27 AI: THE PRESENT AND FUTURE

In which we take stock of where we are and where we are going, this being a good thing to do before continuing.

In Chapter 2, we suggested that it would be helpful to view the AI task as that of designing rational agents—that is, agents whose actions maximize their expected utility given their percept histories. We showed that the design problem depends on the percepts and actions available to the agent, the utility function that the agent's behavior should satisfy, and the nature of the environment. A variety of different agent designs are possible, ranging from reflex agents to fully deliberative, knowledge-based, decision-theoretic agents. Moreover, the components of these designs can have a number of different instantiations—for example, logical or probabilistic reasoning, and atomic, factored, or structured representations of states. The intervening chapters presented the principles by which these components operate.

For all the agent designs and components, there has been tremendous progress both in our scientific understanding and in our technological capabilities. In this chapter, we stand back from the details and ask, *"Will all this progress lead to a general-purpose intelligent agent that can perform well in a wide variety of environments?"* Section 27.1 looks at the components of an intelligent agent to assess what's known and what's missing. Section 27.2 does the same for the overall agent architecture. Section 27.3 asks whether designing rational agents is the right goal in the first place. (The answer is, "Not really, but it's OK for now.") Finally, Section 27.4 examines the consequences of success in our endeavors.

27.1 Agent Components

Chapter 2 presented several agent designs and their components. To focus our discussion here, we will look at the utility-based agent, which we show again in Figure 27.1. When endowed with a learning component (Figure 2.15), this is the most general of our agent designs. Let's see where the state of the art stands for each of the components.

Interaction with the environment through sensors and actuators: For much of the history of AI, this has been a glaring weak point. With a few honorable exceptions, AI systems were built in such a way that humans had to supply the inputs and interpret the outputs,

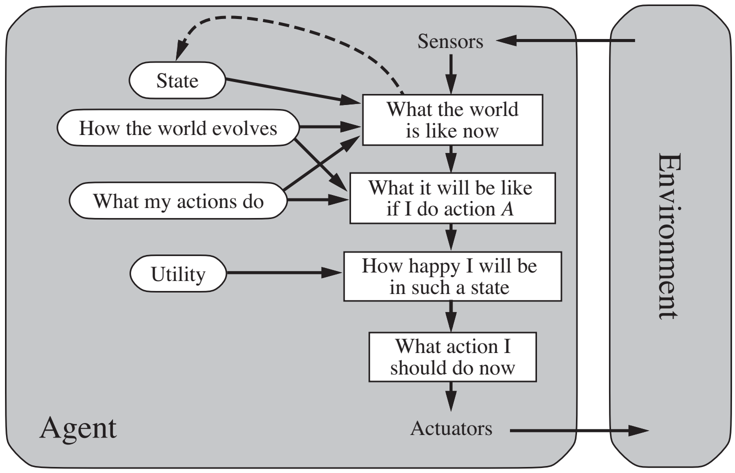

Figure 27.1 A model-based, utility-based agent, as first presented in Figure 2.14.

while robotic systems focused on low-level tasks in which high-level reasoning and planning were largely absent. This was due in part to the great expense and engineering effort required to get real robots to work at all. The situation has changed rapidly in recent years with the availability of ready-made programmable robots. These, in turn, have benefited from small, cheap, high-resolution CCD cameras and compact, reliable motor drives. MEMS (micro-electromechanical systems) technology has supplied miniaturized accelerometers, gyroscopes, and actuators for an artificial flying insect (Floreano *et al.*, 2009). It may also be possible to combine millions of MEMS devices to produce powerful macroscopic actuators.

Thus, we see that AI systems are at the cusp of moving from primarily software-only systems to embedded robotic systems. The state of robotics today is roughly comparable to the state of personal computers in about 1980: at that time researchers and hobbyists could experiment with PCs, but it would take another decade before they became commonplace.

Keeping track of the state of the world: This is one of the core capabilities required for an intelligent agent. It requires both perception and updating of internal representations. Chapter 4 showed how to keep track of atomic state representations; Chapter 7 described how to do it for factored (propositional) state representations; Chapter 12 extended this to first-order logic; and Chapter 15 described **filtering** algorithms for probabilistic reasoning in uncertain environments. Current filtering and perception algorithms can be combined to do a reasonable job of reporting low-level predicates such as "the cup is on the table." Detecting higher-level actions, such as "Dr. Russell is having a cup of tea with Dr. Norvig while discussing plans for next week," is more difficult. Currently it can be done (see Figure 24.25 on page 961) only with the help of annotated examples.

Another problem is that, although the approximate filtering algorithms from Chapter 15 can handle quite large environments, they are still dealing with a factored representation—they have random variables, but do not represent objects and relations explicitly. Section 14.6 explained how probability and first-order logic can be combined to solve this problem, and

Section 14.6.3 showed how we can handle uncertainty about the identity of objects. We expect that the application of these ideas for tracking complex environments will yield huge benefits. However, we are still faced with a daunting task of defining general, reusable representation schemes for complex domains. As discussed in Chapter 12, we don't yet know how to do that in general; only for isolated, simple domains. It is possible that a new focus on probabilistic rather than logical representation coupled with aggressive machine learning (rather than hand-encoding of knowledge) will allow for progress.

Projecting, evaluating, and selecting future courses of action: The basic knowledge-representation requirements here are the same as for keeping track of the world; the primary difficulty is coping with courses of action—such as having a conversation or a cup of tea—that consist eventually of thousands or millions of primitive steps for a real agent. It is only by imposing **hierarchical structure** on behavior that we humans cope at all. We saw in Section 11.2 how to use hierarchical representations to handle problems of this scale; furthermore, work in **hierarchical reinforcement learning** has succeeded in combining some of these ideas with the techniques for decision making under uncertainty described in Chapter 17. As yet, algorithms for the partially observable case (POMDPs) are using the same atomic state representation we used for the search algorithms of Chapter 3. There is clearly a great deal of work to do here, but the technical foundations are largely in place. Section 27.2 discusses the question of how the search for effective long-range plans might be controlled.

Utility as an expression of preferences: In principle, basing rational decisions on the maximization of expected utility is completely general and avoids many of the problems of purely goal-based approaches, such as conflicting goals and uncertain attainment. As yet, however, there has been very little work on constructing *realistic* utility functions—imagine, for example, the complex web of interacting preferences that must be understood by an agent operating as an office assistant for a human being. It has proven very difficult to decompose preferences over complex states in the same way that Bayes nets decompose beliefs over complex states. One reason may be that preferences over states are really *compiled* from preferences over state histories, which are described by **reward functions** (see Chapter 17). Even if the reward function is simple, the corresponding utility function may be very complex. This suggests that we take seriously the task of knowledge engineering for reward functions as a way of conveying to our agents what it is that we want them to do.

