

7

LOGICAL AGENTS

In which we design agents that can form representations of a complex world, use a process of inference to derive new representations about the world, and use these new representations to deduce what to do.

REASONING
REPRESENTATION
KNOWLEDGE-BASED
AGENTS

Humans, it seems, know things; and what they know helps them do things. These are not empty statements. They make strong claims about how the intelligence of humans is achieved—not by purely reflex mechanisms but by processes of **reasoning** that operate on internal **representations** of knowledge. In AI, this approach to intelligence is embodied in **knowledge-based agents**.

The problem-solving agents of Chapters 3 and 4 know things, but only in a very limited, inflexible sense. For example, the transition model for the 8-puzzle—knowledge of what the actions do—is hidden inside the domain-specific code of the `RESULT` function. It can be used to predict the outcome of actions but not to deduce that two tiles cannot occupy the same space or that states with odd parity cannot be reached from states with even parity. The atomic representations used by problem-solving agents are also very limiting. In a partially observable environment, an agent’s only choice for representing what it knows about the current state is to list all possible concrete states—a hopeless prospect in large environments.

LOGIC

Chapter 6 introduced the idea of representing states as assignments of values to variables; this is a step in the right direction, enabling some parts of the agent to work in a domain-independent way and allowing for more efficient algorithms. In this chapter and those that follow, we take this step to its logical conclusion, so to speak—we develop **logic** as a general class of representations to support knowledge-based agents. Such agents can combine and recombine information to suit myriad purposes. Often, this process can be quite far removed from the needs of the moment—as when a mathematician proves a theorem or an astronomer calculates the earth’s life expectancy. Knowledge-based agents can accept new tasks in the form of explicitly described goals; they can achieve competence quickly by being told or learning new knowledge about the environment; and they can adapt to changes in the environment by updating the relevant knowledge.

We begin in Section 7.1 with the overall agent design. Section 7.2 introduces a simple new environment, the wumpus world, and illustrates the operation of a knowledge-based agent without going into any technical detail. Then we explain the general principles of **logic**

in Section 7.3 and the specifics of **propositional logic** in Section 7.4. While less expressive than **first-order logic** (Chapter 8), propositional logic illustrates all the basic concepts of logic; it also comes with well-developed inference technologies, which we describe in sections 7.5 and 7.6. Finally, Section 7.7 combines the concept of knowledge-based agents with the technology of propositional logic to build some simple agents for the wumpus world.

7.1 KNOWLEDGE-BASED AGENTS

KNOWLEDGE BASE
SENTENCE

KNOWLEDGE
REPRESENTATION
LANGUAGE
AXIOM

The central component of a knowledge-based agent is its **knowledge base**, or KB. A knowledge base is a set of **sentences**. (Here “sentence” is used as a technical term. It is related but not identical to the sentences of English and other natural languages.) Each sentence is expressed in a language called a **knowledge representation language** and represents some assertion about the world. Sometimes we dignify a sentence with the name **axiom**, when the sentence is taken as given without being derived from other sentences.

INFERENCE

There must be a way to add new sentences to the knowledge base and a way to query what is known. The standard names for these operations are TELL and ASK, respectively. Both operations may involve **inference**—that is, deriving new sentences from old. Inference must obey the requirement that when one ASKS a question of the knowledge base, the answer should follow from what has been told (or TELLED) to the knowledge base previously. Later in this chapter, we will be more precise about the crucial word “follow.” For now, take it to mean that the inference process should not make things up as it goes along.

BACKGROUND
KNOWLEDGE

Figure 7.1 shows the outline of a knowledge-based agent program. Like all our agents, it takes a percept as input and returns an action. The agent maintains a knowledge base, *KB*, which may initially contain some **background knowledge**.

Each time the agent program is called, it does three things. First, it TELLS the knowledge base what it perceives. Second, it ASKS the knowledge base what action it should perform. In the process of answering this query, extensive reasoning may be done about the current state of the world, about the outcomes of possible action sequences, and so on. Third, the agent program TELLS the knowledge base which action was chosen, and the agent executes the action.

The details of the representation language are hidden inside three functions that implement the interface between the sensors and actuators on one side and the core representation and reasoning system on the other. MAKE-PERCEPT-SENTENCE constructs a sentence asserting that the agent perceived the given percept at the given time. MAKE-ACTION-QUERY constructs a sentence that asks what action should be done at the current time. Finally, MAKE-ACTION-SENTENCE constructs a sentence asserting that the chosen action was executed. The details of the inference mechanisms are hidden inside TELL and ASK. Later sections will reveal these details.

The agent in Figure 7.1 appears quite similar to the agents with internal state described in Chapter 2. Because of the definitions of TELL and ASK, however, the knowledge-based agent is not an arbitrary program for calculating actions. It is amenable to a description at

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function KB-AGENT(percept) returns an action
  persistent: KB, a knowledge base
               t, a counter, initially 0, indicating time

