeat and perfect the process itself, and over time it will perform the assembly without any programming at all.

Frank Kirchner, head of the Robotics Innovation Center at the German Research Center for Artificial Intelligence, also sees an intelligent robot emerging. "In contrast to the standard robots familiar to manufacturers, which are no more than 'automation tools', the intelligent robot is equipped with sensors and computing equipment, and can not only read sensor data but also interpret it and modify its actions according to this interpretation." Mr Kirchner and his colleagues foresee "hybrid social teams" working on the production floor in the not-too-distant future, consisting of both stationary and mobile robots, working in direct, "handshaking" interaction with one or more human beings.

Beyond greater operating efficiency, the chief benefit for manufacturers will be much greater flexibility, believes Mr Nerseth. "Consumers want to have more specialised products and shorter delivery times. This means production will need to get closer to the market again, requiring much greater production flexibility." Machine learning will be one the agents of such specialisation. Its companion agent, he emphasises, is the Internet of Things and its multitudes of embedded sensors connecting devices to production machinery.

It will take a few years, however, before AI-powered machinery becomes commonplace on the shop floor, says Mr Nerseth. Manufacturers will likely deploy it first in front-office functions. The reason is the need for absolute certainty of reliability. "When it comes to high-volume manufacturing, no management team would risk [deploying AI] before they are 100% sure of a system's reliability. They need to be certain of very high levels of uptime. An outage of just 15 minutes could be devastating for large producers."

5 A question of disruption

Notwithstanding the title of his recent book ("Humans need not apply"), Jerry Kaplan does not share the alarm some economists have voiced about the threat AI poses to employment. He sees AI as essentially an advanced form of automation. "AI has a big public relations problem," he says, "All we are doing is developing a set of new engineering techniques that can automate tasks that have resisted automation in the past." On the subject of jobs, he adds that "AI doesn't just replace people. There will be all kinds of new things that people will be able to do but can't do now."

> "AI will actually create more jobs in healthcare than it replaces. There is so much unmet demand [for health services] that needs to be addressed. If you equip healthcare professionals with tools like AI you can have more people join the industry and use these tools to service the unmet demand."
>
> Jared Teo, senior program officer, Health Innovation Fund, California Health Care Foundation

His views on job displacement are echoed by other experts. James Hendler of Rensselaer Polytechnic acknowledges that AI will inevitably eliminate some human roles, but for the most part will take over certain, especially repetitive, tasks performed by humans today and not necessarily entire jobs. "Most AI applications today need a human in the loop to some degree. We're seeing more interaction between the human and the machine but the human is still very involved."

Mr Berlucchi believes the displacement theory will not apply to healthcare any time soon. "It is true that AI and machines will perform many tasks performed by medical or clinical staff today. But because everyone is overworked by at least 100%, there will be few job losses; AI will optimise the professionals' work and relieve the pressure on the system."

The manufacturing sector has more experience than others in dealing with the fallout from automation, including from robots on the production floor. Mr Lorenz believes manufacturers will again see displacement of humans being partially attenuated by re-skilling. He relates that one of his clients is currently replacing some shop-floor employees with intelligent systems. Many of these individuals, however, are being trained to work with virtual reality (VR) headsets to help them become expert field service engineers, of which it currently has a shortage—and, he adds, command relatively high wages.

An exception to the optimism is John Straw, who believes significant job losses will be unavoidable in the retail industry. He cites a McKinsey report which suggests that by 2025 up to 40m white and blue collar workers will be out of a job in the West due to automation. "Unfortunately I think an awful lot of those are going to be in retail, and the channel will need to repurpose and retrain." He explains that a large number of retail jobs have a very precise and tight job description, with a large number of repetitive tasks. These jobs, he points out, lend themselves to AI-based automation. "You will still need retail workers at a senior level to teach the robots, but that is an interim step to full singularity where the robots will learn from each other. Such technology is already with us."

Happier employees?

Another retail industry representative, Eric Colson, chief algorithms officer of Stitch Fix, an online apparel shopping service, sees AI as a complement to the work of its human clothing stylists rather than a replacement. Their work is heavily influenced by the analysis and suggestions of the company's "styling algorithms". Mr Colson finds it more than a coincidence that measured job satisfaction amongst the stylists is highest than in any other category of employee in the company. [See "Algorithms for your evening wear".]