Learning: Chapters 18 to 21 described how learning in an agent can be formulated as inductive learning (supervised, unsupervised, or reinforcement-based) of the functions that constitute the various components of the agent. Very powerful logical and statistical techniques have been developed that can cope with quite large problems, reaching or exceeding human capabilities in many tasks—as long as we are dealing with a predefined vocabulary of features and concepts. On the other hand, machine learning has made very little progress on the important problem of constructing new representations at levels of abstraction higher than the input vocabulary. In computer vision, for example, learning complex concepts such as $Classroom$ and $Cafeteria$ would be made unnecessarily difficult if the agent were forced to work from pixels as the input representation; instead, the agent needs to be able to form intermediate concepts first, such as $Desk$ and $Tray$, without explicit human supervision. Similar considerations apply to learning behavior: $HavingACupOfTea$ is a very important high-level step in many plans, but how does it get into an action library that initially contains much simpler actions such as $RaiseArm$ and $Swallow$? Perhaps this will incorporate some of the ideas of **deep belief networks**—Bayesian networks that have multiple layers of hidden variables, as in the work of Hinton *et al.* (2006), Hawkins and Blakeslee (2004), and Bengio and LeCun (2007).

DEEP BELIEF NETWORKS

The vast majority of machine learning research today assumes a factored representation, learning a function $h : \mathbb{R}^n \to \mathbb{R}$ for regression and $h : \mathbb{R}^n \to \{0, 1\}$ for classification. Learning researchers will need to adapt their very successful techniques for factored representations to structured representations, particularly hierarchical representations. The work on inductive logic programming in Chapter 19 is a first step in this direction; the logical next step is to combine these ideas with the probabilistic languages of Section 14.6.

Unless we understand such issues, we are faced with the daunting task of constructing large commonsense knowledge bases by hand, an approach that has not fared well to date. There is great promise in using the Web as a source of natural language text, images, and videos to serve as a comprehensive knowledge base, but so far machine learning algorithms are limited in the amount of organized knowledge they can extract from these sources.

27.2 AGENT ARCHITECTURES

It is natural to ask, "Which of the agent architectures in Chapter 2 should an agent use?" The answer is, "All of them!" We have seen that reflex responses are needed for situations in which time is of the essence, whereas knowledge-based deliberation allows the agent to plan ahead. A complete agent must be able to do both, using a **hybrid architecture**. One important property of hybrid architectures is that the boundaries between different decision components are not fixed. For example, **compilation** continually converts declarative information at the deliberative level into more efficient representations, eventually reaching the reflex level—see Figure 27.2. (This is the purpose of explanation-based learning, as discussed in Chapter 19.) Agent architectures such as SOAR (Laird *et al.*, 1987) and THEO (Mitchell, 1990) have exactly this structure. Every time they solve a problem by explicit deliberation, they save away a generalized version of the solution for use by the reflex component. A less studied problem is the *reversal* of this process: when the environment changes, learned reflexes may no longer be appropriate and the agent must return to the deliberative level to produce new behaviors.

HYBRID ARCHITECTURE

Agents also need ways to control their own deliberations. They must be able to cease deliberating when action is demanded, and they must be able to use the time available for deliberation to execute the most profitable computations. For example, a taxi-driving agent that sees an accident ahead must decide in a split second either to brake or to take evasive action. It should also spend that split second thinking about the most important questions, such as whether the lanes to the left and right are clear and whether there is a large truck close behind, rather than worrying about wear and tear on the tires or where to pick up the next passenger. These issues are usually studied under the heading of **real-time AI**. As AI

REAL-TIME AI

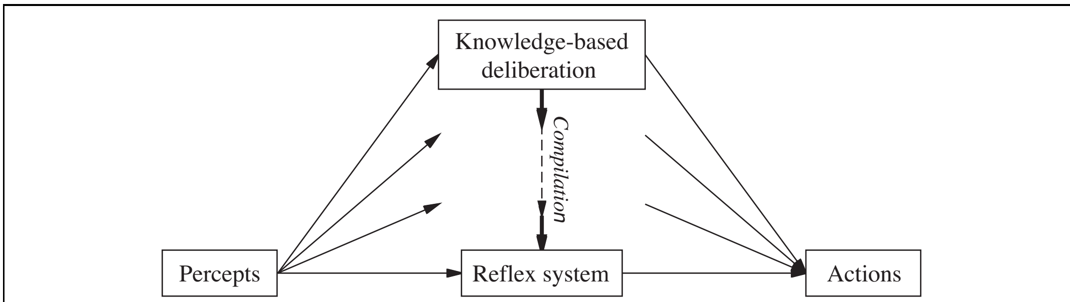

Figure 27.2 Compilation serves to convert deliberative decision making into more efficient, reflexive mechanisms.

systems move into more complex domains, all problems will become real-time, because the agent will never have long enough to solve the decision problem exactly.

ANYTIME ALGORITHM

Clearly, there is a pressing need for *general* methods of controlling deliberation, rather than specific recipes for what to think about in each situation. The first useful idea is to employ **anytime algorithms** (Dean and Boddy, 1988; Horvitz, 1987). An anytime algorithm is an algorithm whose output quality improves gradually over time, so that it has a reasonable decision ready whenever it is interrupted. Such algorithms are controlled by a **metalevel** decision procedure that assesses whether further computation is worthwhile. (See Section 3.5.4 for a brief description of metalevel decision making.) Example of an anytime algorithms include iterative deepening in game-tree search and MCMC in Bayesian networks.

DECISION-THEORETIC METAREASONING

The second technique for controlling deliberation is **decision-theoretic metareasoning** (Russell and Wefald, 1989, 1991; Horvitz, 1989; Horvitz and Breese, 1996). This method applies the theory of information value (Chapter 16) to the selection of individual computations. The value of a computation depends on both its cost (in terms of delaying action) and its benefits (in terms of improved decision quality). Metareasoning techniques can be used to design better search algorithms and to guarantee that the algorithms have the anytime property. Metareasoning is expensive, of course, and compilation methods can be applied so that the overhead is small compared to the costs of the computations being controlled. Metalevel reinforcement learning may provide another way to acquire effective policies for controlling deliberation: in essence, computations that lead to better decisions are reinforced, while those that turn out to have no effect are penalized. This approach avoids the myopia problems of the simple value-of-information calculation.