  TELL(KB, MAKE-PERCEPT-SENTENCE(percept, t))
  action ← ASK(KB, MAKE-ACTION-QUERY(t))
  TELL(KB, MAKE-ACTION-SENTENCE(action, t))
  t ← t + 1
  return action

```

Figure 7.1 A generic knowledge-based agent. Given a percept, the agent adds the percept to its knowledge base, asks the knowledge base for the best action, and tells the knowledge base that it has in fact taken that action.

KNOWLEDGE LEVEL

the **knowledge level**, where we need specify only what the agent knows and what its goals are, in order to fix its behavior. For example, an automated taxi might have the goal of taking a passenger from San Francisco to Marin County and might know that the Golden Gate Bridge is the only link between the two locations. Then we can expect it to cross the Golden Gate Bridge *because it knows that that will achieve its goal*. Notice that this analysis is independent of how the taxi works at the **implementation level**. It doesn't matter whether its geographical knowledge is implemented as linked lists or pixel maps, or whether it reasons by manipulating strings of symbols stored in registers or by propagating noisy signals in a network of neurons.

IMPLEMENTATION LEVEL

DECLARATIVE

A knowledge-based agent can be built simply by TELLing it what it needs to know. Starting with an empty knowledge base, the agent designer can TELL sentences one by one until the agent knows how to operate in its environment. This is called the **declarative** approach to system building. In contrast, the **procedural** approach encodes desired behaviors directly as program code. In the 1970s and 1980s, advocates of the two approaches engaged in heated debates. We now understand that a successful agent often combines both declarative and procedural elements in its design, and that declarative knowledge can often be compiled into more efficient procedural code.

We can also provide a knowledge-based agent with mechanisms that allow it to learn for itself. These mechanisms, which are discussed in Chapter 18, create general knowledge about the environment from a series of percepts. A learning agent can be fully autonomous.

7.2 THE WUMPUS WORLD

WUMPUS WORLD

In this section we describe an environment in which knowledge-based agents can show their worth. The **wumpus world** is a cave consisting of rooms connected by passageways. Lurking somewhere in the cave is the terrible wumpus, a beast that eats anyone who enters its room. The wumpus can be shot by an agent, but the agent has only one arrow. Some rooms contain

bottomless pits that will trap anyone who wanders into these rooms (except for the wumpus, which is too big to fall in). The only mitigating feature of this bleak environment is the possibility of finding a heap of gold. Although the wumpus world is rather tame by modern computer game standards, it illustrates some important points about intelligence.

A sample wumpus world is shown in Figure 7.2. The precise definition of the task environment is given, as suggested in Section 2.3, by the PEAS description:

- **Performance measure:** +1000 for climbing out of the cave with the gold, −1000 for falling into a pit or being eaten by the wumpus, −1 for each action taken and −10 for using up the arrow. The game ends either when the agent dies or when the agent climbs out of the cave.
- **Environment:** A 4×4 grid of rooms. The agent always starts in the square labeled [1,1], facing to the right. The locations of the gold and the wumpus are chosen randomly, with a uniform distribution, from the squares other than the start square. In addition, each square other than the start can be a pit, with probability 0.2.
- **Actuators:** The agent can move *Forward*, *TurnLeft* by 90° , or *TurnRight* by 90° . The agent dies a miserable death if it enters a square containing a pit or a live wumpus. (It is safe, albeit smelly, to enter a square with a dead wumpus.) If an agent tries to move forward and bumps into a wall, then the agent does not move. The action *Grab* can be used to pick up the gold if it is in the same square as the agent. The action *Shoot* can be used to fire an arrow in a straight line in the direction the agent is facing. The arrow continues until it either hits (and hence kills) the wumpus or hits a wall. The agent has only one arrow, so only the first *Shoot* action has any effect. Finally, the action *Climb* can be used to climb out of the cave, but only from square [1,1].
- **Sensors:** The agent has five sensors, each of which gives a single bit of information:
 - In the square containing the wumpus and in the directly (not diagonally) adjacent squares, the agent will perceive a *Stench*.
 - In the squares directly adjacent to a pit, the agent will perceive a *Breeze*.
 - In the square where the gold is, the agent will perceive a *Glitter*.
 - When an agent walks into a wall, it will perceive a *Bump*.
 - When the wumpus is killed, it emits a woeful *Scream* that can be perceived anywhere in the cave.

The percepts will be given to the agent program in the form of a list of five symbols; for example, if there is a stench and a breeze, but no glitter, bump, or scream, the agent program will get [*Stench*, *Breeze*, *None*, *None*, *None*].

We can characterize the wumpus environment along the various dimensions given in Chapter 2. Clearly, it is discrete, static, and single-agent. (The wumpus doesn't move, fortunately.) It is sequential, because rewards may come only after many actions are taken. It is partially observable, because some aspects of the state are not directly perceivable: the agent's location, the wumpus's state of health, and the availability of an arrow. As for the locations of the pits and the wumpus: we could treat them as unobserved parts of the state that happen to be immutable—in which case, the transition model for the environment is completely

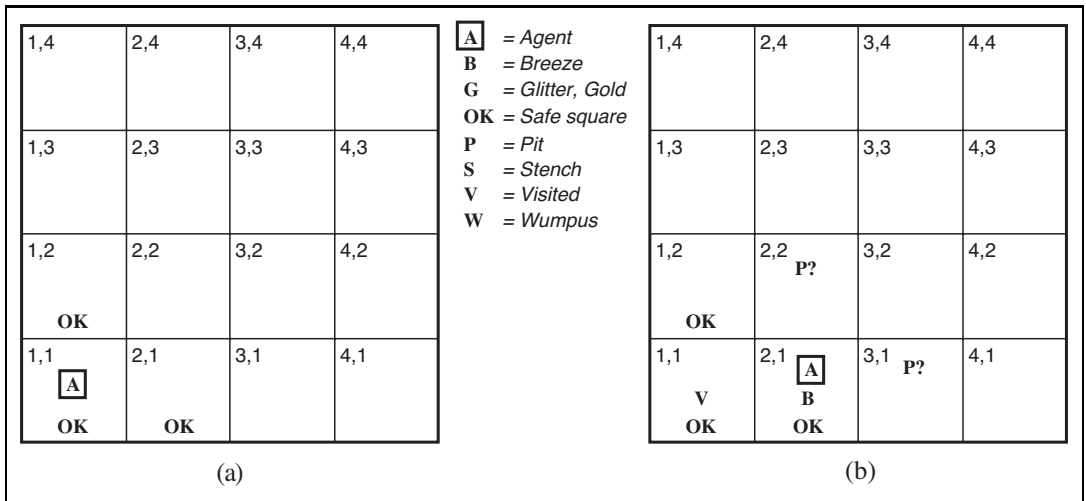


Figure 7.3 The first step taken by the agent in the wumpus world. (a) The initial situation, after percept *[None, None, None, None, None]*. (b) After one move, with percept *[None, Breeze, None, None, None]*.

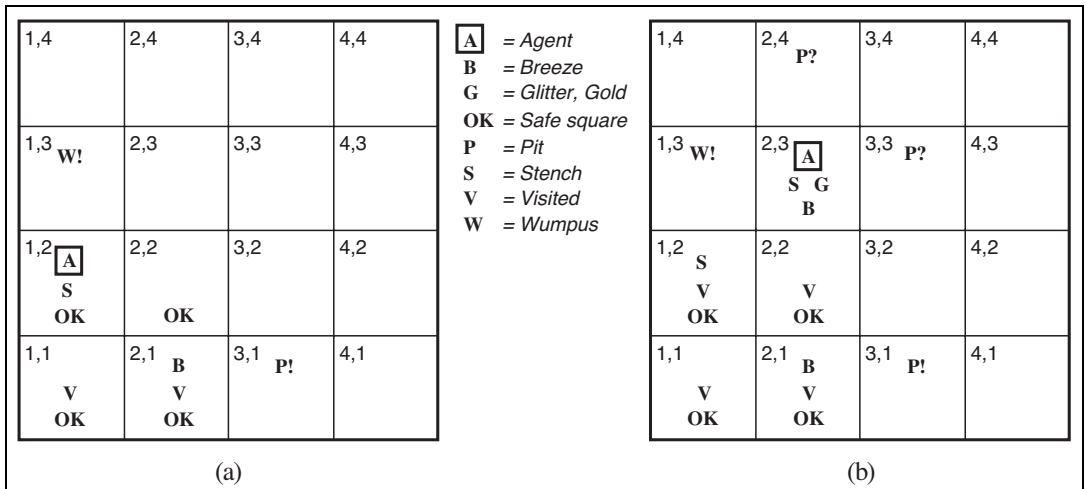


Figure 7.4 Two later stages in the progress of the agent. (a) After the third move, with percept *[Stench, None, None, None, None]*. (b) After the fifth move, with percept *[Stench, Breeze, Glitter, None, None]*.

wumpus cannot be in [1,1], by the rules of the game, and it cannot be in [2,2] (or the agent would have detected a stench when it was in [2,1]). Therefore, the agent can infer that the wumpus is in [1,3]. The notation **W!** indicates this inference. Moreover, the lack of a breeze in [1,2] implies that there is no pit in [2,2]. Yet the agent has already inferred that there must be a pit in either [2,2] or [3,1], so this means it must be in [3,1]. This is a fairly difficult inference, because it combines knowledge gained at different times in different places and relies on the lack of a percept to make one crucial step.

The agent has now proved to itself that there is neither a pit nor a wumpus in [2,2], so it is OK to move there. We do not show the agent's state of knowledge at [2,2]; we just assume that the agent turns and moves to [2,3], giving us Figure 7.4(b). In [2,3], the agent detects a glitter, so it should grab the gold and then return home.

Note that in each case for which the agent draws a conclusion from the available information, that conclusion is *guaranteed* to be correct if the available information is correct. This is a fundamental property of logical reasoning. In the rest of this chapter, we describe how to build logical agents that can represent information and draw conclusions such as those described in the preceding paragraphs.

7.3 LOGIC

This section summarizes the fundamental concepts of logical representation and reasoning. These beautiful ideas are independent of any of logic's particular forms. We therefore postpone the technical details of those forms until the next section, using instead the familiar example of ordinary arithmetic.

SYNTAX

In Section 7.1, we said that knowledge bases consist of sentences. These sentences are expressed according to the **syntax** of the representation language, which specifies all the sentences that are well formed. The notion of syntax is clear enough in ordinary arithmetic: “ $x + y = 4$ ” is a well-formed sentence, whereas “ $x4y+ =$ ” is not.

SEMANTICS

TRUTH

POSSIBLE WORLD

A logic must also define the **semantics** or meaning of sentences. The semantics defines the **truth** of each sentence with respect to each **possible world**. For example, the semantics for arithmetic specifies that the sentence “ $x + y = 4$ ” is true in a world where x is 2 and y is 2, but false in a world where x is 1 and y is 1. In standard logics, every sentence must be either true or false in each possible world—there is no “in between.”¹

MODEL

When we need to be precise, we use the term **model** in place of “possible world.” Whereas possible worlds might be thought of as (potentially) real environments that the agent might or might not be in, models are mathematical abstractions, each of which simply fixes the truth or falsehood of every relevant sentence. Informally, we may think of a possible world as, for example, having x men and y women sitting at a table playing bridge, and the sentence $x + y = 4$ is true when there are four people in total. Formally, the possible models are just all possible assignments of real numbers to the variables x and y . Each such assignment fixes the truth of any sentence of arithmetic whose variables are x and y . If a sentence α is true in model m , we say that m **satisfies** α or sometimes m **is a model of** α . We use the notation $M(\alpha)$ to mean the set of all models of α .

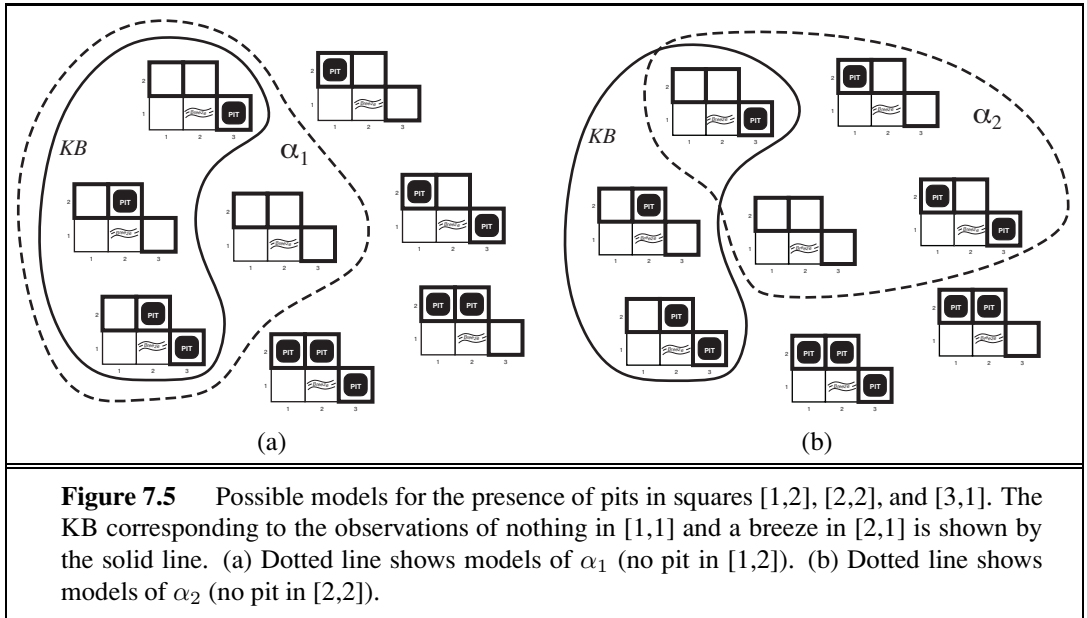
SATISFACTION

ENTAILMENT

Now that we have a notion of truth, we are ready to talk about logical reasoning. This involves the relation of logical **entailment** between sentences—the idea that a sentence *follows logically* from another sentence. In mathematical notation, we write

$$\alpha \models \beta$$

¹ **Fuzzy logic**, discussed in Chapter 14, allows for degrees of truth.



to mean that the sentence α entails the sentence β . The formal definition of entailment is this: $\alpha \models \beta$ if and only if, in every model in which α is true, β is also true. Using the notation just introduced, we can write

$$\alpha \models \beta \text{ if and only if } M(\alpha) \subseteq M(\beta) .$$

(Note the direction of the \subseteq here: if $\alpha \models \beta$, then α is a *stronger* assertion than β : it rules out *more* possible worlds.) The relation of entailment is familiar from arithmetic; we are happy with the idea that the sentence $x = 0$ entails the sentence $xy = 0$. Obviously, in any model where x is zero, it is the case that xy is zero (regardless of the value of y).

We can apply the same kind of analysis to the wumpus-world reasoning example given in the preceding section. Consider the situation in Figure 7.3(b): the agent has detected nothing in [1,1] and a breeze in [2,1]. These percepts, combined with the agent's knowledge of the rules of the wumpus world, constitute the KB. The agent is interested (among other things) in whether the adjacent squares [1,2], [2,2], and [3,1] contain pits. Each of the three squares might or might not contain a pit, so (for the purposes of this example) there are $2^3 = 8$ possible models. These eight models are shown in Figure 7.5.²

The KB can be thought of as a set of sentences or as a single sentence that asserts all the individual sentences. The KB is false in models that contradict what the agent knows—for example, the KB is false in any model in which [1,2] contains a pit, because there is no breeze in [1,1]. There are in fact just three models in which the KB is true, and these are

² Although the figure shows the models as partial wumpus worlds, they are really nothing more than assignments of *true* and *false* to the sentences “there is a pit in [1,2]” etc. Models, in the mathematical sense, do not need to have ‘orrible’ airy wumpuses in them.

shown surrounded by a solid line in Figure 7.5. Now let us consider two possible conclusions:

$\alpha_1 = \text{“There is no pit in [1,2].”}$

$\alpha_2 = \text{“There is no pit in [2,2].”}$

We have surrounded the models of α_1 and α_2 with dotted lines in Figures 7.5(a) and 7.5(b), respectively. By inspection, we see the following:

in every model in which KB is true, α_1 is also true.

Hence, $KB \models \alpha_1$: there is no pit in [1,2]. We can also see that

in some models in which KB is true, α_2 is false.

Hence, $KB \not\models \alpha_2$: the agent *cannot* conclude that there is no pit in [2,2]. (Nor can it conclude that there *is* a pit in [2,2].)³

LOGICAL INFERENCE

MODEL CHECKING

The preceding example not only illustrates entailment but also shows how the definition of entailment can be applied to derive conclusions—that is, to carry out **logical inference**. The inference algorithm illustrated in Figure 7.5 is called **model checking**, because it enumerates all possible models to check that α is true in all models in which KB is true, that is, that $M(KB) \subseteq M(\alpha)$.

In understanding entailment and inference, it might help to think of the set of all consequences of KB as a haystack and of α as a needle. Entailment is like the needle being in the haystack; inference is like finding it. This distinction is embodied in some formal notation: if an inference algorithm i can derive α from KB , we write

$$KB \vdash_i \alpha,$$

which is pronounced “ α is derived from KB by i ” or “ i derives α from KB .”

SOUND

TRUTH-PRESERVING

An inference algorithm that derives only entailed sentences is called **sound** or **truth-preserving**. Soundness is a highly desirable property. An unsound inference procedure essentially makes things up as it goes along—it announces the discovery of nonexistent needles. It is easy to see that model checking, when it is applicable,⁴ is a sound procedure.

COMPLETENESS

The property of **completeness** is also desirable: an inference algorithm is complete if it can derive any sentence that is entailed. For real haystacks, which are finite in extent, it seems obvious that a systematic examination can always decide whether the needle is in the haystack. For many knowledge bases, however, the haystack of consequences is infinite, and completeness becomes an important issue.⁵ Fortunately, there are complete inference procedures for logics that are sufficiently expressive to handle many knowledge bases.

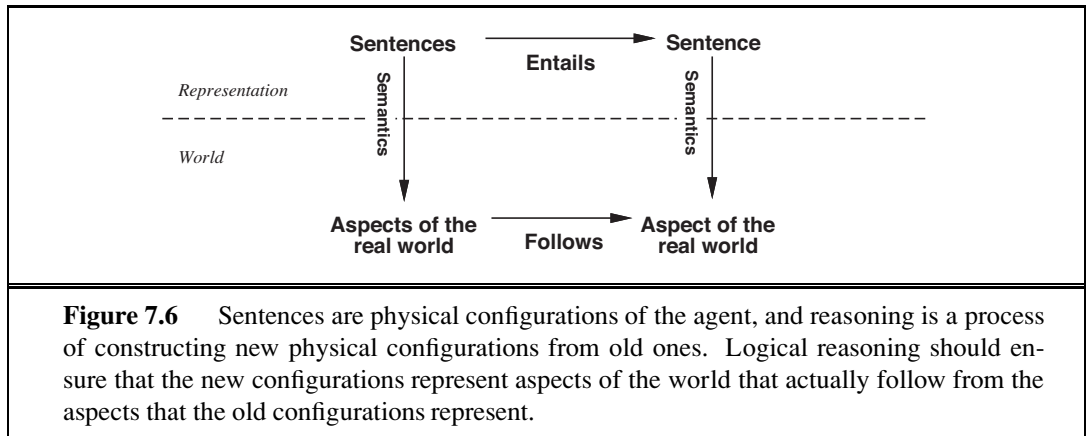


We have described a reasoning process whose conclusions are guaranteed to be true in any world in which the premises are true; in particular, *if KB is true in the real world, then any sentence α derived from KB by a sound inference procedure is also true in the real world*. So, while an inference process operates on “syntax”—internal physical configurations such as bits in registers or patterns of electrical blips in brains—the process *corresponds*

³ The agent can calculate the *probability* that there is a pit in [2,2]; Chapter 13 shows how.

⁴ Model checking works if the space of models is finite—for example, in wumpus worlds of fixed size. For arithmetic, on the other hand, the space of models is infinite: even if we restrict ourselves to the integers, there are infinitely many pairs of values for x and y in the sentence $x + y = 4$.

⁵ Compare with the case of infinite search spaces in Chapter 3, where depth-first search is not complete.



to the real-world relationship whereby some aspect of the real world is the case⁶ by virtue of other aspects of the real world being the case. This correspondence between world and representation is illustrated in Figure 7.6.

GROUNDING



The final issue to consider is **grounding**—the connection between logical reasoning processes and the real environment in which the agent exists. In particular, *how do we know that KB is true in the real world?* (After all, *KB* is just “syntax” inside the agent’s head.) This is a philosophical question about which many, many books have been written. (See Chapter 26.) A simple answer is that the agent’s sensors create the connection. For example, our wumpus-world agent has a smell sensor. The agent program creates a suitable sentence whenever there is a smell. Then, whenever that sentence is in the knowledge base, it is true in the real world. Thus, the meaning and truth of percept sentences are defined by the processes of sensing and sentence construction that produce them. What about the rest of the agent’s knowledge, such as its belief that wumpuses cause smells in adjacent squares? This is not a direct representation of a single percept, but a general rule—derived, perhaps, from perceptual experience but not identical to a statement of that experience. General rules like this are produced by a sentence construction process called **learning**, which is the subject of Part V. Learning is fallible. It could be the case that wumpuses cause smells *except on February 29 in leap years*, which is when they take their baths. Thus, *KB* may not be true in the real world, but with good learning procedures, there is reason for optimism.

7.4 PROPOSITIONAL LOGIC: A VERY SIMPLE LOGIC

PROPOSITIONAL LOGIC

We now present a simple but powerful logic called **propositional logic**. We cover the syntax of propositional logic and its semantics—the way in which the truth of sentences is determined. Then we look at **entailment**—the relation between a sentence and another sentence that follows from it—and see how this leads to a simple algorithm for logical inference. Everything takes place, of course, in the wumpus world.

⁶ As Wittgenstein (1922) put it in his famous *Tractatus*: “The world is everything that is the case.”

Figure 7.7 gives a formal grammar of propositional logic; see page 1060 if you are not familiar with the BNF notation. The BNF grammar by itself is ambiguous; a sentence with several operators can be parsed by the grammar in multiple ways. To eliminate the ambiguity we define a precedence for each operator. The “not” operator (\neg) has the highest precedence, which means that in the sentence $\neg A \wedge B$ the \neg binds most tightly, giving us the equivalent of $(\neg A) \wedge B$ rather than $\neg(A \wedge B)$. (The notation for ordinary arithmetic is the same: $-2 + 4$ is 2, not -6 .) When in doubt, use parentheses to make sure of the right interpretation. Square brackets mean the same thing as parentheses; the choice of square brackets or parentheses is solely to make it easier for a human to read a sentence.

7.4.2 Semantics

TRUTH VALUE

Having specified the syntax of propositional logic, we now specify its semantics. The semantics defines the rules for determining the truth of a sentence with respect to a particular model. In propositional logic, a model simply fixes the **truth value**—*true* or *false*—for every proposition symbol. For example, if the sentences in the knowledge base make use of the proposition symbols $P_{1,2}$, $P_{2,2}$, and $P_{3,1}$, then one possible model is

$$m_1 = \{P_{1,2} = \text{false}, P_{2,2} = \text{false}, P_{3,1} = \text{true}\}.$$

With three proposition symbols, there are $2^3 = 8$ possible models—exactly those depicted in Figure 7.5. Notice, however, that the models are purely mathematical objects with no necessary connection to wumpus worlds. $P_{1,2}$ is just a symbol; it might mean “there is a pit in [1,2]” or “I’m in Paris today and tomorrow.”

The semantics for propositional logic must specify how to compute the truth value of *any* sentence, given a model. This is done recursively. All sentences are constructed from atomic sentences and the five connectives; therefore, we need to specify how to compute the truth of atomic sentences and how to compute the truth of sentences formed with each of the five connectives. Atomic sentences are easy:

- *True* is true in every model and *False* is false in every model.
- The truth value of every other proposition symbol must be specified directly in the model. For example, in the model m_1 given earlier, $P_{1,2}$ is false.

For complex sentences, we have five rules, which hold for any subsentences P and Q in any model m (here “iff” means “if and only if”):

- $\neg P$ is true iff P is false in m .
- $P \wedge Q$ is true iff both P and Q are true in m .
- $P \vee Q$ is true iff either P or Q is true in m .
- $P \Rightarrow Q$ is true unless P is true and Q is false in m .
- $P \Leftrightarrow Q$ is true iff P and Q are both true or both false in m .

TRUTH TABLE

The rules can also be expressed with **truth tables** that specify the truth value of a complex sentence for each possible assignment of truth values to its components. Truth tables for the five connectives are given in Figure 7.8. From these tables, the truth value of any sentence s can be computed with respect to any model m by a simple recursive evaluation. For example,

P	Q	$\neg P$	$P \wedge Q$	$P \vee Q$	$P \Rightarrow Q$	$P \Leftrightarrow Q$
false	false	true	false	false	true	true
false	true	true	false	true	true	false
true	false	false	false	true	false	false
true	true	false	true	true	true	true

Figure 7.8 Truth tables for the five logical connectives. To use the table to compute, for example, the value of $P \vee Q$ when P is true and Q is false, first look on the left for the row where P is true and Q is false (the third row). Then look in that row under the $P \vee Q$ column to see the result: *true*.

the sentence $\neg P_{1,2} \wedge (P_{2,2} \vee P_{3,1})$, evaluated in m_1 , gives $\text{true} \wedge (\text{false} \vee \text{true}) = \text{true} \wedge \text{true} = \text{true}$. Exercise 7.3 asks you to write the algorithm PL-TRUE?(s, m), which computes the truth value of a propositional logic sentence s in a model m .

The truth tables for “and,” “or,” and “not” are in close accord with our intuitions about the English words. The main point of possible confusion is that $P \vee Q$ is true when P is true or Q is true *or both*. A different connective, called “exclusive or” (“xor” for short), yields false when both disjuncts are true.⁷ There is no consensus on the symbol for exclusive or; some choices are $\dot{\vee}$ or \neq or \oplus .

The truth table for \Rightarrow may not quite fit one’s intuitive understanding of “ P implies Q ” or “if P then Q .” For one thing, propositional logic does not require any relation of *causation* or *relevance* between P and Q . The sentence “5 is odd implies Tokyo is the capital of Japan” is a true sentence of propositional logic (under the normal interpretation), even though it is a decidedly odd sentence of English. Another point of confusion is that any implication is true whenever its antecedent is false. For example, “5 is even implies Sam is smart” is true, regardless of whether Sam is smart. This seems bizarre, but it makes sense if you think of “ $P \Rightarrow Q$ ” as saying, “If P is true, then I am claiming that Q is true. Otherwise I am making no claim.” The only way for this sentence to be *false* is if P is true but Q is false.

The biconditional, $P \Leftrightarrow Q$, is true whenever both $P \Rightarrow Q$ and $Q \Rightarrow P$ are true. In English, this is often written as “ P if and only if Q .” Many of the rules of the wumpus world are best written using \Leftrightarrow . For example, a square is breezy *if* a neighboring square has a pit, and a square is breezy *only if* a neighboring square has a pit. So we need a biconditional,

$$B_{1,1} \Leftrightarrow (P_{1,2} \vee P_{2,1}),$$

where $B_{1,1}$ means that there is a breeze in [1,1].

7.4.3 A simple knowledge base

Now that we have defined the semantics for propositional logic, we can construct a knowledge base for the wumpus world. We focus first on the *immutable* aspects of the wumpus world, leaving the mutable aspects for a later section. For now, we need the following symbols for each $[x, y]$ location:

⁷ Latin has a separate word, *aut*, for exclusive or.

$P_{x,y}$ is true if there is a pit in $[x, y]$.

$W_{x,y}$ is true if there is a wumpus in $[x, y]$, dead or alive.

$B_{x,y}$ is true if the agent perceives a breeze in $[x, y]$.

$S_{x,y}$ is true if the agent perceives a stench in $[x, y]$.

The sentences we write will suffice to derive $\neg P_{1,2}$ (there is no pit in $[1,2]$), as was done informally in Section 7.3. We label each sentence R_i so that we can refer to them:

- There is no pit in $[1,1]$:

$$R_1 : \neg P_{1,1} .$$

- A square is breezy if and only if there is a pit in a neighboring square. This has to be stated for each square; for now, we include just the relevant squares:

$$R_2 : B_{1,1} \Leftrightarrow (P_{1,2} \vee P_{2,1}) .$$

$$R_3 : B_{2,1} \Leftrightarrow (P_{1,1} \vee P_{2,2} \vee P_{3,1}) .$$

- The preceding sentences are true in all wumpus worlds. Now we include the breeze percepts for the first two squares visited in the specific world the agent is in, leading up to the situation in Figure 7.3(b).

$$R_4 : \neg B_{1,1} .$$

$$R_5 : B_{2,1} .$$

7.4.4 A simple inference procedure

Our goal now is to decide whether $KB \models \alpha$ for some sentence α . For example, is $\neg P_{1,2}$ entailed by our KB ? Our first algorithm for inference is a model-checking approach that is a direct implementation of the definition of entailment: enumerate the models, and check that α is true in every model in which KB is true. Models are assignments of *true* or *false* to every proposition symbol. Returning to our wumpus-world example, the relevant proposition symbols are $B_{1,1}$, $B_{2,1}$, $P_{1,1}$, $P_{1,2}$, $P_{2,1}$, $P_{2,2}$, and $P_{3,1}$. With seven symbols, there are $2^7 = 128$ possible models; in three of these, KB is true (Figure 7.9). In those three models, $\neg P_{1,2}$ is true, hence there is no pit in $[1,2]$. On the other hand, $P_{2,2}$ is true in two of the three models and false in one, so we cannot yet tell whether there is a pit in $[2,2]$.

Figure 7.9 reproduces in a more precise form the reasoning illustrated in Figure 7.5. A general algorithm for deciding entailment in propositional logic is shown in Figure 7.10. Like the BACKTRACKING-SEARCH algorithm on page 215, TT-ENTAILS? performs a recursive enumeration of a finite space of assignments to symbols. The algorithm is **sound** because it implements directly the definition of entailment, and **complete** because it works for any KB and α and always terminates—there are only finitely many models to examine.

Of course, “finitely many” is not always the same as “few.” If KB and α contain n symbols in all, then there are 2^n models. Thus, the time complexity of the algorithm is $O(2^n)$. (The space complexity is only $O(n)$ because the enumeration is depth-first.) Later in this chapter we show algorithms that are much more efficient in many cases. Unfortunately, propositional entailment is co-NP-complete (i.e., probably no easier than NP-complete—see Appendix A), so *every known inference algorithm for propositional logic has a worst-case complexity that is exponential in the size of the input.*



$B_{1,1}$	$B_{2,1}$	$P_{1,1}$	$P_{1,2}$	$P_{2,1}$	$P_{2,2}$	$P_{3,1}$	R_1	R_2	R_3	R_4	R_5	KB
false	false	false	false	false	false	false	true	true	true	true	false	false
false	false	false	false	false	false	true	true	true	false	true	false	false
\vdots	\vdots	\vdots	\vdots	\vdots	\vdots	\vdots	\vdots	\vdots	\vdots	\vdots	\vdots	\vdots
false	true	false	false	false	false	false	true	true	false	true	true	false
false	true	false	false	false	false	true	true	true	true	true	true	<u>true</u>
false	true	false	false	false	true	false	true	true	true	true	true	<u>true</u>
false	true	false	false	false	true	true	true	true	true	true	true	<u>true</u>
false	true	false	false	true	false	false	true	false	false	true	true	false
\vdots	\vdots	\vdots	\vdots	\vdots	\vdots	\vdots	\vdots	\vdots	\vdots	\vdots	\vdots	\vdots
true	true	true	true	true	true	true	false	true	true	false	true	false

Figure 7.9 A truth table constructed for the knowledge base given in the text. KB is true if R_1 through R_5 are true, which occurs in just 3 of the 128 rows (the ones underlined in the right-hand column). In all 3 rows, $P_{1,2}$ is false, so there is no pit in [1,2]. On the other hand, there might (or might not) be a pit in [2,2].