46% of executives anticipate that AI will displace humans from certain roles within the next 5 years

The majority of survey respondents believe this will be the case for themselves and their organisations. Over four in 10 anticipate that AI technologies will begin displacing humans from certain roles in their industry within the next five years (figure 13). Even more (46%) believe their own job is likely to be performed by an AI-based technology in the same time frame. However, most respondents perceive this in a positive rather than negative light. Nearly 8 in 10 believe AI will make their job easier and make them more efficient.

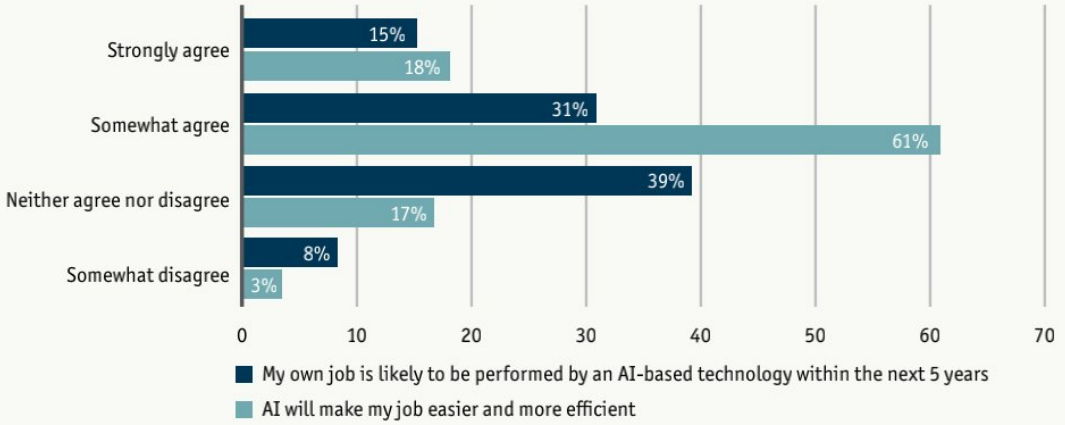
79% of executives believe AI will make their job easier and more efficient

"A guy working 30 years on an automotive manufacturing line comes to the shop floor one day and there's an intelligent robot there in place of his old colleague. What is this guy going to think? It will be a drastic change for him. This will happen in the next five years."

Frank Kirchner, head, Robotics Innovation Center, German Research Center for Artificial Intelligence

Slightly more than half of executives also believe that machines "will never be able to make the types of intelligent business decisions that managers make."

Figure 13: AI stands to replace or improve most jobs
Executives expect AI will replace some jobs and bring more efficiency (% of respondents)



Yann LeCun isn't as sure: "Never say never. AI-based systems making business decisions on their own may not emerge tomorrow or in a couple of decades. It doesn't make sense for businesses to worry about this today. But it will happen, no question. It's a matter of time."

6 Conclusion: Embracing the unknown

How disruptive, then, will AI prove to be? Most survey respondents expect big changes at a broad level: seven in 10 believe that, like the Internet, AI will lead eventually to the creation of new industries and the demise of others. The experts we interviewed for the study stop short of such dramatic predictions, at least with the medium term in view. Some expect AI to have a transformative effect on their respective industries, but in the short and medium terms more in operational terms. Another anticipates the emergence of new business models but does not expect a major restructuring of sectors because of AI.

If AI realises its business potential in the next 3-5 years, there is little question that it will lead to significant improvements in processes, as well as in the precision and reliability, and possibly the speed, of operational business decisions. AI is also more likely to enhance security and improve risk management than to weaken them, although some have concerns about AI's potential misuse.

The greatest risks that AI poses to companies probably lie less in its potential for disruption, and more in the unknowns surrounding it. After all, AI has only recently made it out of the laboratory, and business leaders are only now realising its commercial potential. Scientists believe there is a long way to go before they even scratch the surface of AI's capabilities. It cannot be discounted that AI will take businesses and industries in directions they do not want to go. But its future development is at least as likely to uncover new and exciting applications that will benefit companies and consumers alike.

Either way, businesses cannot ignore AI's development. Some may decide AI is not right for them, but existing or future competitors will inevitably lay down a challenge with it.