REFLECTIVE ARCHITECTURE

Metareasoning is one specific example of a **reflective architecture**—that is, an architecture that enables deliberation about the computational entities and actions occurring within the architecture itself. A theoretical foundation for reflective architectures can be built by defining a joint state space composed from the environment state and the computational state of the agent itself. Decision-making and learning algorithms can be designed that operate over this joint state space and thereby serve to implement and improve the agent's computational activities. Eventually, we expect task-specific algorithms such as alpha–beta search and backward chaining to disappear from AI systems, to be replaced by general methods that direct the agent's computations toward the efficient generation of high-quality decisions.

27.3 Are We Going in the Right Direction?

The preceding section listed many advances and many opportunities for further progress. But where is this all leading? Dreyfus (1992) gives the analogy of trying to get to the moon by climbing a tree; one can report steady progress, all the way to the top of the tree. In this section, we consider whether AI's current path is more like a tree climb or a rocket trip.

In Chapter 1, we said that our goal was to build agents that *act rationally*. However, we also said 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.

Now it is time to consider again what exactly the goal of AI is. We want to build agents, but with what specification in mind? Here are four possibilities:

PERFECT RATIONALITY

Perfect rationality. A perfectly rational agent acts at every instant in such a way as to maximize its expected utility, given the information it has acquired from the environment. We have seen that the calculations necessary to achieve perfect rationality in most environments are too time consuming, so perfect rationality is not a realistic goal.

CALCULATIVE RATIONALITY

Calculative rationality. This is the notion of rationality that we have used implicitly in designing logical and decision-theoretic agents, and most of theoretical AI research has focused on this property. A calculatively rational agent *eventually* returns what *would have been* the rational choice at the beginning of its deliberation. This is an interesting property for a system to exhibit, but in most environments, the right answer at the wrong time is of no value. In practice, AI system designers are forced to compromise on decision quality to obtain reasonable overall performance; unfortunately, the theoretical basis of calculative rationality does not provide a well-founded way to make such compromises.

BOUNDED RATIONALITY

Bounded rationality. Herbert Simon (1957) rejected the notion of perfect (or even approximately perfect) rationality and replaced it with bounded rationality, a descriptive theory of decision making by real agents. He wrote,

> The capacity of the human mind for formulating and solving complex problems is very small compared with the size of the problems whose solution is required for objectively rational behavior in the real world—or even for a reasonable approximation to such objective rationality.

He suggested that bounded rationality works primarily by **satisficing**—that is, deliberating only long enough to come up with an answer that is "good enough." Simon won the Nobel Prize in economics for this work and has written about it in depth (Simon, 1982). It appears to be a useful model of human behaviors in many cases. It is not a formal specification for intelligent agents, however, because the definition of "good enough" is not given by the theory. Furthermore, satisficing seems to be just one of a large range of methods used to cope with bounded resources.

BOUNDED OPTIMALITY

Bounded optimality (BO). A bounded optimal agent behaves as well as possible, *given its computational resources*. That is, the expected utility of the agent program for a bounded optimal agent is at least as high as the expected utility of any other agent program running on the same machine.

Of these four possibilities, bounded optimality seems to offer the best hope for a strong theoretical foundation for AI. It has the advantage of being possible to achieve: there is always at least one best program—something that perfect rationality lacks. Bounded optimal agents are actually useful in the real world, whereas calculatively rational agents usually are not, and satisficing agents might or might not be, depending on how ambitious they are.

The traditional approach in AI has been to start with calculative rationality and then make compromises to meet resource constraints. If the problems imposed by the constraints are minor, one would expect the final design to be similar to a BO agent design. But as the resource constraints become more critical—for example, as the environment becomes more complex—one would expect the two designs to diverge. In the theory of bounded optimality, these constraints can be handled in a principled fashion.

As yet, little is known about bounded optimality. It is possible to construct bounded optimal programs for very simple machines and for somewhat restricted kinds of environments (Etzioni, 1989; Russell *et al.*, 1993), but as yet we have no idea what BO programs are like for large, general-purpose computers in complex environments. If there is to be a constructive theory of bounded optimality, we have to hope that the design of bounded optimal programs does not depend too strongly on the details of the computer being used. It would make scientific research very difficult if adding a few kilobytes of memory to a gigabyte machine made a significant difference to the design of the BO program. One way to make sure this cannot happen is to be slightly more relaxed about the criteria for bounded optimality. By analogy with the notion of asymptotic complexity (Appendix A), we can define **asymptotic bounded optimality** (ABO) as follows (Russell and Subramanian, 1995). Suppose a program P is bounded optimal for a machine M in a class of environments **E**, where the complexity of environments in **E** is unbounded. Then program P' is ABO for M in **E** if it can outperform P by running on a machine kM that is k times faster (or larger) than M. Unless k were enormous, we would be happy with a program that was ABO for a nontrivial environment on a nontrivial architecture. There would be little point in putting enormous effort into finding BO rather than ABO programs, because the size and speed of available machines tends to increase by a constant factor in a fixed amount of time anyway.

ASYMPTOTIC BOUNDED OPTIMALITY

We can hazard a guess that BO or ABO programs for powerful computers in complex environments will not necessarily have a simple, elegant structure. We have already seen that general-purpose intelligence requires some reflex capability and some deliberative capability; a variety of forms of knowledge and decision making; learning and compilation mechanisms for all of those forms; methods for controlling reasoning; and a large store of domain-specific knowledge. A bounded optimal agent must adapt to the environment in which it finds itself, so that eventually its internal organization will reflect optimizations that are specific to the particular environment. This is only to be expected, and it is similar to the way in which racing cars restricted by engine capacity have evolved into extremely complex designs. We suspect that a science of artificial intelligence based on bounded optimality will involve a good deal of study of the processes that allow an agent program to converge to bounded optimality and perhaps less concentration on the details of the messy programs that result.

In sum, the concept of bounded optimality is proposed as a formal task for AI research that is both well defined and feasible. Bounded optimality specifies optimal *programs* rather than optimal *actions*. Actions are, after all, generated by programs, and it is over programs that designers have control.

27.4 What If AI Does Succeed?

In David Lodge's *Small World* (1984), a novel about the academic world of literary criticism, the protagonist causes consternation by asking a panel of eminent but contradictory literary theorists the following question: "*What if you were right?*" None of the theorists seems to have considered this question before, perhaps because debating unfalsifiable theories is an end in itself. Similar confusion can be evoked by asking AI researchers, "*What if you succeed?*"

As Section 26.3 relates, there are ethical issues to consider. Intelligent computers are more powerful than dumb ones, but will that power be used for good or ill? Those who strive to develop AI have a responsibility to see that the impact of their work is a positive one. The scope of the impact will depend on the degree of success of AI. Even modest successes in AI have already changed the ways in which computer science is taught (Stein, 2002) and software development is practiced. AI has made possible new applications such as speech recognition systems, inventory control systems, surveillance systems, robots, and search engines.