```

function TT-ENTAILS?( $KB, \alpha$ ) returns true or false
  inputs:  $KB$ , the knowledge base, a sentence in propositional logic
            $\alpha$ , the query, a sentence in propositional logic

   $symbols \leftarrow$  a list of the proposition symbols in  $KB$  and  $\alpha$ 
  return TT-CHECK-ALL( $KB, \alpha, symbols, \{ \}$ )



---


function TT-CHECK-ALL( $KB, \alpha, symbols, model$ ) returns true or false
  if EMPTY?( $symbols$ ) then
    if PL-TRUE?( $KB, model$ ) then return PL-TRUE?( $\alpha, model$ )
    else return true // when  $KB$  is false, always return true
  else do
     $P \leftarrow$  FIRST( $symbols$ )
     $rest \leftarrow$  REST( $symbols$ )
    return (TT-CHECK-ALL( $KB, \alpha, rest, model \cup \{P = true\}$ )
           and
           TT-CHECK-ALL( $KB, \alpha, rest, model \cup \{P = false\}$ ))

```

Figure 7.10 A truth-table enumeration algorithm for deciding propositional entailment. (TT stands for truth table.) PL-TRUE? returns *true* if a sentence holds within a model. The variable $model$ represents a partial model—an assignment to some of the symbols. The keyword “**and**” is used here as a logical operation on its two arguments, returning *true* or *false*.

$(\alpha \wedge \beta) \equiv (\beta \wedge \alpha)$	commutativity of \wedge
$(\alpha \vee \beta) \equiv (\beta \vee \alpha)$	commutativity of \vee
$((\alpha \wedge \beta) \wedge \gamma) \equiv (\alpha \wedge (\beta \wedge \gamma))$	associativity of \wedge
$((\alpha \vee \beta) \vee \gamma) \equiv (\alpha \vee (\beta \vee \gamma))$	associativity of \vee
$\neg(\neg\alpha) \equiv \alpha$	double-negation elimination
$(\alpha \Rightarrow \beta) \equiv (\neg\beta \Rightarrow \neg\alpha)$	contraposition
$(\alpha \Rightarrow \beta) \equiv (\neg\alpha \vee \beta)$	implication elimination
$(\alpha \Leftrightarrow \beta) \equiv ((\alpha \Rightarrow \beta) \wedge (\beta \Rightarrow \alpha))$	biconditional elimination
$\neg(\alpha \wedge \beta) \equiv (\neg\alpha \vee \neg\beta)$	De Morgan
$\neg(\alpha \vee \beta) \equiv (\neg\alpha \wedge \neg\beta)$	De Morgan
$(\alpha \wedge (\beta \vee \gamma)) \equiv ((\alpha \wedge \beta) \vee (\alpha \wedge \gamma))$	distributivity of \wedge over \vee
$(\alpha \vee (\beta \wedge \gamma)) \equiv ((\alpha \vee \beta) \wedge (\alpha \vee \gamma))$	distributivity of \vee over \wedge

Figure 7.11 Standard logical equivalences. The symbols α , β , and γ stand for arbitrary sentences of propositional logic.

7.5 PROPOSITIONAL THEOREM PROVING

THEOREM PROVING

So far, we have shown how to determine entailment by *model checking*: enumerating models and showing that the sentence must hold in all models. In this section, we show how entailment can be done by **theorem proving**—applying rules of inference directly to the sentences in our knowledge base to construct a proof of the desired sentence without consulting models. If the number of models is large but the length of the proof is short, then theorem proving can be more efficient than model checking.

LOGICAL
EQUIVALENCE

Before we plunge into the details of theorem-proving algorithms, we will need some additional concepts related to entailment. The first concept is **logical equivalence**: two sentences α and β are logically equivalent if they are true in the same set of models. We write this as $\alpha \equiv \beta$. For example, we can easily show (using truth tables) that $P \wedge Q$ and $Q \wedge P$ are logically equivalent; other equivalences are shown in Figure 7.11. These equivalences play much the same role in logic as arithmetic identities do in ordinary mathematics. An alternative definition of equivalence is as follows: any two sentences α and β are equivalent only if each of them entails the other:

$$\alpha \equiv \beta \quad \text{if and only if} \quad \alpha \models \beta \text{ and } \beta \models \alpha.$$

VALIDITY

TAUTOLOGY

The second concept we will need is **validity**. A sentence is valid if it is true in *all* models. For example, the sentence $P \vee \neg P$ is valid. Valid sentences are also known as **tautologies**—they are *necessarily* true. Because the sentence *True* is true in all models, every valid sentence is logically equivalent to *True*. What good are valid sentences? From our definition of entailment, we can derive the **deduction theorem**, which was known to the ancient Greeks:

DEDUCTION
THEOREM



For any sentences α and β , $\alpha \models \beta$ if and only if the sentence $(\alpha \Rightarrow \beta)$ is valid.

(Exercise 7.5 asks for a proof.) Hence, we can decide if $\alpha \models \beta$ by checking that $(\alpha \Rightarrow \beta)$ is true in every model—which is essentially what the inference algorithm in Figure 7.10 does—

or by proving that $(\alpha \Rightarrow \beta)$ is equivalent to *True*. Conversely, the deduction theorem states that every valid implication sentence describes a legitimate inference.

SATISFIABILITY

The final concept we will need is **satisfiability**. A sentence is satisfiable if it is true in, or satisfied by, *some* model. For example, the knowledge base given earlier, $(R_1 \wedge R_2 \wedge R_3 \wedge R_4 \wedge R_5)$, is satisfiable because there are three models in which it is true, as shown in Figure 7.9. Satisfiability can be checked by enumerating the possible models until one is found that satisfies the sentence. The problem of determining the satisfiability of sentences in propositional logic—the **SAT** problem—was the first problem proved to be NP-complete. Many problems in computer science are really satisfiability problems. For example, all the constraint satisfaction problems in Chapter 6 ask whether the constraints are satisfiable by some assignment.

SAT

Validity and satisfiability are of course connected: α is valid iff $\neg\alpha$ is unsatisfiable; contrapositively, α is satisfiable iff $\neg\alpha$ is not valid. We also have the following useful result:

$\alpha \models \beta$ if and only if the sentence $(\alpha \wedge \neg\beta)$ is unsatisfiable.

REDUCTIO AD
ABSURDUM

REFUTATION

CONTRADICTION

Proving β from α by checking the unsatisfiability of $(\alpha \wedge \neg\beta)$ corresponds exactly to the standard mathematical proof technique of *reductio ad absurdum* (literally, “reduction to an absurd thing”). It is also called proof by **refutation** or proof by **contradiction**. One assumes a sentence β to be false and shows that this leads to a contradiction with known axioms α . This contradiction is exactly what is meant by saying that the sentence $(\alpha \wedge \neg\beta)$ is unsatisfiable.

7.5.1 Inference and proofs

INFERENCE RULES

PROOF

MODUS PONENS

This section covers **inference rules** that can be applied to derive a **proof**—a chain of conclusions that leads to the desired goal. The best-known rule is called **Modus Ponens** (Latin for *mode that affirms*) and is written

$$\frac{\alpha \Rightarrow \beta, \quad \alpha}{\beta}.$$

The notation means that, whenever any sentences of the form $\alpha \Rightarrow \beta$ and α are given, then the sentence β can be inferred. For example, if $(WumpusAhead \wedge WumpusAlive) \Rightarrow Shoot$ and $(WumpusAhead \wedge WumpusAlive)$ are given, then *Shoot* can be inferred.

AND-ELIMINATION

Another useful inference rule is **And-Elimination**, which says that, from a conjunction, any of the conjuncts can be inferred:

$$\frac{\alpha \wedge \beta}{\alpha}.$$

For example, from $(WumpusAhead \wedge WumpusAlive)$, *WumpusAlive* can be inferred.

By considering the possible truth values of α and β , one can show easily that Modus Ponens and And-Elimination are sound once and for all. These rules can then be used in any particular instances where they apply, generating sound inferences without the need for enumerating models.

All of the logical equivalences in Figure 7.11 can be used as inference rules. For example, the equivalence for biconditional elimination yields the two inference rules

$$\frac{\alpha \Leftrightarrow \beta}{(\alpha \Rightarrow \beta) \wedge (\beta \Rightarrow \alpha)} \quad \text{and} \quad \frac{(\alpha \Rightarrow \beta) \wedge (\beta \Rightarrow \alpha)}{\alpha \Leftrightarrow \beta}.$$

Not all inference rules work in both directions like this. For example, we cannot run Modus Ponens in the opposite direction to obtain $\alpha \Rightarrow \beta$ and α from β .

Let us see how these inference rules and equivalences can be used in the wumpus world. We start with the knowledge base containing R_1 through R_5 and show how to prove $\neg P_{1,2}$, that is, there is no pit in [1,2]. First, we apply biconditional elimination to R_2 to obtain

$$R_6 : (B_{1,1} \Rightarrow (P_{1,2} \vee P_{2,1})) \wedge ((P_{1,2} \vee P_{2,1}) \Rightarrow B_{1,1}) .$$

Then we apply And-Elimination to R_6 to obtain

$$R_7 : ((P_{1,2} \vee P_{2,1}) \Rightarrow B_{1,1}) .$$

Logical equivalence for contrapositives gives

$$R_8 : (\neg B_{1,1} \Rightarrow \neg(P_{1,2} \vee P_{2,1})) .$$

Now we can apply Modus Ponens with R_8 and the percept R_4 (i.e., $\neg B_{1,1}$), to obtain

$$R_9 : \neg(P_{1,2} \vee P_{2,1}) .$$

Finally, we apply De Morgan's rule, giving the conclusion

$$R_{10} : \neg P_{1,2} \wedge \neg P_{2,1} .$$

That is, neither [1,2] nor [2,1] contains a pit.

We found this proof by hand, but we can apply any of the search algorithms in Chapter 3 to find a sequence of steps that constitutes a proof. We just need to define a proof problem as follows:

- INITIAL STATE: the initial knowledge base.
- ACTIONS: the set of actions consists of all the inference rules applied to all the sentences that match the top half of the inference rule.
- RESULT: the result of an action is to add the sentence in the bottom half of the inference rule.
- GOAL: the goal is a state that contains the sentence we are trying to prove.



Thus, searching for proofs is an alternative to enumerating models. In many practical cases *finding a proof can be more efficient because the proof can ignore irrelevant propositions, no matter how many of them there are*. For example, the proof given earlier leading to $\neg P_{1,2} \wedge \neg P_{2,1}$ does not mention the propositions $B_{2,1}$, $P_{1,1}$, $P_{2,2}$, or $P_{3,1}$. They can be ignored because the goal proposition, $P_{1,2}$, appears only in sentence R_2 ; the other propositions in R_2 appear only in R_4 and R_2 ; so R_1 , R_3 , and R_5 have no bearing on the proof. The same would hold even if we added a million more sentences to the knowledge base; the simple truth-table algorithm, on the other hand, would be overwhelmed by the exponential explosion of models.

One final property of logical systems is **monotonicity**, which says that the set of entailed sentences can only *increase* as information is added to the knowledge base.⁸ For any sentences α and β ,

$$\text{if } KB \models \alpha \text{ then } KB \wedge \beta \models \alpha .$$

⁸ **Nonmonotonic** logics, which violate the monotonicity property, capture a common property of human reasoning: changing one's mind. They are discussed in Section 12.6.

For example, suppose the knowledge base contains the additional assertion β stating that there are exactly eight pits in the world. This knowledge might help the agent draw *additional* conclusions, but it cannot invalidate any conclusion α already inferred—such as the conclusion that there is no pit in [1,2]. Monotonicity means that inference rules can be applied whenever suitable premises are found in the knowledge base—the conclusion of the rule must follow *regardless of what else is in the knowledge base*.

7.5.2 Proof by resolution

We have argued that the inference rules covered so far are *sound*, but we have not discussed the question of *completeness* for the inference algorithms that use them. Search algorithms such as iterative deepening search (page 89) are complete in the sense that they will find any reachable goal, but if the available inference rules are inadequate, then the goal is not reachable—no proof exists that uses only those inference rules. For example, if we removed the biconditional elimination rule, the proof in the preceding section would not go through. The current section introduces a single inference rule, **resolution**, that yields a complete inference algorithm when coupled with any complete search algorithm.

We begin by using a simple version of the resolution rule in the wumpus world. Let us consider the steps leading up to Figure 7.4(a): the agent returns from [2,1] to [1,1] and then goes to [1,2], where it perceives a stench, but no breeze. We add the following facts to the knowledge base:

$$\begin{aligned} R_{11} : & \quad \neg B_{1,2} . \\ R_{12} : & \quad B_{1,2} \Leftrightarrow (P_{1,1} \vee P_{2,2} \vee P_{1,3}) . \end{aligned}$$

By the same process that led to R_{10} earlier, we can now derive the absence of pits in [2,2] and [1,3] (remember that [1,1] is already known to be pitless):

$$\begin{aligned} R_{13} : & \quad \neg P_{2,2} . \\ R_{14} : & \quad \neg P_{1,3} . \end{aligned}$$

We can also apply biconditional elimination to R_3 , followed by Modus Ponens with R_5 , to obtain the fact that there is a pit in [1,1], [2,2], or [3,1]:

$$R_{15} : \quad P_{1,1} \vee P_{2,2} \vee P_{3,1} .$$

Now comes the first application of the resolution rule: the literal $\neg P_{2,2}$ in R_{13} *resolves with* the literal $P_{2,2}$ in R_{15} to give the **resolvent**

$$R_{16} : \quad P_{1,1} \vee P_{3,1} .$$

In English; if there's a pit in one of [1,1], [2,2], and [3,1] and it's not in [2,2], then it's in [1,1] or [3,1]. Similarly, the literal $\neg P_{1,1}$ in R_1 resolves with the literal $P_{1,1}$ in R_{16} to give

$$R_{17} : \quad P_{3,1} .$$

In English: if there's a pit in [1,1] or [3,1] and it's not in [1,1], then it's in [3,1]. These last two inference steps are examples of the **unit resolution** inference rule,

$$\frac{\ell_1 \vee \cdots \vee \ell_k, \quad m}{\ell_1 \vee \cdots \vee \ell_{i-1} \vee \ell_{i+1} \vee \cdots \vee \ell_k} ,$$

where each ℓ is a literal and ℓ_i and m are **complementary literals** (i.e., one is the negation

RESOLVENT

UNIT RESOLUTION

COMPLEMENTARY
LITERALS

CLAUSE

of the other). Thus, the unit resolution rule takes a **clause**—a disjunction of literals—and a literal and produces a new clause. Note that a single literal can be viewed as a disjunction of one literal, also known as a **unit clause**.

UNIT CLAUSE

RESOLUTION

The unit resolution rule can be generalized to the full **resolution** rule,

$$\frac{\ell_1 \vee \cdots \vee \ell_k, \quad m_1 \vee \cdots \vee m_n}{\ell_1 \vee \cdots \vee \ell_{i-1} \vee \ell_{i+1} \vee \cdots \vee \ell_k \vee m_1 \vee \cdots \vee m_{j-1} \vee m_{j+1} \vee \cdots \vee m_n},$$

where ℓ_i and m_j are complementary literals. This says that resolution takes two clauses and produces a new clause containing all the literals of the two original clauses *except* the two complementary literals. For example, we have

$$\frac{P_{1,1} \vee P_{3,1}, \quad \neg P_{1,1} \vee \neg P_{2,2}}{P_{3,1} \vee \neg P_{2,2}}.$$

FACTORING

There is one more technical aspect of the resolution rule: the resulting clause should contain only one copy of each literal.⁹ The removal of multiple copies of literals is called **factoring**. For example, if we resolve $(A \vee B)$ with $(A \vee \neg B)$, we obtain $(A \vee A)$, which is reduced to just A .

The *soundness* of the resolution rule can be seen easily by considering the literal ℓ_i that is complementary to literal m_j in the other clause. If ℓ_i is true, then m_j is false, and hence $m_1 \vee \cdots \vee m_{j-1} \vee m_{j+1} \vee \cdots \vee m_n$ must be true, because $m_1 \vee \cdots \vee m_n$ is given. If ℓ_i is false, then $\ell_1 \vee \cdots \vee \ell_{i-1} \vee \ell_{i+1} \vee \cdots \vee \ell_k$ must be true because $\ell_1 \vee \cdots \vee \ell_k$ is given. Now ℓ_i is either true or false, so one or other of these conclusions holds—exactly as the resolution rule states.



What is more surprising about the resolution rule is that it forms the basis for a family of *complete* inference procedures. A *resolution-based theorem prover* can, for any sentences α and β in propositional logic, decide whether $\alpha \models \beta$. The next two subsections explain how resolution accomplishes this.

Conjunctive normal form

The resolution rule applies only to clauses (that is, disjunctions of literals), so it would seem to be relevant only to knowledge bases and queries consisting of clauses. How, then, can it lead to a complete inference procedure for all of propositional logic? The answer is that *every sentence of propositional logic is logically equivalent to a conjunction of clauses*. A sentence expressed as a conjunction of clauses is said to be in **conjunctive normal form** or **CNF** (see Figure 7.14). We now describe a procedure for converting to CNF. We illustrate the procedure by converting the sentence $B_{1,1} \Leftrightarrow (P_{1,2} \vee P_{2,1})$ into CNF. The steps are as follows:



1. Eliminate \Leftrightarrow , replacing $\alpha \Leftrightarrow \beta$ with $(\alpha \Rightarrow \beta) \wedge (\beta \Rightarrow \alpha)$.

$$(B_{1,1} \Rightarrow (P_{1,2} \vee P_{2,1})) \wedge ((P_{1,2} \vee P_{2,1}) \Rightarrow B_{1,1}).$$
2. Eliminate \Rightarrow , replacing $\alpha \Rightarrow \beta$ with $\neg\alpha \vee \beta$:

$$(\neg B_{1,1} \vee P_{1,2} \vee P_{2,1}) \wedge (\neg(P_{1,2} \vee P_{2,1}) \vee B_{1,1}).$$

⁹ If a clause is viewed as a *set* of literals, then this restriction is automatically respected. Using set notation for clauses makes the resolution rule much cleaner, at the cost of introducing additional notation.

3. CNF requires \neg to appear only in literals, so we “move \neg inwards” by repeated application of the following equivalences from Figure 7.11:

$$\begin{aligned}\neg(\neg\alpha) &\equiv \alpha \quad (\text{double-negation elimination}) \\ \neg(\alpha \wedge \beta) &\equiv (\neg\alpha \vee \neg\beta) \quad (\text{De Morgan}) \\ \neg(\alpha \vee \beta) &\equiv (\neg\alpha \wedge \neg\beta) \quad (\text{De Morgan})\end{aligned}$$

In the example, we require just one application of the last rule:

$$(\neg B_{1,1} \vee P_{1,2} \vee P_{2,1}) \wedge ((\neg P_{1,2} \wedge \neg P_{2,1}) \vee B_{1,1}) .$$

4. Now we have a sentence containing nested \wedge and \vee operators applied to literals. We apply the distributivity law from Figure 7.11, distributing \vee over \wedge wherever possible.

$$(\neg B_{1,1} \vee P_{1,2} \vee P_{2,1}) \wedge (\neg P_{1,2} \vee B_{1,1}) \wedge (\neg P_{2,1} \vee B_{1,1}) .$$

The original sentence is now in CNF, as a conjunction of three clauses. It is much harder to read, but it can be used as input to a resolution procedure.

A resolution algorithm

Inference procedures based on resolution work by using the principle of proof by contradiction introduced on page 250. That is, to show that $KB \models \alpha$, we show that $(KB \wedge \neg\alpha)$ is unsatisfiable. We do this by proving a contradiction.

A resolution algorithm is shown in Figure 7.12. First, $(KB \wedge \neg\alpha)$ is converted into CNF. Then, the resolution rule is applied to the resulting clauses. Each pair that contains complementary literals is resolved to produce a new clause, which is added to the set if it is not already present. The process continues until one of two things happens:

- there are no new clauses that can be added, in which case KB does not entail α ; or,
- two clauses resolve to yield the *empty* clause, in which case KB entails α .

The empty clause—a disjunction of no disjuncts—is equivalent to *False* because a disjunction is true only if at least one of its disjuncts is true. Another way to see that an empty clause represents a contradiction is to observe that it arises only from resolving two complementary unit clauses such as P and $\neg P$.

We can apply the resolution procedure to a very simple inference in the wumpus world. When the agent is in [1,1], there is no breeze, so there can be no pits in neighboring squares. The relevant knowledge base is

$$KB = R_2 \wedge R_4 = (B_{1,1} \Leftrightarrow (P_{1,2} \vee P_{2,1})) \wedge \neg B_{1,1}$$

and we wish to prove α which is, say, $\neg P_{1,2}$. When we convert $(KB \wedge \neg\alpha)$ into CNF, we obtain the clauses shown at the top of Figure 7.13. The second row of the figure shows clauses obtained by resolving pairs in the first row. Then, when $P_{1,2}$ is resolved with $\neg P_{1,2}$, we obtain the empty clause, shown as a small square. Inspection of Figure 7.13 reveals that many resolution steps are pointless. For example, the clause $B_{1,1} \vee \neg B_{1,1} \vee P_{1,2}$ is equivalent to $True \vee P_{1,2}$ which is equivalent to *True*. Deducing that *True* is true is not very helpful. Therefore, any clause in which two complementary literals appear can be discarded.