We can expect that medium-level successes in AI would affect all kinds of people in their daily lives. So far, computerized communication networks, such as cell phones and the Internet, have had this kind of pervasive effect on society, but AI has not. AI has been at work behind the scenes—for example, in automatically approving or denying credit card transactions for every purchase made on the Web—but has not been visible to the average consumer. We can imagine that truly useful personal assistants for the office or the home would have a large positive impact on people's lives, although they might cause some economic dislocation in the short term. Automated assistants for driving could prevent accidents, saving tens of thousands of lives per year. A technological capability at this level might also be applied to the development of autonomous weapons, which many view as undesirable. Some of the biggest societal problems we face today—such as the harnessing of genomic information for treating disease, the efficient management of energy resources, and the verification of treaties concerning nuclear weapons—are being addressed with the help of AI technologies.

Finally, it seems likely that a large-scale success in AI—the creation of human-level intelligence and beyond—would change the lives of a majority of humankind. The very nature of our work and play would be altered, as would our view of intelligence, consciousness, and the future destiny of the human race. AI systems at this level of capability could threaten human autonomy, freedom, and even survival. For these reasons, we cannot divorce AI research from its ethical consequences (see Section 26.3).

Which way will the future go? Science fiction authors seem to favor dystopian futures over utopian ones, probably because they make for more interesting plots. But so far, AI seems to fit in with other revolutionary technologies (printing, plumbing, air travel, telephony) whose negative repercussions are outweighed by their positive aspects.

In conclusion, we see that AI has made great progress in its short history, but the final sentence of Alan Turing's (1950) essay on *Computing Machinery and Intelligence* is still valid today:

We can see only a short distance ahead,
but we can see that much remains to be done.

A MATHEMATICAL BACKGROUND

A.1 COMPLEXITY ANALYSIS AND O() NOTATION

Computer scientists are often faced with the task of comparing algorithms to see how fast they run or how much memory they require. There are two approaches to this task. The first is **benchmarking**—running the algorithms on a computer and measuring speed in seconds and memory consumption in bytes. Ultimately, this is what really matters, but a benchmark can be unsatisfactory because it is so specific: it measures the performance of a particular program written in a particular language, running on a particular computer, with a particular compiler and particular input data. From the single result that the benchmark provides, it can be difficult to predict how well the algorithm would do on a different compiler, computer, or data set. The second approach relies on a mathematical **analysis of algorithms**, independently of the particular implementation and input, as discussed below.

BENCHMARKING

ANALYSIS OF ALGORITHMS

A.1.1 Asymptotic analysis

We will consider algorithm analysis through the following example, a program to compute the sum of a sequence of numbers:

```
function SUMMATION(sequence) returns a number
   sum ← 0
   for i = 1 to LENGTH(sequence) do
       sum ← sum + sequence[i]
   return sum
```

The first step in the analysis is to abstract over the input, in order to find some parameter or parameters that characterize the size of the input. In this example, the input can be characterized by the length of the sequence, which we will call n. The second step is to abstract over the implementation, to find some measure that reflects the running time of the algorithm but is not tied to a particular compiler or computer. For the SUMMATION program, this could be just the number of lines of code executed, or it could be more detailed, measuring the number of additions, assignments, array references, and branches executed by the algorithm.

Either way gives us a characterization of the total number of steps taken by the algorithm as a function of the size of the input. We will call this characterization $T(n)$. If we count lines of code, we have $T(n) = 2n + 2$ for our example.

If all programs were as simple as SUMMATION, the analysis of algorithms would be a trivial field. But two problems make it more complicated. First, it is rare to find a parameter like n that completely characterizes the number of steps taken by an algorithm. Instead, the best we can usually do is compute the worst case $T_{\text{worst}}(n)$ or the average case $T_{\text{avg}}(n)$. Computing an average means that the analyst must assume some distribution of inputs.

The second problem is that algorithms tend to resist exact analysis. In that case, it is necessary to fall back on an approximation. We say that the SUMMATION algorithm is $O(n)$, meaning that its measure is at most a constant times n, with the possible exception of a few small values of n. More formally,

$$T(n) \text{ is } O(f(n)) \text{ if } T(n) \leq kf(n) \text{ for some } k, \text{ for all } n > n_0 .$$

ASYMPTOTIC ANALYSIS

The $O()$ notation gives us what is called an **asymptotic analysis**. We can say without question that, as n asymptotically approaches infinity, an $O(n)$ algorithm is better than an $O(n^2)$ algorithm. A single benchmark figure could not substantiate such a claim.

The $O()$ notation abstracts over constant factors, which makes it easier to use, but less precise, than the $T()$ notation. For example, an $O(n^2)$ algorithm will always be worse than an $O(n)$ in the long run, but if the two algorithms are $T(n^2 + 1)$ and $T(100n + 1000)$, then the $O(n^2)$ algorithm is actually better for $n < 110$.

Despite this drawback, asymptotic analysis is the most widely used tool for analyzing algorithms. It is precisely because the analysis abstracts over both the exact number of operations (by ignoring the constant factor k) and the exact content of the input (by considering only its size n) that the analysis becomes mathematically feasible. The $O()$ notation is a good compromise between precision and ease of analysis.

A.1.2 NP and inherently hard problems

COMPLEXITY ANALYSIS

The analysis of algorithms and the $O()$ notation allow us to talk about the efficiency of a particular algorithm. However, they have nothing to say about whether there could be a better algorithm for the problem at hand. The field of **complexity analysis** analyzes problems rather than algorithms. The first gross division is between problems that can be solved in polynomial time and problems that cannot be solved in polynomial time, no matter what algorithm is used. The class of polynomial problems—those which can be solved in time $O(n^k)$ for some k—is called P. These are sometimes called "easy" problems, because the class contains those problems with running times like $O(\log n)$ and $O(n)$. But it also contains those with time $O(n^{1000})$, so the name "easy" should not be taken too literally.

Another important class of problems is NP, the class of nondeterministic polynomial problems. A problem is in this class if there is some algorithm that can guess a solution and then verify whether the guess is correct in polynomial time. The idea is that if you have an arbitrarily large number of processors, so that you can try all the guesses at once, or you are very lucky and always guess right the first time, then the NP problems become P problems. One of the biggest open questions in computer science is whether the class NP is equivalent to the class P when one does not have the luxury of an infinite number of processors or omniscient guessing. Most computer scientists are convinced that P $\neq$ NP; that NP problems are inherently hard and have no polynomial-time algorithms. But this has never been proven.

NP-COMPLETE

Those who are interested in deciding whether P = NP look at a subclass of NP called the **NP-complete** problems. The word "complete" is used here in the sense of "most extreme" and thus refers to the hardest problems in the class NP. It has been proven that either all the NP-complete problems are in P or none of them is. This makes the class theoretically interesting, but the class is also of practical interest because many important problems are known to be NP-complete. An example is the satisfiability problem: given a sentence of propositional logic, is there an assignment of truth values to the proposition symbols of the sentence that makes it true? Unless a miracle occurs and P = NP, there can be no algorithm that solves *all* satisfiability problems in polynomial time. However, AI is more interested in whether there are algorithms that perform efficiently on *typical* problems drawn from a predetermined distribution; as we saw in Chapter 7, there are algorithms such as WALKSAT that do quite well on many problems.

CO-NP

CO-NP-COMPLETE

The class **co-NP** is the complement of NP, in the sense that, for every decision problem in NP, there is a corresponding problem in co-NP with the "yes" and "no" answers reversed. We know that P is a subset of both NP and co-NP, and it is believed that there are problems in co-NP that are not in P. The **co-NP-complete** problems are the hardest problems in co-NP.

The class #P (pronounced "sharp P") is the set of counting problems corresponding to the decision problems in NP. Decision problems have a yes-or-no answer: is there a solution to this 3-SAT formula? Counting problems have an integer answer: how many solutions are there to this 3-SAT formula? In some cases, the counting problem is much harder than the decision problem. For example, deciding whether a bipartite graph has a perfect matching can be done in time $O(VE)$ (where the graph has V vertices and E edges), but the counting problem "how many perfect matches does this bipartite graph have" is #P-complete, meaning that it is hard as any problem in #P and thus at least as hard as any NP problem.

Another class is the class of PSPACE problems—those that require a polynomial amount of space, even on a nondeterministic machine. It is believed that PSPACE-hard problems are worse than NP-complete problems, although it could turn out that NP = PSPACE, just as it could turn out that P = NP.

A.2 VECTORS, MATRICES, AND LINEAR ALGEBRA

VECTOR

Mathematicians define a **vector** as a member of a vector space, but we will use a more concrete definition: a vector is an ordered sequence of values. For example, in two-dimensional space, we have vectors such as $\mathbf{x} = \langle 3, 4 \rangle$ and $\mathbf{y} = \langle 0, 2 \rangle$. We follow the convention of boldface characters for vector names, although some authors use arrows or bars over the names: $\vec{x}$ or $\bar{y}$. The elements of a vector can be accessed using subscripts: $\mathbf{z} = \langle z_1, z_2, \ldots, z_n \rangle$. One confusing point: this book is synthesizing work from many subfields, which variously call their sequences vectors, lists, or tuples, and variously use the notations $\langle 1, 2 \rangle$, [1, 2], or (1, 2).

The two fundamental operations on vectors are vector addition and scalar multiplication. The vector addition $\mathbf{x}+\mathbf{y}$ is the elementwise sum: $\mathbf{x}+\mathbf{y}=\langle 3+0,4+2\rangle=\langle 3,6\rangle$. Scalar multiplication multiplies each element by a constant: $5\mathbf{x}=\langle 5\times 3, 5\times 4\rangle=\langle 15,20\rangle$.

The length of a vector is denoted $|\mathbf{x}|$ and is computed by taking the square root of the sum of the squares of the elements: $|\mathbf{x}|=\sqrt{(3^2+4^2)}=5$. The dot product $\mathbf{x}\cdot\mathbf{y}$ (also called scalar product) of two vectors is the sum of the products of corresponding elements, that is, $\mathbf{x}\cdot\mathbf{y}=\sum_i x_i y_i$, or in our particular case, $\mathbf{x}\cdot\mathbf{y}=3\times 0+4\times 2=8$.

Vectors are often interpreted as directed line segments (arrows) in an n-dimensional Euclidean space. Vector addition is then equivalent to placing the tail of one vector at the head of the other, and the dot product $\mathbf{x}\cdot\mathbf{y}$ is equal to $|\mathbf{x}|\ |\mathbf{y}|\ \cos\theta$, where θ is the angle between $\mathbf{x}$ and $\mathbf{y}$.

MATRIX

A **matrix** is a rectangular array of values arranged into rows and columns. Here is a matrix $\mathbf{A}$ of size 3×4:

$$\begin{pmatrix} \mathbf{A}_{1,1} & \mathbf{A}_{1,2} & \mathbf{A}_{1,3} & \mathbf{A}_{1,4} \\ \mathbf{A}_{2,1} & \mathbf{A}_{2,2} & \mathbf{A}_{2,3} & \mathbf{A}_{2,4} \\ \mathbf{A}_{3,1} & \mathbf{A}_{3,2} & \mathbf{A}_{3,3} & \mathbf{A}_{3,4} \end{pmatrix}$$

The first index of $\mathbf{A}_{i,j}$ specifies the row and the second the column. In programming languages, $\mathbf{A}_{i,j}$ is often written `A[i,j]` or `A[i][j]`.

The sum of two matrices is defined by adding their corresponding elements; for example $(\mathbf{A}+\mathbf{B})_{i,j}=\mathbf{A}_{i,j}+\mathbf{B}_{i,j}$. (The sum is undefined if $\mathbf{A}$ and $\mathbf{B}$ have different sizes.) We can also define the multiplication of a matrix by a scalar: $(c\mathbf{A})_{i,j}=c\mathbf{A}_{i,j}$. Matrix multiplication (the product of two matrices) is more complicated. The product $\mathbf{AB}$ is defined only if $\mathbf{A}$ is of size $a\times b$ and $\mathbf{B}$ is of size $b\times c$ (i.e., the second matrix has the same number of rows as the first has columns); the result is a matrix of size $a\times c$. If the matrices are of appropriate size, then the result is

$$(\mathbf{AB})_{i,k}=\sum_j \mathbf{A}_{i,j}\mathbf{B}_{j,k}\ .$$

Matrix multiplication is not commutative, even for square matrices: $\mathbf{AB}\neq\mathbf{BA}$ in general. It is, however, associative: $(\mathbf{AB})\mathbf{C}=\mathbf{A}(\mathbf{BC})$. Note that the dot product can be expressed in terms of a transpose and a matrix multiplication:$\mathbf{x}\cdot\mathbf{y}=\mathbf{x}^\top\mathbf{y}$.