```

function PL-RESOLUTION( $KB, \alpha$ ) returns true or false
  inputs:  $KB$ , the knowledge base, a sentence in propositional logic
            $\alpha$ , the query, a sentence in propositional logic

   $clauses \leftarrow$  the set of clauses in the CNF representation of  $KB \wedge \neg\alpha$ 
   $new \leftarrow \{ \}$ 
  loop do
    for each pair of clauses  $C_i, C_j$  in  $clauses$  do
       $resolvents \leftarrow$  PL-RESOLVE( $C_i, C_j$ )
      if  $resolvents$  contains the empty clause then return true
       $new \leftarrow new \cup resolvents$ 
    if  $new \subseteq clauses$  then return false
     $clauses \leftarrow clauses \cup new$ 

```

Figure 7.12 A simple resolution algorithm for propositional logic. The function PL-RESOLVE returns the set of all possible clauses obtained by resolving its two inputs.

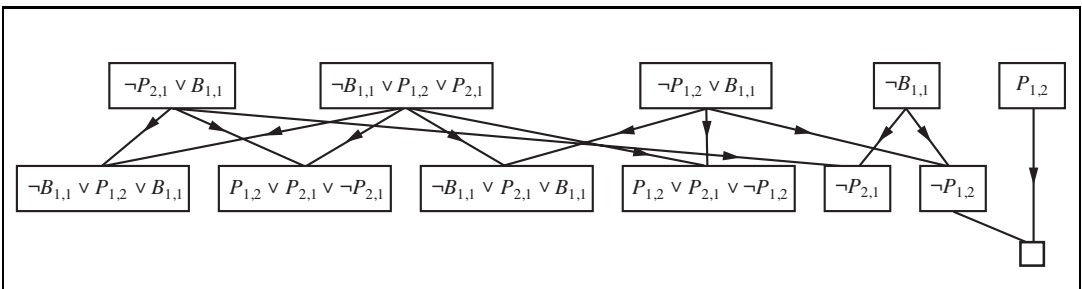


Figure 7.13 Partial application of PL-RESOLUTION to a simple inference in the wumpus world. $\neg P_{1,2}$ is shown to follow from the first four clauses in the top row.

Completeness of resolution

To conclude our discussion of resolution, we now show why PL-RESOLUTION is complete. To do this, we introduce the **resolution closure** $RC(S)$ of a set of clauses S , which is the set of all clauses derivable by repeated application of the resolution rule to clauses in S or their derivatives. The resolution closure is what PL-RESOLUTION computes as the final value of the variable $clauses$. It is easy to see that $RC(S)$ must be finite, because there are only finitely many distinct clauses that can be constructed out of the symbols P_1, \dots, P_k that appear in S . (Notice that this would not be true without the factoring step that removes multiple copies of literals.) Hence, PL-RESOLUTION always terminates.

The completeness theorem for resolution in propositional logic is called the **ground resolution theorem**:

If a set of clauses is unsatisfiable, then the resolution closure of those clauses contains the empty clause.

This theorem is proved by demonstrating its contrapositive: if the closure $RC(S)$ does *not*

RESOLUTION
CLOSURE

GROUND
RESOLUTION
THEOREM

contain the empty clause, then S is satisfiable. In fact, we can construct a model for S with suitable truth values for P_1, \dots, P_k . The construction procedure is as follows:

For i from 1 to k ,

- If a clause in $RC(S)$ contains the literal $\neg P_i$ and all its other literals are false under the assignment chosen for P_1, \dots, P_{i-1} , then assign *false* to P_i .
- Otherwise, assign *true* to P_i .

This assignment to P_1, \dots, P_k is a model of S . To see this, assume the opposite—that, at some stage i in the sequence, assigning symbol P_i causes some clause C to become false. For this to happen, it must be the case that all the *other* literals in C must already have been falsified by assignments to P_1, \dots, P_{i-1} . Thus, C must now look like either $(false \vee false \vee \dots false \vee P_i)$ or like $(false \vee false \vee \dots false \vee \neg P_i)$. If just one of these two is in $RC(S)$, then the algorithm will assign the appropriate truth value to P_i to make C true, so C can only be falsified if *both* of these clauses are in $RC(S)$. Now, since $RC(S)$ is closed under resolution, it will contain the resolvent of these two clauses, and that resolvent will have all of its literals already falsified by the assignments to P_1, \dots, P_{i-1} . This contradicts our assumption that the first falsified clause appears at stage i . Hence, we have proved that the construction never falsifies a clause in $RC(S)$; that is, it produces a model of $RC(S)$ and thus a model of S itself (since S is contained in $RC(S)$).

7.5.3 Horn clauses and definite clauses

The completeness of resolution makes it a very important inference method. In many practical situations, however, the full power of resolution is not needed. Some real-world knowledge bases satisfy certain restrictions on the form of sentences they contain, which enables them to use a more restricted and efficient inference algorithm.

DEFINITE CLAUSE

One such restricted form is the **definite clause**, which is a disjunction of literals of which *exactly one is positive*. For example, the clause $(\neg L_{1,1} \vee \neg Breeze \vee B_{1,1})$ is a definite clause, whereas $(\neg B_{1,1} \vee P_{1,2} \vee P_{2,1})$ is not.

HORN CLAUSE

Slightly more general is the **Horn clause**, which is a disjunction of literals of which *at most one is positive*. So all definite clauses are Horn clauses, as are clauses with no positive literals; these are called **goal clauses**. Horn clauses are closed under resolution: if you resolve two Horn clauses, you get back a Horn clause.

GOAL CLAUSES

Knowledge bases containing only definite clauses are interesting for three reasons:

1. Every definite clause can be written as an implication whose premise is a conjunction of positive literals and whose conclusion is a single positive literal. (See Exercise 7.13.) For example, the definite clause $(\neg L_{1,1} \vee \neg Breeze \vee B_{1,1})$ can be written as the implication $(L_{1,1} \wedge Breeze) \Rightarrow B_{1,1}$. In the implication form, the sentence is easier to understand: it says that if the agent is in [1,1] and there is a breeze, then [1,1] is breezy. In Horn form, the premise is called the **body** and the conclusion is called the **head**. A sentence consisting of a single positive literal, such as $L_{1,1}$, is called a **fact**. It too can be written in implication form as $True \Rightarrow L_{1,1}$, but it is simpler to write just $L_{1,1}$.

BODY

HEAD

FACT

$$\begin{aligned}
\text{CNFSentence} &\rightarrow \text{Clause}_1 \wedge \cdots \wedge \text{Clause}_n \\
\text{Clause} &\rightarrow \text{Literal}_1 \vee \cdots \vee \text{Literal}_m \\
\text{Literal} &\rightarrow \text{Symbol} \mid \neg \text{Symbol} \\
\text{Symbol} &\rightarrow P \mid Q \mid R \mid \dots \\
\text{HornClauseForm} &\rightarrow \text{DefiniteClauseForm} \mid \text{GoalClauseForm} \\
\text{DefiniteClauseForm} &\rightarrow (\text{Symbol}_1 \wedge \cdots \wedge \text{Symbol}_l) \Rightarrow \text{Symbol} \\
\text{GoalClauseForm} &\rightarrow (\text{Symbol}_1 \wedge \cdots \wedge \text{Symbol}_l) \Rightarrow \text{False}
\end{aligned}$$

Figure 7.14 A grammar for conjunctive normal form, Horn clauses, and definite clauses. A clause such as $A \wedge B \Rightarrow C$ is still a definite clause when it is written as $\neg A \vee \neg B \vee C$, but only the former is considered the canonical form for definite clauses. One more class is the k -CNF sentence, which is a CNF sentence where each clause has at most k literals.

FORWARD-CHAINING
BACKWARD-
CHAINING

2. Inference with Horn clauses can be done through the **forward-chaining** and **backward-chaining** algorithms, which we explain next. Both of these algorithms are natural, in that the inference steps are obvious and easy for humans to follow. This type of inference is the basis for **logic programming**, which is discussed in Chapter 9.
3. Deciding entailment with Horn clauses can be done in time that is *linear* in the size of the knowledge base—a pleasant surprise.

7.5.4 Forward and backward chaining

The forward-chaining algorithm $\text{PL-FC-ENTAILS?}(KB, q)$ determines if a single proposition symbol q —the query—is entailed by a knowledge base of definite clauses. It begins from known facts (positive literals) in the knowledge base. If all the premises of an implication are known, then its conclusion is added to the set of known facts. For example, if $L_{1,1}$ and *Breeze* are known and $(L_{1,1} \wedge \textit{Breeze}) \Rightarrow B_{1,1}$ is in the knowledge base, then $B_{1,1}$ can be added. This process continues until the query q is added or until no further inferences can be made. The detailed algorithm is shown in Figure 7.15; the main point to remember is that it runs in linear time.

The best way to understand the algorithm is through an example and a picture. Figure 7.16(a) shows a simple knowledge base of Horn clauses with A and B as known facts. Figure 7.16(b) shows the same knowledge base drawn as an **AND-OR graph** (see Chapter 4). In AND-OR graphs, multiple links joined by an arc indicate a conjunction—every link must be proved—while multiple links without an arc indicate a disjunction—any link can be proved. It is easy to see how forward chaining works in the graph. The known leaves (here, A and B) are set, and inference propagates up the graph as far as possible. Whenever a conjunction appears, the propagation waits until all the conjuncts are known before proceeding. The reader is encouraged to work through the example in detail.


```

function PL-FC-ENTAILS?(KB, q) returns true or false
  inputs: KB, the knowledge base, a set of propositional definite clauses
           q, the query, a proposition symbol
  count  $\leftarrow$  a table, where count[c] is the number of symbols in c's premise
  inferred  $\leftarrow$  a table, where inferred[s] is initially false for all symbols
  agenda  $\leftarrow$  a queue of symbols, initially symbols known to be true in KB

  while agenda is not empty do
    p  $\leftarrow$  POP(agenda)
    if p = q then return true
    if inferred[p] = false then
      inferred[p]  $\leftarrow$  true
      for each clause c in KB where p is in c.PREMISE do
        decrement count[c]
        if count[c] = 0 then add c.CONCLUSION to agenda
  return false

```

Figure 7.15 The forward-chaining algorithm for propositional logic. The *agenda* keeps track of symbols known to be true but not yet “processed.” The *count* table keeps track of how many premises of each implication are as yet unknown. Whenever a new symbol *p* from the agenda is processed, the count is reduced by one for each implication in whose premise *p* appears (easily identified in constant time with appropriate indexing.) If a count reaches zero, all the premises of the implication are known, so its conclusion can be added to the agenda. Finally, we need to keep track of which symbols have been processed; a symbol that is already in the set of inferred symbols need not be added to the agenda again. This avoids redundant work and prevents loops caused by implications such as $P \Rightarrow Q$ and $Q \Rightarrow P$.

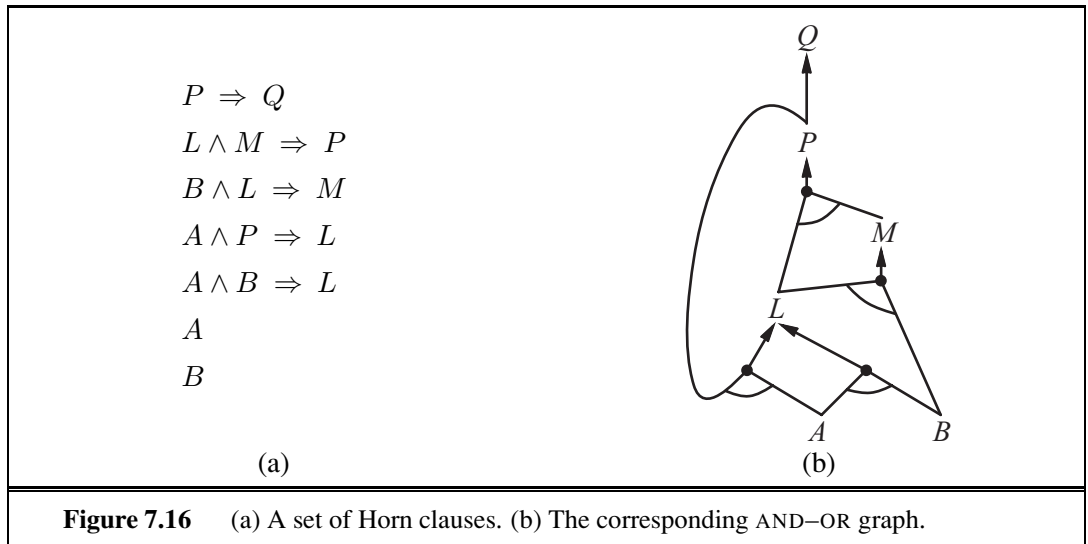
It is easy to see that forward chaining is **sound**: every inference is essentially an application of Modus Ponens. Forward chaining is also **complete**: every entailed atomic sentence will be derived. The easiest way to see this is to consider the final state of the *inferred* table (after the algorithm reaches a **fixed point** where no new inferences are possible). The table contains *true* for each symbol inferred during the process, and *false* for all other symbols. We can view the table as a logical model; moreover, *every definite clause in the original KB is true in this model*. To see this, assume the opposite, namely that some clause $a_1 \wedge \dots \wedge a_k \Rightarrow b$ is false in the model. Then $a_1 \wedge \dots \wedge a_k$ must be true in the model and *b* must be false in the model. But this contradicts our assumption that the algorithm has reached a fixed point! We can conclude, therefore, that the set of atomic sentences inferred at the fixed point defines a model of the original KB. Furthermore, any atomic sentence *q* that is entailed by the KB must be true in all its models and in this model in particular. Hence, every entailed atomic sentence *q* must be inferred by the algorithm.

Forward chaining is an example of the general concept of **data-driven** reasoning—that is, reasoning in which the focus of attention starts with the known data. It can be used within an agent to derive conclusions from incoming percepts, often without a specific query in mind. For example, the wumpus agent might TELL its percepts to the knowledge base using

FIXED POINT



DATA-DRIVEN



an incremental forward-chaining algorithm in which new facts can be added to the agenda to initiate new inferences. In humans, a certain amount of data-driven reasoning occurs as new information arrives. For example, if I am indoors and hear rain starting to fall, it might occur to me that the picnic will be canceled. Yet it will probably not occur to me that the seventeenth petal on the largest rose in my neighbor’s garden will get wet; humans keep forward chaining under careful control, lest they be swamped with irrelevant consequences.

The backward-chaining algorithm, as its name suggests, works backward from the query. If the query q is known to be true, then no work is needed. Otherwise, the algorithm finds those implications in the knowledge base whose conclusion is q . If all the premises of one of those implications can be proved true (by backward chaining), then q is true. When applied to the query Q in Figure 7.16, it works back down the graph until it reaches a set of known facts, A and B , that forms the basis for a proof. The algorithm is essentially identical to the AND-OR-GRAPH-SEARCH algorithm in Figure 4.11. As with forward chaining, an efficient implementation runs in linear time.

GOAL-DIRECTED
REASONING

Backward chaining is a form of **goal-directed reasoning**. It is useful for answering specific questions such as “What shall I do now?” and “Where are my keys?” Often, the cost of backward chaining is *much less* than linear in the size of the knowledge base, because the process touches only relevant facts.

7.6 EFFECTIVE PROPOSITIONAL MODEL CHECKING

In this section, we describe two families of efficient algorithms for general propositional inference based on model checking: One approach based on backtracking search, and one on local hill-climbing search. These algorithms are part of the “technology” of propositional logic. This section can be skimmed on a first reading of the chapter.

The algorithms we describe are for checking satisfiability: the SAT problem. (As noted earlier, testing entailment, $\alpha \models \beta$, can be done by testing *unsatisfiability* of $\alpha \wedge \neg\beta$.) We have already noted the connection between finding a satisfying model for a logical sentence and finding a solution for a constraint satisfaction problem, so it is perhaps not surprising that the two families of algorithms closely resemble the backtracking algorithms of Section 6.3 and the local search algorithms of Section 6.4. They are, however, extremely important in their own right because so many combinatorial problems in computer science can be reduced to checking the satisfiability of a propositional sentence. Any improvement in satisfiability algorithms has huge consequences for our ability to handle complexity in general.

7.6.1 A complete backtracking algorithm

DAVIS-PUTNAM
ALGORITHM

The first algorithm we consider is often called the **Davis–Putnam algorithm**, after the seminal paper by Martin Davis and Hilary Putnam (1960). The algorithm is in fact the version described by Davis, Logemann, and Loveland (1962), so we will call it DPLL after the initials of all four authors. DPLL takes as input a sentence in conjunctive normal form—a set of clauses. Like BACKTRACKING-SEARCH and TT-ENTAILS?, it is essentially a recursive, depth-first enumeration of possible models. It embodies three improvements over the simple scheme of TT-ENTAILS?:

- *Early termination*: The algorithm detects whether the sentence must be true or false, even with a partially completed model. A clause is true if *any* literal is true, even if the other literals do not yet have truth values; hence, the sentence as a whole could be judged true even before the model is complete. For example, the sentence $(A \vee B) \wedge (A \vee C)$ is true if A is true, regardless of the values of B and C . Similarly, a sentence is false if *any* clause is false, which occurs when each of its literals is false. Again, this can occur long before the model is complete. Early termination avoids examination of entire subtrees in the search space.
- *Pure symbol heuristic*: A **pure symbol** is a symbol that always appears with the same “sign” in all clauses. For example, in the three clauses $(A \vee \neg B)$, $(\neg B \vee \neg C)$, and $(C \vee A)$, the symbol A is pure because only the positive literal appears, B is pure because only the negative literal appears, and C is impure. It is easy to see that if a sentence has a model, then it has a model with the pure symbols assigned so as to make their literals *true*, because doing so can never make a clause false. Note that, in determining the purity of a symbol, the algorithm can ignore clauses that are already known to be true in the model constructed so far. For example, if the model contains $B = \text{false}$, then the clause $(\neg B \vee \neg C)$ is already true, and in the remaining clauses C appears only as a positive literal; therefore C becomes pure.
- *Unit clause heuristic*: A **unit clause** was defined earlier as a clause with just one literal. In the context of DPLL, it also means clauses in which all literals but one are already assigned *false* by the model. For example, if the model contains $B = \text{true}$, then $(\neg B \vee \neg C)$ simplifies to $\neg C$, which is a unit clause. Obviously, for this clause to be true, C must be set to *false*. The unit clause heuristic assigns all such symbols before branching on the remainder. One important consequence of the heuristic is that

PURE SYMBOL