IDENTITY MATRIX
TRANSPOSE
INVERSE
SINGULAR

The **identity matrix I** has elements $\mathbf{I}_{i,j}$ equal to 1 when $i=j$ and equal to 0 otherwise. It has the property that $\mathbf{AI}=\mathbf{A}$ for all $\mathbf{A}$. The **transpose** of $\mathbf{A}$, written $\mathbf{A}^\top$ is formed by turning rows into columns and vice versa, or, more formally, by $\mathbf{A}^\top{}_{i,j}=\mathbf{A}_{j,i}$. The **inverse** of a square matrix $\mathbf{A}$ is another square matrix $\mathbf{A}^{-1}$ such that $\mathbf{A}^{-1}\mathbf{A}=\mathbf{I}$. For a **singular** matrix, the inverse does not exist. For a nonsingular matrix, it can be computed in $O(n^3)$ time.

Matrices are used to solve systems of linear equations in $O(n^3)$ time; the time is dominated by inverting a matrix of coefficients. Consider the following set of equations, for which we want a solution in x, y, and z:

$$\begin{aligned} +2x+y-z &= 8 \\ -3x-y+2z &= -11 \\ -2x+y+2z &= -3\ . \end{aligned}$$

We can represent this system as the matrix equation $\mathbf{A}\,\mathbf{x} = \mathbf{b}$, where

$$\mathbf{A} = \begin{pmatrix} 2 & 1 & -1 \\ -3 & -1 & 2 \\ -2 & 1 & 2 \end{pmatrix}, \qquad \mathbf{x} = \begin{pmatrix} x \\ y \\ z \end{pmatrix}, \qquad \mathbf{b} = \begin{pmatrix} 8 \\ -11 \\ -3 \end{pmatrix}.$$

To solve $\mathbf{A}\,\mathbf{x} = \mathbf{b}$ we multiply both sides by $\mathbf{A}^{-1}$, yielding $\mathbf{A}^{-1}\mathbf{A}\mathbf{x} = \mathbf{A}^{-1}\mathbf{b}$, which simplifies to $\mathbf{x} = \mathbf{A}^{-1}\mathbf{b}$. After inverting $\mathbf{A}$ and multiplying by $\mathbf{b}$, we get the answer

$$\mathbf{x} = \begin{pmatrix} x \\ y \\ z \end{pmatrix} = \begin{pmatrix} 2 \\ 3 \\ -1 \end{pmatrix}.$$

A.3 PROBABILITY DISTRIBUTIONS

A probability is a measure over a set of events that satisfies three axioms:

1. The measure of each event is between 0 and 1. We write this as $0 \leq P(X=x_i) \leq 1$, where X is a random variable representing an event and x_i are the possible values of X. In general, random variables are denoted by uppercase letters and their values by lowercase letters.
2. The measure of the whole set is 1; that is, $\sum_{i=1}^{n} P(X=x_i) = 1$.
3. The probability of a union of disjoint events is the sum of the probabilities of the individual events; that is, $P(X=x_1 \vee X=x_2) = P(X=x_1) + P(X=x_2)$, where x_1 and x_2 are disjoint.

A **probabilistic model** consists of a sample space of mutually exclusive possible outcomes, together with a probability measure for each outcome. For example, in a model of the weather tomorrow, the outcomes might be *sunny, cloudy, rainy*, and *snowy*. A subset of these outcomes constitutes an event. For example, the event of precipitation is the subset consisting of $\{$*rainy, snowy*$\}$.

We use $\mathbf{P}(X)$ to denote the vector of values $\langle P(X=x_1), \ldots, P(X=x_n)\rangle$. We also use $P(x_i)$ as an abbreviation for $P(X=x_i)$ and $\sum_x P(x)$ for $\sum_{i=1}^{n} P(X=x_i)$.

The conditional probability $P(B|A)$ is defined as $P(B \cap A)/P(A)$. A and B are conditionally independent if $P(B|A) = P(B)$ (or equivalently, $P(A|B) = P(A)$). For continuous variables, there are an infinite number of values, and unless there are point spikes, the probability of any one value is 0. Therefore, we define a **probability density function**, which we also denote as $P(\cdot)$, but which has a slightly different meaning from the discrete probability function. The density function $P(x)$ for a random variable X, which might be thought of as $P(X=x)$, is intuitively defined as the ratio of the probability that X falls into an interval around x, divided by the width of the interval, as the interval width goes to zero:

PROBABILITY DENSITY FUNCTION

$$P(x) = \lim_{dx \to 0} P(x \leq X \leq x + dx)/dx\ .$$

The density function must be nonnegative for all x and must have

$$\int_{-\infty}^{\infty} P(x)\, dx = 1 \; .$$

CUMULATIVE PROBABILITY DENSITY FUNCTION

We can also define a **cumulative probability density function** $F_X(x)$, which is the probability of a random variable being less than x:

$$F_X(x) = P(X \leq x) = \int_{-\infty}^{x} P(u)\, du \; .$$

Note that the probability density function has units, whereas the discrete probability function is unitless. For example, if values of X are measured in seconds, then the density is measured in Hz (i.e., 1/sec). If values of **X** are points in three-dimensional space measured in meters, then density is measured in $1/m^3$.

GAUSSIAN DISTRIBUTION

One of the most important probability distributions is the **Gaussian distribution**, also known as the **normal distribution**. A Gaussian distribution with mean μ and standard deviation σ (and therefore variance σ^2) is defined as

$$P(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-(x-\mu)^2/(2\sigma^2)} \; ,$$

STANDARD NORMAL DISTRIBUTION

MULTIVARIATE GAUSSIAN

where x is a continuous variable ranging from $-\infty$ to $+\infty$. With mean $\mu = 0$ and variance $\sigma^2 = 1$, we get the special case of the **standard normal distribution**. For a distribution over a vector **x** in n dimensions, there is the **multivariate Gaussian** distribution:

$$P(\mathbf{x}) = \frac{1}{\sqrt{(2\pi)^n |\mathbf{\Sigma}|}} e^{-\frac{1}{2}\left((\mathbf{x}-\boldsymbol{\mu})^\top \mathbf{\Sigma}^{-1} (\mathbf{x}-\boldsymbol{\mu})\right)} \; ,$$

where $\boldsymbol{\mu}$ is the mean vector and $\mathbf{\Sigma}$ is the **covariance matrix** (see below).

CUMULATIVE DISTRIBUTION

In one dimension, we can define the **cumulative distribution** function $F(x)$ as the probability that a random variable will be less than x. For the normal distribution, this is

$$F(x) = \int_{-\infty}^{x} P(z) dz = \frac{1}{2}(1 + \mathrm{erf}(\frac{z-\mu}{\sigma\sqrt{2}})) \; ,$$

where $\mathrm{erf}(x)$ is the so-called **error function**, which has no closed-form representation.

CENTRAL LIMIT THEOREM

The **central limit theorem** states that the distribution formed by sampling n independent random variables and taking their mean tends to a normal distribution as n tends to infinity. This holds for almost any collection of random variables, even if they are not strictly independent, unless the variance of any finite subset of variables dominates the others.

EXPECTATION

The **expectation** of a random variable, $E(X)$, is the mean or average value, weighted by the probability of each value. For a discrete variable it is:

$$E(X) = \sum_i x_i \, P(X = x_i) \; .$$

For a continuous variable, replace the summation with an integral over the probability density function, $P(x)$:

$$E(X) = \int_{-\infty}^{\infty} x P(x)\, dx \; ,$$

ROOT MEAN SQUARE The **root mean square**, RMS, of a set of values (often samples of a random variable) is the square root of the mean of the squares of the values,

$$RMS(x_1, \ldots, x_n) = \sqrt{\frac{x_1^2 + \ldots + x_n^2}{n}} .$$

COVARIANCE The **covariance** of two random variables is the expectation of the product of their differences from their means:

$$\text{cov}(X, Y) = E((X - \mu_X)(Y - \mu_Y)) .$$

COVARIANCE MATRIX The **covariance matrix**, often denoted $\mathbf{\Sigma}$, is a matrix of covariances between elements of a vector of random variables. Given $\mathbf{X} = \langle X_1, \ldots X_n \rangle^\top$, the entries of the covariance matrix are as follows:

$$\mathbf{\Sigma}_{i,j} = \text{cov}(X_i, X_j) = E((X_i - \mu_i)(X_j - \mu_j)) .$$

A few more miscellaneous points: we use $\log(x)$ for the natural logarithm, $\log_e(x)$. We use $\text{argmax}_x\, f(x)$ for the value of x for which $f(x)$ is maximal.

BIBLIOGRAPHICAL AND HISTORICAL NOTES

The $O()$ notation so widely used in computer science today was first introduced in the context of number theory by the German mathematician P. G. H. Bachmann (1894). The concept of NP-completeness was invented by Cook (1971), and the modern method for establishing a reduction from one problem to another is due to Karp (1972). Cook and Karp have both won the Turing award, the highest honor in computer science, for their work.

Classic works on the analysis and design of algorithms include those by Knuth (1973) and Aho, Hopcroft, and Ullman (1974); more recent contributions are by Tarjan (1983) and Cormen, Leiserson, and Rivest (1990). These books place an emphasis on designing and analyzing algorithms to solve tractable problems. For the theory of NP-completeness and other forms of intractability, see Garey and Johnson (1979) or Papadimitriou (1994). Good texts on probability include Chung (1979), Ross (1988), and Bertsekas and Tsitsiklis (2008).

B NOTES ON LANGUAGES AND ALGORITHMS

B.1 DEFINING LANGUAGES WITH BACKUS–NAUR FORM (BNF)

In this book, we define several languages, including the languages of propositional logic (page 243), first-order logic (page 293), and a subset of English (page 899). A formal language is defined as a set of strings where each string is a sequence of symbols. The languages we are interested in consist of an infinite set of strings, so we need a concise way to characterize the set. We do that with a **grammar**. The particular type of grammar we use is called a **context-free grammar**, because each expression has the same form in any context. We write our grammars in a formalism called **Backus–Naur form (BNF)**. There are four components to a BNF grammar:

CONTEXT-FREE GRAMMAR
BACKUS–NAUR FORM (BNF)

TERMINAL SYMBOL

- A set of **terminal symbols**. These are the symbols or words that make up the strings of the language. They could be letters (**A, B, C,** . . .) or words (**a, aardvark, abacus,** . . .), or whatever symbols are appropriate for the domain.

NONTERMINAL SYMBOL

- A set of **nonterminal symbols** that categorize subphrases of the language. For example, the nonterminal symbol $NounPhrase$ in English denotes an infinite set of strings including "you" and "the big slobbery dog."

START SYMBOL

- A **start symbol**, which is the nonterminal symbol that denotes the complete set of strings of the language. In English, this is $Sentence$; for arithmetic, it might be $Expr$, and for programming languages it is $Program$.
- A set of **rewrite rules**, of the form $LHS \rightarrow RHS$, where LHS is a nonterminal symbol and RHS is a sequence of zero or more symbols. These can be either terminal or nonterminal symbols, or the symbol ϵ, which is used to denote the empty string.

A rewrite rule of the form

$$Sentence \rightarrow NounPhrase\ VerbPhrase$$

means that whenever we have two strings categorized as a $NounPhrase$ and a $VerbPhrase$, we can append them together and categorize the result as a $Sentence$. As an abbreviation, the two rules ($S \rightarrow A$) and ($S \rightarrow B$) can be written ($S \rightarrow A \mid B$).

Here is a BNF grammar for simple arithmetic expressions:

$$
\begin{array}{lll}
\mathit{Expr} & \rightarrow & \mathit{Expr}\ \mathit{Operator}\ \mathit{Expr} \mid \textbf{(}\ \mathit{Expr}\ \textbf{)} \mid \mathit{Number} \\
\mathit{Number} & \rightarrow & \mathit{Digit} \mid \mathit{Number}\ \mathit{Digit} \\
\mathit{Digit} & \rightarrow & \textbf{0} \mid \textbf{1} \mid \textbf{2} \mid \textbf{3} \mid \textbf{4} \mid \textbf{5} \mid \textbf{6} \mid \textbf{7} \mid \textbf{8} \mid \textbf{9} \\
\mathit{Operator} & \rightarrow & + \mid - \mid \div \mid \times
\end{array}
$$

We cover languages and grammars in more detail in Chapter 22. Be aware that other books use slightly different notations for BNF; for example, you might see $\langle \mathit{Digit} \rangle$ instead of *Digit* for a nonterminal, 'word' instead of **word** for a terminal, or **::=** instead of $\rightarrow$ in a rule.

B.2 Describing Algorithms with Pseudocode

The algorithms in this book are described in pseudocode. Most of the pseudocode should be familiar to users of languages like Java, C++, or Lisp. In some places we use mathematical formulas or ordinary English to describe parts that would otherwise be more cumbersome. A few idiosyncrasies should be noted.