```

function DPLL-SATISFIABLE?(s) returns true or false
  inputs: s, a sentence in propositional logic

  clauses  $\leftarrow$  the set of clauses in the CNF representation of s
  symbols  $\leftarrow$  a list of the proposition symbols in s
  return DPLL(clauses, symbols, { })

```

```

function DPLL(clauses, symbols, model) returns true or false

  if every clause in clauses is true in model then return true
  if some clause in clauses is false in model then return false
  P, value  $\leftarrow$  FIND-PURE-SYMBOL(symbols, clauses, model)
  if P is non-null then return DPLL(clauses, symbols – P, model  $\cup$  {P=value})
  P, value  $\leftarrow$  FIND-UNIT-CLAUSE(clauses, model)
  if P is non-null then return DPLL(clauses, symbols – P, model  $\cup$  {P=value})
  P  $\leftarrow$  FIRST(symbols); rest  $\leftarrow$  REST(symbols)
  return DPLL(clauses, rest, model  $\cup$  {P=true}) or
    DPLL(clauses, rest, model  $\cup$  {P=false})

```

Figure 7.17 The DPLL algorithm for checking satisfiability of a sentence in propositional logic. The ideas behind FIND-PURE-SYMBOL and FIND-UNIT-CLAUSE are described in the text; each returns a symbol (or null) and the truth value to assign to that symbol. Like TT-ENTAILS?, DPLL operates over partial models.

any attempt to prove (by refutation) a literal that is already in the knowledge base will succeed immediately (Exercise 7.23). Notice also that assigning one unit clause can create another unit clause—for example, when C is set to *false*, $(C \vee A)$ becomes a unit clause, causing *true* to be assigned to A . This “cascade” of forced assignments is called **unit propagation**. It resembles the process of forward chaining with definite clauses, and indeed, if the CNF expression contains only definite clauses then DPLL essentially replicates forward chaining. (See Exercise 7.24.)

UNIT PROPAGATION

The DPLL algorithm is shown in Figure 7.17, which gives the the essential skeleton of the search process.

What Figure 7.17 does not show are the tricks that enable SAT solvers to scale up to large problems. It is interesting that most of these tricks are in fact rather general, and we have seen them before in other guises:

1. **Component analysis** (as seen with Tasmania in CSPs): As DPLL assigns truth values to variables, the set of clauses may become separated into disjoint subsets, called **components**, that share no unassigned variables. Given an efficient way to detect when this occurs, a solver can gain considerable speed by working on each component separately.
2. **Variable and value ordering** (as seen in Section 6.3.1 for CSPs): Our simple implementation of DPLL uses an arbitrary variable ordering and always tries the value *true* before *false*. The **degree heuristic** (see page 216) suggests choosing the variable that appears most frequently over all remaining clauses.

3. **Intelligent backtracking** (as seen in Section 6.3 for CSPs): Many problems that cannot be solved in hours of run time with chronological backtracking can be solved in seconds with intelligent backtracking that backs up all the way to the relevant point of conflict. All SAT solvers that do intelligent backtracking use some form of **conflict clause learning** to record conflicts so that they won't be repeated later in the search. Usually a limited-size set of conflicts is kept, and rarely used ones are dropped.
4. **Random restarts** (as seen on page 124 for hill-climbing): Sometimes a run appears not to be making progress. In this case, we can start over from the top of the search tree, rather than trying to continue. After restarting, different random choices (in variable and value selection) are made. Clauses that are learned in the first run are retained after the restart and can help prune the search space. Restarting does not guarantee that a solution will be found faster, but it does reduce the variance on the time to solution.
5. **Clever indexing** (as seen in many algorithms): The speedup methods used in DPLL itself, as well as the tricks used in modern solvers, require fast indexing of such things as “the set of clauses in which variable X_i appears as a positive literal.” This task is complicated by the fact that the algorithms are interested only in the clauses that have not yet been satisfied by previous assignments to variables, so the indexing structures must be updated dynamically as the computation proceeds.

With these enhancements, modern solvers can handle problems with tens of millions of variables. They have revolutionized areas such as hardware verification and security protocol verification, which previously required laborious, hand-guided proofs.

7.6.2 Local search algorithms

We have seen several local search algorithms so far in this book, including HILL-CLIMBING (page 122) and SIMULATED-ANNEALING (page 126). These algorithms can be applied directly to satisfiability problems, provided that we choose the right evaluation function. Because the goal is to find an assignment that satisfies every clause, an evaluation function that counts the number of unsatisfied clauses will do the job. In fact, this is exactly the measure used by the MIN-CONFLICTS algorithm for CSPs (page 221). All these algorithms take steps in the space of complete assignments, flipping the truth value of one symbol at a time. The space usually contains many local minima, to escape from which various forms of randomness are required. In recent years, there has been a great deal of experimentation to find a good balance between greediness and randomness.

One of the simplest and most effective algorithms to emerge from all this work is called WALKSAT (Figure 7.18). On every iteration, the algorithm picks an unsatisfied clause and picks a symbol in the clause to flip. It chooses randomly between two ways to pick which symbol to flip: (1) a “min-conflicts” step that minimizes the number of unsatisfied clauses in the new state and (2) a “random walk” step that picks the symbol randomly.

When WALKSAT returns a model, the input sentence is indeed satisfiable, but when it returns *failure*, there are two possible causes: either the sentence is unsatisfiable or we need to give the algorithm more time. If we set $max_flips = \infty$ and $p > 0$, WALKSAT will eventually return a model (if one exists), because the random-walk steps will eventually hit

```

function WALKSAT(clauses, p, max_flips) returns a satisfying model or failure
  inputs: clauses, a set of clauses in propositional logic
           p, the probability of choosing to do a “random walk” move, typically around 0.5
           max_flips, number of flips allowed before giving up

  model  $\leftarrow$  a random assignment of true/false to the symbols in clauses
  for i = 1 to max_flips do
    if model satisfies clauses then return model
    clause  $\leftarrow$  a randomly selected clause from clauses that is false in model
    with probability p flip the value in model of a randomly selected symbol from clause
    else flip whichever symbol in clause maximizes the number of satisfied clauses
  return failure

```

Figure 7.18 The WALKSAT algorithm for checking satisfiability by randomly flipping the values of variables. Many versions of the algorithm exist.

upon the solution. Alas, if *max_flips* is infinity and the sentence is unsatisfiable, then the algorithm never terminates!

For this reason, WALKSAT is most useful when we expect a solution to exist—for example, the problems discussed in Chapters 3 and 6 usually have solutions. On the other hand, WALKSAT cannot always detect *unsatisfiability*, which is required for deciding entailment. For example, an agent cannot *reliably* use WALKSAT to prove that a square is safe in the wumpus world. Instead, it can say, “I thought about it for an hour and couldn’t come up with a possible world in which the square *isn’t* safe.” This may be a good empirical indicator that the square is safe, but it’s certainly not a proof.

7.6.3 The landscape of random SAT problems

Some SAT problems are harder than others. *Easy* problems can be solved by any old algorithm, but because we know that SAT is NP-complete, at least some problem instances must require exponential run time. In Chapter 6, we saw some surprising discoveries about certain kinds of problems. For example, the *n*-queens problem—thought to be quite tricky for backtracking search algorithms—turned out to be trivially easy for local search methods, such as min-conflicts. This is because solutions are very densely distributed in the space of assignments, and any initial assignment is guaranteed to have a solution nearby. Thus, *n*-queens is easy because it is **underconstrained**.

UNDERCONSTRAINED

When we look at satisfiability problems in conjunctive normal form, an underconstrained problem is one with relatively *few* clauses constraining the variables. For example, here is a randomly generated 3-CNF sentence with five symbols and five clauses:

$$(\neg D \vee \neg B \vee C) \wedge (B \vee \neg A \vee \neg C) \wedge (\neg C \vee \neg B \vee E) \\ \wedge (E \vee \neg D \vee B) \wedge (B \vee E \vee \neg C).$$

Sixteen of the 32 possible assignments are models of this sentence, so, on average, it would take just two random guesses to find a model. This is an easy satisfiability problem, as are

most such underconstrained problems. On the other hand, an *overconstrained* problem has many clauses relative to the number of variables and is likely to have no solutions.

To go beyond these basic intuitions, we must define exactly how random sentences are generated. The notation $CNF_k(m, n)$ denotes a k -CNF sentence with m clauses and n symbols, where the clauses are chosen uniformly, independently, and without replacement from among all clauses with k different literals, which are positive or negative at random. (A symbol may not appear twice in a clause, nor may a clause appear twice in a sentence.)

Given a source of random sentences, we can measure the probability of satisfiability. Figure 7.19(a) plots the probability for $CNF_3(m, 50)$, that is, sentences with 50 variables and 3 literals per clause, as a function of the clause/symbol ratio, m/n . As we expect, for small m/n the probability of satisfiability is close to 1, and at large m/n the probability is close to 0. The probability drops fairly sharply around $m/n = 4.3$. Empirically, we find that the “cliff” stays in roughly the same place (for $k = 3$) and gets sharper and sharper as n increases. Theoretically, the **satisfiability threshold conjecture** says that for every $k \geq 3$, there is a threshold ratio r_k such that, as n goes to infinity, the probability that $CNF_k(n, rn)$ is satisfiable becomes 1 for all values of r below the threshold, and 0 for all values above. The conjecture remains unproven.

SATISFIABILITY
THRESHOLD
CONJECTURE

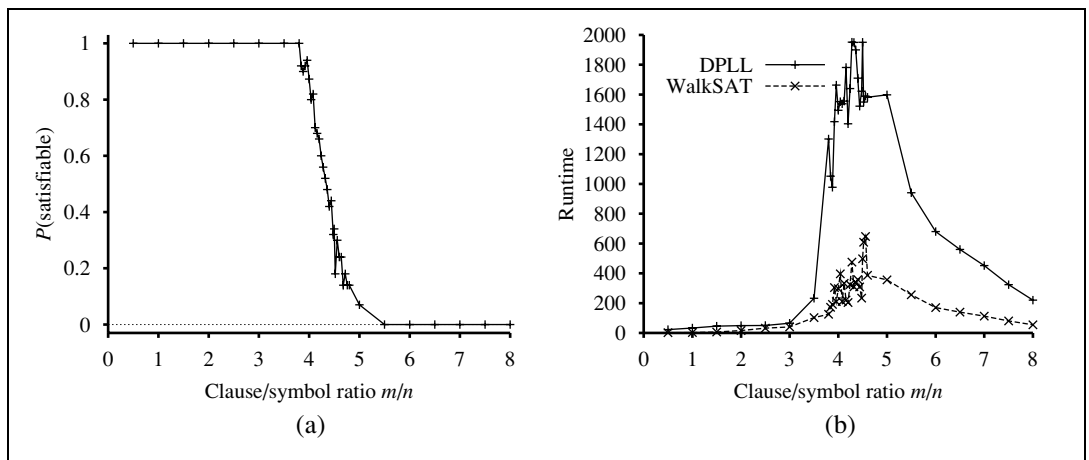


Figure 7.19 (a) Graph showing the probability that a random 3-CNF sentence with $n = 50$ symbols is satisfiable, as a function of the clause/symbol ratio m/n . (b) Graph of the median run time (measured in number of recursive calls to DPLL, a good proxy) on random 3-CNF sentences. The most difficult problems have a clause/symbol ratio of about 4.3.

Now that we have a good idea where the satisfiable and unsatisfiable problems are, the next question is, where are the hard problems? It turns out that they are also often at the threshold value. Figure 7.19(b) shows that 50-symbol problems at the threshold value of 4.3 are about 20 times more difficult to solve than those at a ratio of 3.3. The underconstrained problems are easiest to solve (because it is so easy to guess a solution); the overconstrained problems are not as easy as the underconstrained, but still are much easier than the ones right at the threshold.

7.7 AGENTS BASED ON PROPOSITIONAL LOGIC

In this section, we bring together what we have learned so far in order to construct wumpus world agents that use propositional logic. The first step is to enable the agent to deduce, to the extent possible, the state of the world given its percept history. This requires writing down a complete logical model of the effects of actions. We also show how the agent can keep track of the world efficiently without going back into the percept history for each inference. Finally, we show how the agent can use logical inference to construct plans that are guaranteed to achieve its goals.

7.7.1 The current state of the world

As stated at the beginning of the chapter, a logical agent operates by deducing what to do from a knowledge base of sentences about the world. The knowledge base is composed of axioms—general knowledge about how the world works—and percept sentences obtained from the agent’s experience in a particular world. In this section, we focus on the problem of deducing the current state of the wumpus world—where am I, is that square safe, and so on.

We began collecting axioms in Section 7.4.3. The agent knows that the starting square contains no pit ($\neg P_{1,1}$) and no wumpus ($\neg W_{1,1}$). Furthermore, for each square, it knows that the square is breezy if and only if a neighboring square has a pit; and a square is smelly if and only if a neighboring square has a wumpus. Thus, we include a large collection of sentences of the following form:

$$\begin{aligned} B_{1,1} &\Leftrightarrow (P_{1,2} \vee P_{2,1}) \\ S_{1,1} &\Leftrightarrow (W_{1,2} \vee W_{2,1}) \\ &\dots \end{aligned}$$

The agent also knows that there is exactly one wumpus. This is expressed in two parts. First, we have to say that there is *at least one* wumpus:

$$W_{1,1} \vee W_{1,2} \vee \dots \vee W_{4,3} \vee W_{4,4} .$$

Then, we have to say that there is *at most one* wumpus. For each pair of locations, we add a sentence saying that at least one of them must be wumpus-free:

$$\begin{aligned} &\neg W_{1,1} \vee \neg W_{1,2} \\ &\neg W_{1,1} \vee \neg W_{1,3} \\ &\dots \\ &\neg W_{4,3} \vee \neg W_{4,4} . \end{aligned}$$

So far, so good. Now let’s consider the agent’s percepts. If there is currently a stench, one might suppose that a proposition *Stench* should be added to the knowledge base. This is not quite right, however: if there was no stench at the previous time step, then $\neg \text{Stench}$ would already be asserted, and the new assertion would simply result in a contradiction. The problem is solved when we realize that a percept asserts something *only about the current time*. Thus, if the time step (as supplied to MAKE-PERCEPT-SENTENCE in Figure 7.1) is 4, then we add

$Stench^4$ to the knowledge base, rather than $Stench$ —neatly avoiding any contradiction with $\neg Stench^3$. The same goes for the breeze, bump, glitter, and scream percepts.

FLUENT

ATEMPORAL
VARIABLE

The idea of associating propositions with time steps extends to any aspect of the world that changes over time. For example, the initial knowledge base includes $L_{1,1}^0$ —the agent is in square $[1, 1]$ at time 0—as well as $FacingEast^0$, $HaveArrow^0$, and $WumpusAlive^0$. We use the word **fluent** (from the Latin *fluens*, flowing) to refer an aspect of the world that changes. “Fluent” is a synonym for “state variable,” in the sense described in the discussion of factored representations in Section 2.4.7 on page 57. Symbols associated with permanent aspects of the world do not need a time superscript and are sometimes called **atemporal variables**.

We can connect stench and breeze percepts directly to the properties of the squares where they are experienced through the location fluent as follows.¹⁰ For any time step t and any square $[x, y]$, we assert

$$\begin{aligned} L_{x,y}^t &\Rightarrow (Breeze^t \Leftrightarrow B_{x,y}) \\ L_{x,y}^t &\Rightarrow (Stench^t \Leftrightarrow S_{x,y}). \end{aligned}$$

Now, of course, we need axioms that allow the agent to keep track of fluents such as $L_{x,y}^t$. These fluents change as the result of actions taken by the agent, so, in the terminology of Chapter 3, we need to write down the **transition model** of the wumpus world as a set of logical sentences.

First, we need proposition symbols for the occurrences of actions. As with percepts, these symbols are indexed by time; thus, $Forward^0$ means that the agent executes the *Forward* action at time 0. By convention, the percept for a given time step happens first, followed by the action for that time step, followed by a transition to the next time step.

EFFECT AXIOM

To describe how the world changes, we can try writing **effect axioms** that specify the outcome of an action at the next time step. For example, if the agent is at location $[1, 1]$ facing east at time 0 and goes *Forward*, the result is that the agent is in square $[2, 1]$ and no longer is in $[1, 1]$:

$$L_{1,1}^0 \wedge FacingEast^0 \wedge Forward^0 \Rightarrow (L_{2,1}^1 \wedge \neg L_{1,1}^1). \quad (7.1)$$

We would need one such sentence for each possible time step, for each of the 16 squares, and each of the four orientations. We would also need similar sentences for the other actions: *Grab*, *Shoot*, *Climb*, *TurnLeft*, and *TurnRight*.

Let us suppose that the agent does decide to move *Forward* at time 0 and asserts this fact into its knowledge base. Given the effect axiom in Equation (7.1), combined with the initial assertions about the state at time 0, the agent can now deduce that it is in $[2, 1]$. That is, $ASK(KB, L_{2,1}^1) = true$. So far, so good. Unfortunately, the news elsewhere is less good: if we $ASK(KB, HaveArrow^1)$, the answer is *false*, that is, the agent cannot prove it still has the arrow; nor can it prove it *doesn't* have it! The information has been lost because the effect axiom fails to state what remains *unchanged* as the result of an action. The need to do this gives rise to the **frame problem**.¹¹ One possible solution to the frame problem would

FRAME PROBLEM

¹⁰ Section 7.4.3 conveniently glossed over this requirement.

¹¹ The name “frame problem” comes from “frame of reference” in physics—the assumed stationary background with respect to which motion is measured. It also has an analogy to the frames of a movie, in which normally most of the background stays constant while changes occur in the foreground.

FRAME AXIOM

be to add **frame axioms** explicitly asserting all the propositions that remain the same. For example, for each time t we would have

$$\begin{aligned} Forward^t &\Rightarrow (HaveArrow^t \Leftrightarrow HaveArrow^{t+1}) \\ Forward^t &\Rightarrow (WumpusAlive^t \Leftrightarrow WumpusAlive^{t+1}) \\ &\dots \end{aligned}$$

 REPRESENTATIONAL
FRAME PROBLEM

where we explicitly mention every proposition that stays unchanged from time t to time $t + 1$ under the action *Forward*. Although the agent now knows that it still has the arrow after moving forward and that the wumpus hasn't died or come back to life, the proliferation of frame axioms seems remarkably inefficient. In a world with m different actions and n fluents, the set of frame axioms will be of size $O(mn)$. This specific manifestation of the frame problem is sometimes called the **representational frame problem**. Historically, the problem was a significant one for AI researchers; we explore it further in the notes at the end of the chapter.

LOCALITY

 INFERENCE FRAME
PROBLEM

The representational frame problem is significant because the real world has very many fluents, to put it mildly. Fortunately for us humans, each action typically changes no more than some small number k of those fluents—the world exhibits **locality**. Solving the representational frame problem requires defining the transition model with a set of axioms of size $O(mk)$ rather than size $O(mn)$. There is also an **inferential frame problem**: the problem of projecting forward the results of a t step plan of action in time $O(kt)$ rather than $O(nt)$.

 SUCCESSOR-STATE
AXIOM

The solution to the problem involves changing one's focus from writing axioms about *actions* to writing axioms about *fluents*. Thus, for each fluent F , we will have an axiom that defines the truth value of F^{t+1} in terms of fluents (including F itself) at time t and the actions that may have occurred at time t . Now, the truth value of F^{t+1} can be set in one of two ways: either the action at time t causes F to be true at $t + 1$, or F was already true at time t and the action at time t does not cause it to be false. An axiom of this form is called a **successor-state axiom** and has this schema:

$$F^{t+1} \Leftrightarrow ActionCausesF^t \vee (F^t \wedge \neg ActionCausesNotF^t).$$

One of the simplest successor-state axioms is the one for *HaveArrow*. Because there is no action for reloading, the *ActionCausesF^t* part goes away and we are left with

$$HaveArrow^{t+1} \Leftrightarrow (HaveArrow^t \wedge \neg Shoot^t). \quad (7.2)$$

For the agent's location, the successor-state axioms are more elaborate. For example, $L_{1,1}^{t+1}$ is true if either (a) the agent moved *Forward* from $[1, 2]$ when facing south, or from $[2, 1]$ when facing west; or (b) $L_{1,1}^t$ was already true and the action did not cause movement (either because the action was not *Forward* or because the action bumped into a wall). Written out in propositional logic, this becomes

$$\begin{aligned} L_{1,1}^{t+1} &\Leftrightarrow (L_{1,1}^t \wedge (\neg Forward^t \vee Bump^{t+1})) \\ &\vee (L_{1,2}^t \wedge (South^t \wedge Forward^t)) \\ &\vee (L_{2,1}^t \wedge (West^t \wedge Forward^t)). \end{aligned} \quad (7.3)$$

Exercise 7.26 asks you to write out axioms for the remaining wumpus world fluents.

Given a complete set of successor-state axioms and the other axioms listed at the beginning of this section, the agent will be able to ASK and answer any answerable question about the current state of the world. For example, in Section 7.2 the initial sequence of percepts and actions is

$$\begin{aligned}
 &\neg Stench^0 \wedge \neg Breeze^0 \wedge \neg Glitter^0 \wedge \neg Bump^0 \wedge \neg Scream^0 ; Forward^0 \\
 &\neg Stench^1 \wedge Breeze^1 \wedge \neg Glitter^1 \wedge \neg Bump^1 \wedge \neg Scream^1 ; TurnRight^1 \\
 &\neg Stench^2 \wedge Breeze^2 \wedge \neg Glitter^2 \wedge \neg Bump^2 \wedge \neg Scream^2 ; TurnRight^2 \\
 &\neg Stench^3 \wedge Breeze^3 \wedge \neg Glitter^3 \wedge \neg Bump^3 \wedge \neg Scream^3 ; Forward^3 \\
 &\neg Stench^4 \wedge \neg Breeze^4 \wedge \neg Glitter^4 \wedge \neg Bump^4 \wedge \neg Scream^4 ; TurnRight^4 \\
 &\neg Stench^5 \wedge \neg Breeze^5 \wedge \neg Glitter^5 \wedge \neg Bump^5 \wedge \neg Scream^5 ; Forward^5 \\
 &Stench^6 \wedge \neg Breeze^6 \wedge \neg Glitter^6 \wedge \neg Bump^6 \wedge \neg Scream^6
 \end{aligned}$$

At this point, we have $ASK(KB, L_{1,2}^6) = true$, so the agent knows where it is. Moreover, $ASK(KB, W_{1,3}) = true$ and $ASK(KB, P_{3,1}) = true$, so the agent has found the wumpus and one of the pits. The most important question for the agent is whether a square is OK to move into, that is, the square contains no pit nor live wumpus. It's convenient to add axioms for this, having the form

$$OK_{x,y}^t \Leftrightarrow \neg P_{x,y} \wedge \neg (W_{x,y} \wedge WumpusAlive^t).$$

Finally, $ASK(KB, OK_{2,2}^6) = true$, so the square $[2, 2]$ is OK to move into. In fact, given a sound and complete inference algorithm such as DPLL, the agent can answer any answerable question about which squares are OK—and can do so in just a few milliseconds for small-to-medium wumpus worlds.

Solving the representational and inferential frame problems is a big step forward, but a pernicious problem remains: we need to confirm that *all* the necessary preconditions of an action hold for it to have its intended effect. We said that the *Forward* action moves the agent ahead unless there is a wall in the way, but there are many other unusual exceptions that could cause the action to fail: the agent might trip and fall, be stricken with a heart attack, be carried away by giant bats, etc. Specifying all these exceptions is called the **qualification problem**. There is no complete solution within logic; system designers have to use good judgment in deciding how detailed they want to be in specifying their model, and what details they want to leave out. We will see in Chapter 13 that probability theory allows us to summarize all the exceptions without explicitly naming them.

QUALIFICATION
PROBLEM

7.7.2 A hybrid agent

The ability to deduce various aspects of the state of the world can be combined fairly straightforwardly with condition–action rules and with problem-solving algorithms from Chapters 3 and 4 to produce a **hybrid agent** for the wumpus world. Figure 7.20 shows one possible way to do this. The agent program maintains and updates a knowledge base as well as a current plan. The initial knowledge base contains the *atemporal* axioms—those that don't depend on t , such as the axiom relating the breeziness of squares to the presence of pits. At each time step, the new percept sentence is added along with all the axioms that depend on t , such

HYBRID AGENT

as the successor-state axioms. (The next section explains why the agent doesn't need axioms for *future* time steps.) Then, the agent uses logical inference, by ASKing questions of the knowledge base, to work out which squares are safe and which have yet to be visited.

The main body of the agent program constructs a plan based on a decreasing priority of goals. First, if there is a glitter, the program constructs a plan to grab the gold, follow a route back to the initial location, and climb out of the cave. Otherwise, if there is no current plan, the program plans a route to the closest safe square that it has not visited yet, making sure the route goes through only safe squares. Route planning is done with A* search, not with ASK. If there are no safe squares to explore, the next step—if the agent still has an arrow—is to try to make a safe square by shooting at one of the possible wumpus locations. These are determined by asking where $\text{ASK}(KB, \neg W_{x,y})$ is false—that is, where it is *not* known that there is *not* a wumpus. The function PLAN-SHOT (not shown) uses PLAN-ROUTE to plan a sequence of actions that will line up this shot. If this fails, the program looks for a square to explore that is not provably unsafe—that is, a square for which $\text{ASK}(KB, \neg OK_{x,y}^t)$ returns false. If there is no such square, then the mission is impossible and the agent retreats to [1, 1] and climbs out of the cave.

7.7.3 Logical state estimation

The agent program in Figure 7.20 works quite well, but it has one major weakness: as time goes by, the computational expense involved in the calls to ASK goes up and up. This happens mainly because the required inferences have to go back further and further in time and involve more and more proposition symbols. Obviously, this is unsustainable—we cannot have an agent whose time to process each percept grows in proportion to the length of its life! What we really need is a *constant* update time—that is, independent of t . The obvious answer is to save, or **cache**, the results of inference, so that the inference process at the next time step can build on the results of earlier steps instead of having to start again from scratch.

CACHING

As we saw in Section 4.4, the past history of percepts and all their ramifications can be replaced by the **belief state**—that is, some representation of the set of all possible current states of the world.¹² The process of updating the belief state as new percepts arrive is called **state estimation**. Whereas in Section 4.4 the belief state was an explicit list of states, here we can use a logical sentence involving the proposition symbols associated with the current time step, as well as the atemporal symbols. For example, the logical sentence

$$WumpusAlive^1 \wedge L_{2,1}^1 \wedge B_{2,1} \wedge (P_{3,1} \vee P_{2,2}) \quad (7.4)$$

represents the set of all states at time 1 in which the wumpus is alive, the agent is at [2, 1], that square is breezy, and there is a pit in [3, 1] or [2, 2] or both.

Maintaining an exact belief state as a logical formula turns out not to be easy. If there are n fluent symbols for time t , then there are 2^n possible states—that is, assignments of truth values to those symbols. Now, the set of belief states is the powerset (set of all subsets) of the set of physical states. There are 2^n physical states, hence 2^{2^n} belief states. Even if we used the most compact possible encoding of logical formulas, with each belief state represented

¹² We can think of the percept history itself as a representation of the belief state, but one that makes inference increasingly expensive as the history gets longer.

```

function HYBRID-WUMPUS-AGENT(percept) returns an action
  inputs: percept, a list, [stench,breeze,glitter,bump,scream]
  persistent: KB, a knowledge base, initially the atemporal “wumpus physics”
               t, a counter, initially 0, indicating time
               plan, an action sequence, initially empty

  TELL(KB, MAKE-PERCEPT-SENTENCE(percept, t))
  TELL the KB the temporal “physics” sentences for time t
  safe  $\leftarrow \{[x, y] : \text{ASK}(\text{KB}, OK_{x,y}^t) = \text{true}\}$ 
  if ASK(KB, Glittert) = true then
    plan  $\leftarrow [Grab] + \text{PLAN-ROUTE}(\text{current}, \{[1,1]\}, \text{safe}) + [Climb]$ 
  if plan is empty then
    unvisited  $\leftarrow \{[x, y] : \text{ASK}(\text{KB}, L_{x,y}^{t'}) = \text{false} \text{ for all } t' \leq t\}$ 
    plan  $\leftarrow \text{PLAN-ROUTE}(\text{current}, \text{unvisited} \cap \text{safe}, \text{safe})$ 
  if plan is empty and ASK(KB, HaveArrowt) = true then
    possible_wumpus  $\leftarrow \{[x, y] : \text{ASK}(\text{KB}, \neg W_{x,y}) = \text{false}\}$ 
    plan  $\leftarrow \text{PLAN-SHOT}(\text{current}, \text{possible\_wumpus}, \text{safe})$ 
  if plan is empty then // no choice but to take a risk
    not_unsafe  $\leftarrow \{[x, y] : \text{ASK}(\text{KB}, \neg OK_{x,y}^t) = \text{false}\}$ 
    plan  $\leftarrow \text{PLAN-ROUTE}(\text{current}, \text{unvisited} \cap \text{not\_unsafe}, \text{safe})$ 
  if plan is empty then
    plan  $\leftarrow \text{PLAN-ROUTE}(\text{current}, \{[1,1]\}, \text{safe}) + [Climb]$ 
  action  $\leftarrow \text{POP}(\text{plan})$ 
  TELL(KB, MAKE-ACTION-SENTENCE(action, t))
  t  $\leftarrow t + 1$ 
  return action

```

```

function PLAN-ROUTE(current, goals, allowed) returns an action sequence
  inputs: current, the agent’s current position
          goals, a set of squares; try to plan a route to one of them
          allowed, a set of squares that can form part of the route

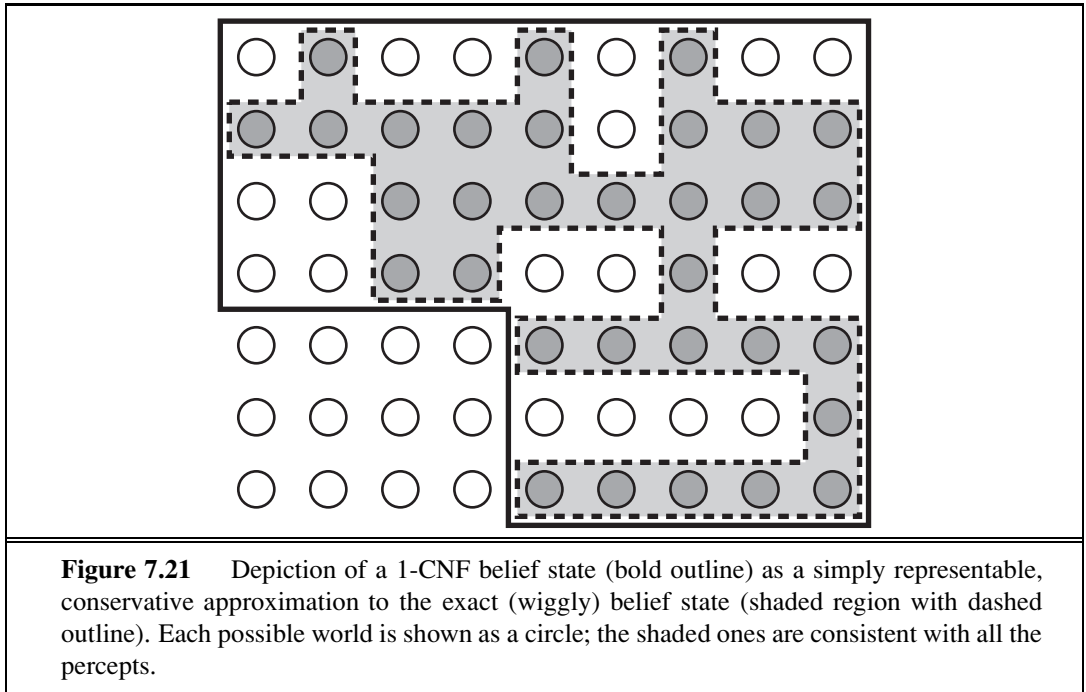
  problem  $\leftarrow \text{ROUTE-PROBLEM}(\text{current}, \text{goals}, \text{allowed})$ 
  return A*-GRAPH-SEARCH(problem)

```

Figure 7.20 A hybrid agent program for the wumpus world. It uses a propositional knowledge base to infer the state of the world, and a combination of problem-solving search and domain-specific code to decide what actions to take.

by a unique binary number, we would need numbers with $\log_2(2^{2^n}) = 2^n$ bits to label the current belief state. That is, exact state estimation may require logical formulas whose size is exponential in the number of symbols.

One very common and natural scheme for *approximate* state estimation is to represent belief states as conjunctions of literals, that is, 1-CNF formulas. To do this, the agent program simply tries to prove X^t and $\neg X^t$ for each symbol X^t (as well as each atemporal symbol whose truth value is not yet known), given the belief state at $t - 1$. The conjunction of



provable literals becomes the new belief state, and the previous belief state is discarded.

It is important to understand that this scheme may lose some information as time goes along. For example, if the sentence in Equation (7.4) were the true belief state, then neither $P_{3,1}$ nor $P_{2,2}$ would be provable individually and neither would appear in the 1-CNF belief state. (Exercise 7.27 explores one possible solution to this problem.) On the other hand, because every literal in the 1-CNF belief state is proved from the previous belief state, and the initial belief state is a true assertion, we know that entire 1-CNF belief state must be true. Thus, *the set of possible states represented by the 1-CNF belief state includes all states that are in fact possible given the full percept history*. As illustrated in Figure 7.21, the 1-CNF belief state acts as a simple outer envelope, or **conservative approximation**, around the exact belief state. We see this idea of conservative approximations to complicated sets as a recurring theme in many areas of AI.



7.7.4 Making plans by propositional inference

The agent in Figure 7.20 uses logical inference to determine which squares are safe, but uses A* search to make plans. In this section, we show how to make plans by logical inference. The basic idea is very simple:

1. Construct a sentence that includes
 - (a) $Init^0$, a collection of assertions about the initial state;
 - (b) $Transition^1, \dots, Transition^t$, the successor-state axioms for all possible actions at each time up to some maximum time t ;
 - (c) the assertion that the goal is achieved at time t : $HaveGold^t \wedge ClimbedOut^t$.

2. Present the whole sentence to a SAT solver. If the solver finds a satisfying model, then the goal is achievable; if the sentence is unsatisfiable, then the planning problem is impossible.
3. Assuming a model is found, extract from the model those variables that represent actions and are assigned *true*. Together they represent a plan to achieve the goals.

A propositional planning procedure, SATPLAN, is shown in Figure 7.22. It implements the basic idea just given, with one twist. Because the agent does not know how many steps it will take to reach the goal, the algorithm tries each possible number of steps t , up to some maximum conceivable plan length T_{\max} . In this way, it is guaranteed to find the shortest plan if one exists. Because of the way SATPLAN searches for a solution, this approach cannot be used in a partially observable environment; SATPLAN would just set the unobservable variables to the values it needs to create a solution.