- **Persistent variables**: We use the keyword **persistent** to say that a variable is given an initial value the first time a function is called and retains that value (or the value given to it by a subsequent assignment statement) on all subsequent calls to the function. Thus, persistent variables are like global variables in that they outlive a single call to their function, but they are accessible only within the function. The agent programs in the book use persistent variables for *memory.* Programs with persistent variables can be implemented as *objects* in object-oriented languages such as C++, Java, Python, and Smalltalk. In functional languages, they can be implemented by *functional closures* over an environment containing the required variables.
- **Functions as values**: Functions and procedures have capitalized names, and variables have lowercase italic names. So most of the time, a function call looks like FN(x). However, we allow the value of a variable to be a function; for example, if the value of the variable f is the square root function, then $f(9)$ returns 3.
- **for each**: The notation "**for each** x **in** c **do**" means that the loop is executed with the variable x bound to successive elements of the collection c.
- **Indentation is significant**: Indentation is used to mark the scope of a loop or conditional, as in the language Python, and unlike Java and C++ (which use braces) or Pascal and Visual Basic (which use **end**).
- **Destructuring assignment**: The notation "$x, y \leftarrow \mathit{pair}$" means that the right-hand side must evaluate to a two-element tuple, and the first element is assigned to x and the second to y. The same idea is used in "**for each** x, y **in** *pairs* **do**" and can be used to swap two variables: "$x, y \leftarrow y, x$"
- **Generators** and **yield**: the notation "**generator** G(x) **yields** numbers" defines G as a generator function. This is best understood by an example. The code fragment shown in

```
generator POWERS-OF-2() yields ints
  i ← 1
  while true do
    yield i
    i ← 2 × i
---
for p in POWERS-OF-2() do
  PRINT(p)
```

Figure B.1 Example of a generator function and its invocation within a loop.

Figure B.1 prints the numbers 1, 2, 4, ..., and never stops. The call to POWERS-OF-2 returns a generator, which in turn yields one value each time the loop code asks for the next element of the collection. Even though the collection is infinite, it is enumerated one element at a time.

- **Lists**: $[x, y, z]$ denotes a list of three elements. $[\mathit{first}|\mathit{rest}]$ denotes a list formed by adding *first* to the list *rest*. In Lisp, this is the `cons` function.
- **Sets**: $\{x, y, z\}$ denotes a set of three elements. $\{x : p(x)\}$ denotes the set of all elements x for which $p(x)$ is true.
- **Arrays start at 1**: Unless stated otherwise, the first index of an array is 1 as in usual mathematical notation, not 0, as in Java and C.

B.3 ONLINE HELP

Most of the algorithms in the book have been implemented in Java, Lisp, and Python at our online code repository:

`aima.cs.berkeley.edu`

The same Web site includes instructions for sending comments, corrections, or suggestions for improving the book, and for joining discussion lists.

Bibliography

The following abbreviations are used for frequently cited conferences and journals:

AAAI	Proceedings of the AAAI Conference on Artificial Intelligence
AAMAS	Proceedings of the International Conference on Autonomous Agents and Multi-agent Systems
ACL	Proceedings of the Annual Meeting of the Association for Computational Linguistics
AIJ	Artificial Intelligence
AIMag	AI Magazine
AIPS	Proceedings of the International Conference on AI Planning Systems
BBS	Behavioral and Brain Sciences
CACM	Communications of the Association for Computing Machinery
COGSCI	Proceedings of the Annual Conference of the Cognitive Science Society
COLING	Proceedings of the International Conference on Computational Linguistics
COLT	Proceedings of the Annual ACM Workshop on Computational Learning Theory
CP	Proceedings of the International Conference on Principles and Practice of Constraint Programming
CVPR	Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition
EC	Proceedings of the ACM Conference on Electronic Commerce
ECAI	Proceedings of the European Conference on Artificial Intelligence
ECCV	Proceedings of the European Conference on Computer Vision
ECML	Proceedings of the The European Conference on Machine Learning
ECP	Proceedings of the European Conference on Planning
FGCS	Proceedings of the International Conference on Fifth Generation Computer Systems
FOCS	Proceedings of the Annual Symposium on Foundations of Computer Science
ICAPS	Proceedings of the International Conference on Automated Planning and Scheduling
ICASSP	Proceedings of the International Conference on Acoustics, Speech, and Signal Processing
ICCV	Proceedings of the International Conference on Computer Vision
ICLP	Proceedings of the International Conference on Logic Programming
ICML	Proceedings of the International Conference on Machine Learning
ICPR	Proceedings of the International Conference on Pattern Recognition
ICRA	Proceedings of the IEEE International Conference on Robotics and Automation
ICSLP	Proceedings of the International Conference on Speech and Language Processing
IJAR	International Journal of Approximate Reasoning
IJCAI	Proceedings of the International Joint Conference on Artificial Intelligence
IJCNN	Proceedings of the International Joint Conference on Neural Networks
IJCV	International Journal of Computer Vision
ILP	Proceedings of the International Workshop on Inductive Logic Programming
ISMIS	Proceedings of the International Symposium on Methodologies for Intelligent Systems
ISRR	Proceedings of the International Symposium on Robotics Research
JACM	Journal of the Association for Computing Machinery
JAIR	Journal of Artificial Intelligence Research
JAR	Journal of Automated Reasoning
JASA	Journal of the American Statistical Association
JMLR	Journal of Machine Learning Research
JSL	Journal of Symbolic Logic
KDD	Proceedings of the International Conference on Knowledge Discovery and Data Mining
KR	Proceedings of the International Conference on Principles of Knowledge Representation and Reasoning
LICS	Proceedings of the IEEE Symposium on Logic in Computer Science
NIPS	Advances in Neural Information Processing Systems
PAMI	IEEE Transactions on Pattern Analysis and Machine Intelligence
PNAS	Proceedings of the National Academy of Sciences of the United States of America
PODS	Proceedings of the ACM International Symposium on Principles of Database Systems
SIGIR	Proceedings of the Special Interest Group on Information Retrieval
SIGMOD	Proceedings of the ACM SIGMOD International Conference on Management of Data
SODA	Proceedings of the Annual ACM–SIAM Symposium on Discrete Algorithms
STOC	Proceedings of the Annual ACM Symposium on Theory of Computing
TARK	Proceedings of the Conference on Theoretical Aspects of Reasoning about Knowledge
UAI	Proceedings of the Conference on Uncertainty in Artificial Intelligence

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