```

function SATPLAN(init, transition, goal,  $T_{\max}$ ) returns solution or failure
  inputs: init, transition, goal, constitute a description of the problem
            $T_{\max}$ , an upper limit for plan length

  for  $t = 0$  to  $T_{\max}$  do
     $cnf \leftarrow$  TRANSLATE-TO-SAT(init, transition, goal,  $t$ )
     $model \leftarrow$  SAT-SOLVER( $cnf$ )
    if  $model$  is not null then
      return EXTRACT-SOLUTION( $model$ )
  return failure

```

Figure 7.22 The SATPLAN algorithm. The planning problem is translated into a CNF sentence in which the goal is asserted to hold at a fixed time step t and axioms are included for each time step up to t . If the satisfiability algorithm finds a model, then a plan is extracted by looking at those proposition symbols that refer to actions and are assigned *true* in the model. If no model exists, then the process is repeated with the goal moved one step later.

The key step in using SATPLAN is the construction of the knowledge base. It might seem, on casual inspection, that the wumpus world axioms in Section 7.7.1 suffice for steps 1(a) and 1(b) above. There is, however, a significant difference between the requirements for entailment (as tested by ASK) and those for satisfiability. Consider, for example, the agent's location, initially $[1, 1]$, and suppose the agent's unambitious goal is to be in $[2, 1]$ at time 1. The initial knowledge base contains $L_{1,1}^0$ and the goal is $L_{2,1}^1$. Using ASK, we can prove $L_{2,1}^1$ if $Forward^0$ is asserted, and, reassuringly, we cannot prove $L_{2,1}^1$ if, say, $Shoot^0$ is asserted instead. Now, SATPLAN will find the plan $[Forward^0]$; so far, so good. Unfortunately, SATPLAN also finds the plan $[Shoot^0]$. How could this be? To find out, we inspect the model that SATPLAN constructs: it includes the assignment $L_{2,1}^0$, that is, the agent can be in $[2, 1]$ at time 1 by being there at time 0 and shooting. One might ask, "Didn't we say the agent is in $[1, 1]$ at time 0?" Yes, we did, but we didn't tell the agent that it can't be in two places at once! For entailment, $L_{2,1}^0$ is unknown and cannot, therefore, be used in a proof; for satisfiability,

on the other hand, $L_{2,1}^0$ is unknown and can, therefore, be set to whatever value helps to make the goal true. For this reason, SATPLAN is a good debugging tool for knowledge bases because it reveals places where knowledge is missing. In this particular case, we can fix the knowledge base by asserting that, at each time step, the agent is in exactly one location, using a collection of sentences similar to those used to assert the existence of exactly one wumpus. Alternatively, we can assert $\neg L_{x,y}^0$ for all locations other than $[1, 1]$; the successor-state axiom for location takes care of subsequent time steps. The same fixes also work to make sure the agent has only one orientation.

SATPLAN has more surprises in store, however. The first is that it finds models with impossible actions, such as shooting with no arrow. To understand why, we need to look more carefully at what the successor-state axioms (such as Equation (7.3)) say about actions whose preconditions are not satisfied. The axioms *do* predict correctly that nothing will happen when such an action is executed (see Exercise 10.14), but they do *not* say that the action cannot be executed! To avoid generating plans with illegal actions, we must add **precondition axioms** stating that an action occurrence requires the preconditions to be satisfied.¹³ For example, we need to say, for each time t , that

$$\text{Shoot}^t \Rightarrow \text{HaveArrow}^t.$$

This ensures that if a plan selects the *Shoot* action at any time, it must be the case that the agent has an arrow at that time.

SATPLAN's second surprise is the creation of plans with multiple simultaneous actions. For example, it may come up with a model in which both Forward^0 and Shoot^0 are true, which is not allowed. To eliminate this problem, we introduce **action exclusion axioms**: for every pair of actions A_i^t and A_j^t we add the axiom

$$\neg A_i^t \vee \neg A_j^t.$$

It might be pointed out that walking forward and shooting at the same time is not so hard to do, whereas, say, shooting and grabbing at the same time is rather impractical. By imposing action exclusion axioms only on pairs of actions that really do interfere with each other, we can allow for plans that include multiple simultaneous actions—and because SATPLAN finds the shortest legal plan, we can be sure that it will take advantage of this capability.

To summarize, SATPLAN finds models for a sentence containing the initial state, the goal, the successor-state axioms, the precondition axioms, and the action exclusion axioms. It can be shown that this collection of axioms is sufficient, in the sense that there are no longer any spurious “solutions.” Any model satisfying the propositional sentence will be a valid plan for the original problem. Modern SAT-solving technology makes the approach quite practical. For example, a DPLL-style solver has no difficulty in generating the 11-step solution for the wumpus world instance shown in Figure 7.2.

This section has described a declarative approach to agent construction: the agent works by a combination of asserting sentences in the knowledge base and performing logical inference. This approach has some weaknesses hidden in phrases such as “for each time t ” and

¹³ Notice that the addition of precondition axioms means that we need not include preconditions for actions in the successor-state axioms.

PRECONDITION
AXIOMS

ACTION EXCLUSION
AXIOM

“for each square $[x, y]$.” For any practical agent, these phrases have to be implemented by code that generates instances of the general sentence schema automatically for insertion into the knowledge base. For a wumpus world of reasonable size—one comparable to a smallish computer game—we might need a 100×100 board and 1000 time steps, leading to knowledge bases with tens or hundreds of millions of sentences. Not only does this become rather impractical, but it also illustrates a deeper problem: we know something about the wumpus world—namely, that the “physics” works the same way across all squares and all time steps—that we cannot express directly in the language of propositional logic. To solve this problem, we need a more expressive language, one in which phrases like “for each time t ” and “for each square $[x, y]$ ” can be written in a natural way. First-order logic, described in Chapter 8, is such a language; in first-order logic a wumpus world of any size and duration can be described in about ten sentences rather than ten million or ten trillion.

7.8 SUMMARY

We have introduced knowledge-based agents and have shown how to define a logic with which such agents can reason about the world. The main points are as follows:

- Intelligent agents need knowledge about the world in order to reach good decisions.
- Knowledge is contained in agents in the form of **sentences** in a **knowledge representation language** that are stored in a **knowledge base**.
- A knowledge-based agent is composed of a knowledge base and an inference mechanism. It operates by storing sentences about the world in its knowledge base, using the inference mechanism to infer new sentences, and using these sentences to decide what action to take.
- A representation language is defined by its **syntax**, which specifies the structure of sentences, and its **semantics**, which defines the **truth** of each sentence in each **possible world** or **model**.
- The relationship of **entailment** between sentences is crucial to our understanding of reasoning. A sentence α entails another sentence β if β is true in all worlds where α is true. Equivalent definitions include the **validity** of the sentence $\alpha \Rightarrow \beta$ and the **unsatisfiability** of the sentence $\alpha \wedge \neg\beta$.
- Inference is the process of deriving new sentences from old ones. **Sound** inference algorithms derive *only* sentences that are entailed; **complete** algorithms derive *all* sentences that are entailed.
- **Propositional logic** is a simple language consisting of **proposition symbols** and **logical connectives**. It can handle propositions that are known true, known false, or completely unknown.
- The set of possible models, given a fixed propositional vocabulary, is finite, so entailment can be checked by enumerating models. Efficient **model-checking** inference algorithms for propositional logic include backtracking and local search methods and can often solve large problems quickly.

- **Inference rules** are patterns of sound inference that can be used to find proofs. The **resolution** rule yields a complete inference algorithm for knowledge bases that are expressed in **conjunctive normal form**. **Forward chaining** and **backward chaining** are very natural reasoning algorithms for knowledge bases in **Horn form**.
- **Local search** methods such as WALKSAT can be used to find solutions. Such algorithms are sound but not complete.
- Logical **state estimation** involves maintaining a logical sentence that describes the set of possible states consistent with the observation history. Each update step requires inference using the transition model of the environment, which is built from **successor-state axioms** that specify how each **fluent** changes.
- Decisions within a logical agent can be made by SAT solving: finding possible models specifying future action sequences that reach the goal. This approach works only for fully observable or sensorless environments.
- Propositional logic does not scale to environments of unbounded size because it lacks the expressive power to deal concisely with time, space, and universal patterns of relationships among objects.

BIBLIOGRAPHICAL AND HISTORICAL NOTES

John McCarthy's paper "Programs with Common Sense" (McCarthy, 1958, 1968) promulgated the notion of agents that use logical reasoning to mediate between percepts and actions. It also raised the flag of declarativism, pointing out that telling an agent what it needs to know is an elegant way to build software. Allen Newell's (1982) article "The Knowledge Level" makes the case that rational agents can be described and analyzed at an abstract level defined by the knowledge they possess rather than the programs they run. The declarative and procedural approaches to AI are analyzed in depth by Boden (1977). The debate was revived by, among others, Brooks (1991) and Nilsson (1991), and continues to this day (Shaparaou *et al.*, 2008). Meanwhile, the declarative approach has spread into other areas of computer science such as networking (Loo *et al.*, 2006).

Logic itself had its origins in ancient Greek philosophy and mathematics. Various logical principles—principles connecting the syntactic structure of sentences with their truth and falsity, with their meaning, or with the validity of arguments in which they figure—are scattered in the works of Plato. The first known systematic study of logic was carried out by Aristotle, whose work was assembled by his students after his death in 322 B.C. as a treatise called the *Organon*. Aristotle's **sylogisms** were what we would now call inference rules. Although the syllogisms included elements of both propositional and first-order logic, the system as a whole lacked the compositional properties required to handle sentences of arbitrary complexity.

The closely related Megarian and Stoic schools (originating in the fifth century B.C. and continuing for several centuries thereafter) began the systematic study of the basic logical connectives. The use of truth tables for defining connectives is due to Philo of Megara. The

Stoics took five basic inference rules as valid without proof, including the rule we now call Modus Ponens. They derived a number of other rules from these five, using, among other principles, the deduction theorem (page 249) and were much clearer about the notion of proof than was Aristotle. A good account of the history of Megarian and Stoic logic is given by Benson Mates (1953).

The idea of reducing logical inference to a purely mechanical process applied to a formal language is due to Wilhelm Leibniz (1646–1716), although he had limited success in implementing the ideas. George Boole (1847) introduced the first comprehensive and workable system of formal logic in his book *The Mathematical Analysis of Logic*. Boole’s logic was closely modeled on the ordinary algebra of real numbers and used substitution of logically equivalent expressions as its primary inference method. Although Boole’s system still fell short of full propositional logic, it was close enough that other mathematicians could quickly fill in the gaps. Schröder (1877) described conjunctive normal form, while Horn form was introduced much later by Alfred Horn (1951). The first comprehensive exposition of modern propositional logic (and first-order logic) is found in Gottlob Frege’s (1879) *Begriffsschrift* (“Concept Writing” or “Conceptual Notation”).

The first mechanical device to carry out logical inferences was constructed by the third Earl of Stanhope (1753–1816). The Stanhope Demonstrator could handle syllogisms and certain inferences in the theory of probability. William Stanley Jevons, one of those who improved upon and extended Boole’s work, constructed his “logical piano” in 1869 to perform inferences in Boolean logic. An entertaining and instructive history of these and other early mechanical devices for reasoning is given by Martin Gardner (1968). The first published computer program for logical inference was the Logic Theorist of Newell, Shaw, and Simon (1957). This program was intended to model human thought processes. Martin Davis (1957) had actually designed a program that came up with a proof in 1954, but the Logic Theorist’s results were published slightly earlier.

Truth tables as a method of testing validity or unsatisfiability in propositional logic were introduced independently by Emil Post (1921) and Ludwig Wittgenstein (1922). In the 1930s, a great deal of progress was made on inference methods for first-order logic. In particular, Gödel (1930) showed that a complete procedure for inference in first-order logic could be obtained via a reduction to propositional logic, using Herbrand’s theorem (Herbrand, 1930). We take up this history again in Chapter 9; the important point here is that the development of efficient propositional algorithms in the 1960s was motivated largely by the interest of mathematicians in an effective theorem prover for first-order logic. The Davis–Putnam algorithm (Davis and Putnam, 1960) was the first effective algorithm for propositional resolution but was in most cases much less efficient than the DPLL backtracking algorithm introduced two years later (1962). The full resolution rule and a proof of its completeness appeared in a seminal paper by J. A. Robinson (1965), which also showed how to do first-order reasoning without resort to propositional techniques.

Stephen Cook (1971) showed that deciding satisfiability of a sentence in propositional logic (the SAT problem) is NP-complete. Since deciding entailment is equivalent to deciding unsatisfiability, it is co-NP-complete. Many subsets of propositional logic are known for which the satisfiability problem is polynomially solvable; Horn clauses are one such subset.

The linear-time forward-chaining algorithm for Horn clauses is due to Dowling and Gallier (1984), who describe their algorithm as a dataflow process similar to the propagation of signals in a circuit.

Early theoretical investigations showed that DPLL has polynomial average-case complexity for certain natural distributions of problems. This potentially exciting fact became less exciting when Franco and Paull (1983) showed that the same problems could be solved in constant time simply by guessing random assignments. The random-generation method described in the chapter produces much harder problems. Motivated by the empirical success of local search on these problems, Koutsoupias and Papadimitriou (1992) showed that a simple hill-climbing algorithm can solve *almost all* satisfiability problem instances very quickly, suggesting that hard problems are rare. Moreover, Schöning (1999) exhibited a randomized hill-climbing algorithm whose *worst-case* expected run time on 3-SAT problems (that is, satisfiability of 3-CNF sentences) is $O(1.333^n)$ —still exponential, but substantially faster than previous worst-case bounds. The current record is $O(1.324^n)$ (Iwama and Tamaki, 2004). Achlioptas *et al.* (2004) and Alekhovich *et al.* (2005) exhibit families of 3-SAT instances for which all known DPLL-like algorithms require exponential running time.

On the practical side, efficiency gains in propositional solvers have been marked. Given ten minutes of computing time, the original DPLL algorithm in 1962 could only solve problems with no more than 10 or 15 variables. By 1995 the SATZ solver (Li and Anbulagan, 1997) could handle 1,000 variables, thanks to optimized data structures for indexing variables. Two crucial contributions were the **watched literal** indexing technique of Zhang and Stickel (1996), which makes unit propagation very efficient, and the introduction of clause (i.e., constraint) learning techniques from the CSP community by Bayardo and Schrag (1997). Using these ideas, and spurred by the prospect of solving industrial-scale circuit verification problems, Moskewicz *et al.* (2001) developed the CHAFF solver, which could handle problems with millions of variables. Beginning in 2002, SAT competitions have been held regularly; most of the winning entries have either been descendants of CHAFF or have used the same general approach. RSAT (Pipatsrisawat and Darwiche, 2007), the 2007 winner, falls in the latter category. Also noteworthy is MINISAT (Een and Sörensson, 2003), an open-source implementation available at <http://minisat.se> that is designed to be easily modified and improved. The current landscape of solvers is surveyed by Gomes *et al.* (2008).

Local search algorithms for satisfiability were tried by various authors throughout the 1980s; all of the algorithms were based on the idea of minimizing the number of unsatisfied clauses (Hansen and Jaumard, 1990). A particularly effective algorithm was developed by Gu (1989) and independently by Selman *et al.* (1992), who called it GSAT and showed that it was capable of solving a wide range of very hard problems very quickly. The WALKSAT algorithm described in the chapter is due to Selman *et al.* (1996).

The “phase transition” in satisfiability of random k -SAT problems was first observed by Simon and Dubois (1989) and has given rise to a great deal of theoretical and empirical research—due, in part, to the obvious connection to phase transition phenomena in statistical physics. Cheeseman *et al.* (1991) observed phase transitions in several CSPs and conjecture that all NP-hard problems have a phase transition. Crawford and Auton (1993) located the 3-SAT transition at a clause/variable ratio of around 4.26, noting that this coincides with a

sharp peak in the run time of their SAT solver. Cook and Mitchell (1997) provide an excellent summary of the early literature on the problem.

The current state of theoretical understanding is summarized by Achlioptas (2009). The **satisfiability threshold conjecture** states that, for each k , there is a sharp satisfiability threshold r_k , such that as the number of variables $n \rightarrow \infty$, instances below the threshold are *satisfiable* with probability 1, while those above the threshold are *unsatisfiable* with probability 1. The conjecture was not quite proved by Friedgut (1999): a sharp threshold exists but its location might depend on n even as $n \rightarrow \infty$. Despite significant progress in asymptotic analysis of the threshold location for large k (Achlioptas and Peres, 2004; Achlioptas *et al.*, 2007), all that can be proved for $k = 3$ is that it lies in the range $[3.52, 4.51]$. Current theory suggests that a peak in the run time of a SAT solver is not necessarily related to the satisfiability threshold, but instead to a phase transition in the solution distribution and structure of SAT instances. Empirical results due to Coarfa *et al.* (2003) support this view. In fact, algorithms such as **survey propagation** (Parisi and Zecchina, 2002; Maneva *et al.*, 2007) take advantage of special properties of random SAT instances near the satisfiability threshold and greatly outperform general SAT solvers on such instances.

The best sources for information on satisfiability, both theoretical and practical, are the *Handbook of Satisfiability* (Biere *et al.*, 2009) and the regular *International Conferences on Theory and Applications of Satisfiability Testing*, known as SAT.

The idea of building agents with propositional logic can be traced back to the seminal paper of McCulloch and Pitts (1943), which initiated the field of neural networks. Contrary to popular supposition, the paper was concerned with the implementation of a Boolean circuit-based agent design in the brain. Circuit-based agents, which perform computation by propagating signals in hardware circuits rather than running algorithms in general-purpose computers, have received little attention in AI, however. The most notable exception is the work of Stan Rosenschein (Rosenstein, 1985; Kaelbling and Rosenschein, 1990), who developed ways to compile circuit-based agents from declarative descriptions of the task environment. (Rosenstein's approach is described at some length in the second edition of this book.) The work of Rod Brooks (1986, 1989) demonstrates the effectiveness of circuit-based designs for controlling robots—a topic we take up in Chapter 25. Brooks (1991) argues that circuit-based designs are *all* that is needed for AI—that representation and reasoning are cumbersome, expensive, and unnecessary. In our view, neither approach is sufficient by itself. Williams *et al.* (2003) show how a hybrid agent design not too different from our wumpus agent has been used to control NASA spacecraft, planning sequences of actions and diagnosing and recovering from faults.

The general problem of keeping track of a partially observable environment was introduced for state-based representations in Chapter 4. Its instantiation for propositional representations was studied by Amir and Russell (2003), who identified several classes of environments that admit efficient state-estimation algorithms and showed that for several other classes the problem is intractable. The **temporal-projection** problem, which involves determining what propositions hold true after an action sequence is executed, can be seen as a special case of state estimation with empty percepts. Many authors have studied this problem because of its importance in planning; some important hardness results were established by

Liberatore (1997). The idea of representing a belief state with propositions can be traced to Wittgenstein (1922).

Logical state estimation, of course, requires a logical representation of the effects of actions—a key problem in AI since the late 1950s. The dominant proposal has been the **situation calculus** formalism (McCarthy, 1963), which is couched within first-order logic. We discuss situation calculus, and various extensions and alternatives, in Chapters 10 and 12. The approach taken in this chapter—using temporal indices on propositional variables—is more restrictive but has the benefit of simplicity. The general approach embodied in the SATPLAN algorithm was proposed by Kautz and Selman (1992). Later generations of SATPLAN were able to take advantage of the advances in SAT solvers, described earlier, and remain among the most effective ways of solving difficult problems (Kautz, 2006).

The **frame problem** was first recognized by McCarthy and Hayes (1969). Many researchers considered the problem unsolvable within first-order logic, and it spurred a great deal of research into nonmonotonic logics. Philosophers from Dreyfus (1972) to Crockett (1994) have cited the frame problem as one symptom of the inevitable failure of the entire AI enterprise. The solution of the frame problem with successor-state axioms is due to Ray Reiter (1991). Thielscher (1999) identifies the inferential frame problem as a separate idea and provides a solution. In retrospect, one can see that Rosenschein's (1985) agents were using circuits that implemented successor-state axioms, but Rosenschein did not notice that the frame problem was thereby largely solved. Foo (2001) explains why the discrete-event control theory models typically used by engineers do not have to explicitly deal with the frame problem: because they are dealing with prediction and control, not with explanation and reasoning about counterfactual situations.

Modern propositional solvers have wide applicability in industrial applications. The application of propositional inference in the synthesis of computer hardware is now a standard technique having many large-scale deployments (Nowick *et al.*, 1993). The SATMC satisfiability checker was used to detect a previously unknown vulnerability in a Web browser user sign-on protocol (Armando *et al.*, 2008).

The wumpus world was invented by Gregory Yob (1975). Ironically, Yob developed it because he was bored with games played on a rectangular grid: the topology of his original wumpus world was a dodecahedron, and we put it back in the boring old grid. Michael Genesereth was the first to suggest that the wumpus world be used as an agent testbed.

EXERCISES

7.1 Suppose the agent has progressed to the point shown in Figure 7.4(a), page 239, having perceived nothing in [1,1], a breeze in [2,1], and a stench in [1,2], and is now concerned with the contents of [1,3], [2,2], and [3,1]. Each of these can contain a pit, and at most one can contain a wumpus. Following the example of Figure 7.5, construct the set of possible worlds. (You should find 32 of them.) Mark the worlds in which the KB is true and those in which

each of the following sentences is true:

$\alpha_2 = \text{"There is no pit in [2,2]."}'$

$\alpha_3 = \text{"There is a wumpus in [1,3]."}'$

Hence show that $KB \models \alpha_2$ and $KB \models \alpha_3$.

7.2 (Adapted from Barwise and Etchemendy (1993).) Given the following, can you prove that the unicorn is mythical? How about magical? Horned?

If the unicorn is mythical, then it is immortal, but if it is not mythical, then it is a mortal mammal. If the unicorn is either immortal or a mammal, then it is horned. The unicorn is magical if it is horned.

7.3 Consider the problem of deciding whether a propositional logic sentence is true in a given model.

- Write a recursive algorithm $PL-TRUE?(s, m)$ that returns *true* if and only if the sentence s is true in the model m (where m assigns a truth value for every symbol in s). The algorithm should run in time linear in the size of the sentence. (Alternatively, use a version of this function from the online code repository.)
- Give three examples of sentences that can be determined to be true or false in a *partial* model that does not specify a truth value for some of the symbols.
- Show that the truth value (if any) of a sentence in a partial model cannot be determined efficiently in general.
- Modify your $PL-TRUE?$ algorithm so that it can sometimes judge truth from partial models, while retaining its recursive structure and linear run time. Give three examples of sentences whose truth in a partial model is *not* detected by your algorithm.
- Investigate whether the modified algorithm makes $TT-ENTAILS?$ more efficient.

7.4 Which of the following are correct?

- $False \models True$.
- $True \models False$.
- $(A \wedge B) \models (A \Leftrightarrow B)$.
- $A \Leftrightarrow B \models A \vee B$.
- $A \Leftrightarrow B \models \neg A \vee B$.
- $(A \wedge B) \Rightarrow C \models (A \Rightarrow C) \vee (B \Rightarrow C)$.
- $(C \vee (\neg A \wedge \neg B)) \equiv ((A \Rightarrow C) \wedge (B \Rightarrow C))$.
- $(A \vee B) \wedge (\neg C \vee \neg D \vee E) \models (A \vee B)$.
- $(A \vee B) \wedge (\neg C \vee \neg D \vee E) \models (A \vee B) \wedge (\neg D \vee E)$.
- $(A \vee B) \wedge \neg(A \Rightarrow B)$ is satisfiable.
- $(A \Leftrightarrow B) \wedge (\neg A \vee B)$ is satisfiable.
- $(A \Leftrightarrow B) \Leftrightarrow C$ has the same number of models as $(A \Leftrightarrow B)$ for any fixed set of proposition symbols that includes A, B, C .

7.5 Prove each of the following assertions:

- a. α is valid if and only if $\text{True} \models \alpha$.
- b. For any α , $\text{False} \models \alpha$.
- c. $\alpha \models \beta$ if and only if the sentence $(\alpha \Rightarrow \beta)$ is valid.
- d. $\alpha \equiv \beta$ if and only if the sentence $(\alpha \Leftrightarrow \beta)$ is valid.
- e. $\alpha \models \beta$ if and only if the sentence $(\alpha \wedge \neg\beta)$ is unsatisfiable.

7.6 Prove, or find a counterexample to, each of the following assertions:

- a. If $\alpha \models \gamma$ or $\beta \models \gamma$ (or both) then $(\alpha \wedge \beta) \models \gamma$
- b. If $\alpha \models (\beta \wedge \gamma)$ then $\alpha \models \beta$ and $\alpha \models \gamma$.
- c. If $\alpha \models (\beta \vee \gamma)$ then $\alpha \models \beta$ or $\alpha \models \gamma$ (or both).

7.7 Consider a vocabulary with only four propositions, A , B , C , and D . How many models are there for the following sentences?

- a. $B \vee C$.
- b. $\neg A \vee \neg B \vee \neg C \vee \neg D$.
- c. $(A \Rightarrow B) \wedge A \wedge \neg B \wedge C \wedge D$.

7.8 We have defined four binary logical connectives.

- a. Are there any others that might be useful?
- b. How many binary connectives can there be?
- c. Why are some of them not very useful?

7.9 Using a method of your choice, verify each of the equivalences in Figure 7.11 (page 249).

7.10 Decide whether each of the following sentences is valid, unsatisfiable, or neither. Verify your decisions using truth tables or the equivalence rules of Figure 7.11 (page 249).

- a. $\text{Smoke} \Rightarrow \text{Smoke}$
- b. $\text{Smoke} \Rightarrow \text{Fire}$
- c. $(\text{Smoke} \Rightarrow \text{Fire}) \Rightarrow (\neg\text{Smoke} \Rightarrow \neg\text{Fire})$
- d. $\text{Smoke} \vee \text{Fire} \vee \neg\text{Fire}$
- e. $((\text{Smoke} \wedge \text{Heat}) \Rightarrow \text{Fire}) \Leftrightarrow ((\text{Smoke} \Rightarrow \text{Fire}) \vee (\text{Heat} \Rightarrow \text{Fire}))$
- f. $(\text{Smoke} \Rightarrow \text{Fire}) \Rightarrow ((\text{Smoke} \wedge \text{Heat}) \Rightarrow \text{Fire})$
- g. $\text{Big} \vee \text{Dumb} \vee (\text{Big} \Rightarrow \text{Dumb})$

7.11 Any propositional logic sentence is logically equivalent to the assertion that each possible world in which it would be false is not the case. From this observation, prove that any sentence can be written in CNF.

7.12 Use resolution to prove the sentence $\neg A \wedge \neg B$ from the clauses in Exercise 7.20.

7.13 This exercise looks into the relationship between clauses and implication sentences.

- a. Show that the clause $(\neg P_1 \vee \dots \vee \neg P_m \vee Q)$ is logically equivalent to the implication sentence $(P_1 \wedge \dots \wedge P_m) \Rightarrow Q$.
- b. Show that every clause (regardless of the number of positive literals) can be written in the form $(P_1 \wedge \dots \wedge P_m) \Rightarrow (Q_1 \vee \dots \vee Q_n)$, where the P s and Q s are proposition symbols. A knowledge base consisting of such sentences is in **implicative normal form** or **Kowalski form** (Kowalski, 1979).
- c. Write down the full resolution rule for sentences in implicative normal form.

7.14 According to some political pundits, a person who is radical (R) is electable (E) if he/she is conservative (C), but otherwise is not electable.

- a. Which of the following are correct representations of this assertion?

- (i) $(R \wedge E) \iff C$
- (ii) $R \Rightarrow (E \iff C)$
- (iii) $R \Rightarrow ((C \Rightarrow E) \vee \neg E)$

- b. Which of the sentences in (a) can be expressed in Horn form?

7.15 This question considers representing satisfiability (SAT) problems as CSPs.

- a. Draw the constraint graph corresponding to the SAT problem

$$(\neg X_1 \vee X_2) \wedge (\neg X_2 \vee X_3) \wedge \dots \wedge (\neg X_{n-1} \vee X_n)$$

for the particular case $n = 5$.

- b. How many solutions are there for this general SAT problem as a function of n ?
- c. Suppose we apply BACKTRACKING-SEARCH (page 215) to find *all* solutions to a SAT CSP of the type given in (a). (To find *all* solutions to a CSP, we simply modify the basic algorithm so it continues searching after each solution is found.) Assume that variables are ordered X_1, \dots, X_n and *false* is ordered before *true*. How much time will the algorithm take to terminate? (Write an $O(\cdot)$ expression as a function of n .)
- d. We know that SAT problems in Horn form can be solved in linear time by forward chaining (unit propagation). We also know that every tree-structured binary CSP with discrete, finite domains can be solved in time linear in the number of variables (Section 6.5). Are these two facts connected? Discuss.

7.16 Explain why every nonempty propositional clause, by itself, is satisfiable. Prove rigorously that every set of five 3-SAT clauses is satisfiable, provided that each clause mentions exactly three distinct variables. What is the smallest set of such clauses that is unsatisfiable? Construct such a set.

7.17 A propositional 2-CNF expression is a conjunction of clauses, each containing *exactly* 2 literals, e.g.,

$$(A \vee B) \wedge (\neg A \vee C) \wedge (\neg B \vee D) \wedge (\neg C \vee G) \wedge (\neg D \vee G) .$$

- a. Prove using resolution that the above sentence entails G .

- b. Two clauses are *semantically distinct* if they are not logically equivalent. How many semantically distinct 2-CNF clauses can be constructed from n proposition symbols?
- c. Using your answer to (b), prove that propositional resolution always terminates in time polynomial in n given a 2-CNF sentence containing no more than n distinct symbols.
- d. Explain why your argument in (c) does not apply to 3-CNF.

7.18 Consider the following sentence:

$$[(Food \Rightarrow Party) \vee (Drinks \Rightarrow Party)] \Rightarrow [(Food \wedge Drinks) \Rightarrow Party] .$$

- a. Determine, using enumeration, whether this sentence is valid, satisfiable (but not valid), or unsatisfiable.
- b. Convert the left-hand and right-hand sides of the main implication into CNF, showing each step, and explain how the results confirm your answer to (a).
- c. Prove your answer to (a) using resolution.

DISJUNCTIVE
NORMAL FORM

7.19 A sentence is in **disjunctive normal form** (DNF) if it is the disjunction of conjunctions of literals. For example, the sentence $(A \wedge B \wedge \neg C) \vee (\neg A \wedge C) \vee (B \wedge \neg C)$ is in DNF.

- a. Any propositional logic sentence is logically equivalent to the assertion that some possible world in which it would be true is in fact the case. From this observation, prove that any sentence can be written in DNF.
- b. Construct an algorithm that converts any sentence in propositional logic into DNF. (*Hint*: The algorithm is similar to the algorithm for conversion to CNF given in Section 7.5.2.)
- c. Construct a simple algorithm that takes as input a sentence in DNF and returns a satisfying assignment if one exists, or reports that no satisfying assignment exists.
- d. Apply the algorithms in (b) and (c) to the following set of sentences:

$$\begin{aligned} A &\Rightarrow B \\ B &\Rightarrow C \\ C &\Rightarrow \neg A . \end{aligned}$$

- e. Since the algorithm in (b) is very similar to the algorithm for conversion to CNF, and since the algorithm in (c) is much simpler than any algorithm for solving a set of sentences in CNF, why is this technique not used in automated reasoning?

7.20 Convert the following set of sentences to clausal form.

$$\begin{aligned} \text{S1: } A &\Leftrightarrow (B \vee E). \\ \text{S2: } E &\Rightarrow D. \\ \text{S3: } C \wedge F &\Rightarrow \neg B. \\ \text{S4: } E &\Rightarrow B. \\ \text{S5: } B &\Rightarrow F. \\ \text{S6: } B &\Rightarrow C \end{aligned}$$

Give a trace of the execution of DPLL on the conjunction of these clauses.

7.21 Is a randomly generated 4-CNF sentence with n symbols and m clauses more or less likely to be solvable than a randomly generated 3-CNF sentence with n symbols and m clauses? Explain.

7.22 Minesweeper, the well-known computer game, is closely related to the wumpus world. A minesweeper world is a rectangular grid of N squares with M invisible mines scattered among them. Any square may be probed by the agent; instant death follows if a mine is probed. Minesweeper indicates the presence of mines by revealing, in each probed square, the *number* of mines that are directly or diagonally adjacent. The goal is to probe every unmined square.

- Let $X_{i,j}$ be true iff square $[i, j]$ contains a mine. Write down the assertion that exactly two mines are adjacent to $[1,1]$ as a sentence involving some logical combination of $X_{i,j}$ propositions.
- Generalize your assertion from (a) by explaining how to construct a CNF sentence asserting that k of n neighbors contain mines.
- Explain precisely how an agent can use DPLL to prove that a given square does (or does not) contain a mine, ignoring the global constraint that there are exactly M mines in all.
- Suppose that the global constraint is constructed from your method from part (b). How does the number of clauses depend on M and N ? Suggest a way to modify DPLL so that the global constraint does not need to be represented explicitly.
- Are any conclusions derived by the method in part (c) invalidated when the global constraint is taken into account?
- Give examples of configurations of probe values that induce *long-range dependencies* such that the contents of a given unprobed square would give information about the contents of a far-distant square. (*Hint*: consider an $N \times 1$ board.)

7.23 How long does it take to prove $KB \models \alpha$ using DPLL when α is a literal *already contained in KB*? Explain.

7.24 Trace the behavior of DPLL on the knowledge base in Figure 7.16 when trying to prove Q , and compare this behavior with that of the forward-chaining algorithm.

7.25 Write a successor-state axiom for the *Locked* predicate, which applies to doors, assuming the only actions available are *Lock* and *Unlock*.

7.26 Section 7.7.1 provides some of the successor-state axioms required for the wumpus world. Write down axioms for all remaining fluent symbols.



7.27 Modify the HYBRID-WUMPUS-AGENT to use the 1-CNF logical state estimation method described on page 271. We noted on that page that such an agent will not be able to acquire, maintain, and use more complex beliefs such as the disjunction $P_{3,1} \vee P_{2,2}$. Suggest a method for overcoming this problem by defining additional proposition symbols, and try it out in the wumpus world. Does it improve the performance of the agent?