12 KNOWLEDGE REPRESENTATION

In which we show how to use first-order logic to represent the most important aspects of the real world, such as action, space, time, thoughts, and shopping.

The previous chapters described the technology for knowledge-based agents: the syntax, semantics, and proof theory of propositional and first-order logic, and the implementation of agents that use these logics. In this chapter we address the question of what *content* to put into such an agent's knowledge base—how to represent facts about the world.

Section 12.1 introduces the idea of a general ontology, which organizes everything in the world into a hierarchy of categories. Section 12.2 covers the basic categories of objects, substances, and measures; Section 12.3 covers events, and Section 12.4 discusses knowledge about beliefs. We then return to consider the technology for reasoning with this content: Section 12.5 discusses reasoning systems designed for efficient inference with categories, and Section 12.6 discusses reasoning with default information. Section 12.7 brings all the knowledge together in the context of an Internet shopping environment.

12.1 ONTOLOGICAL ENGINEERING

In "toy" domains, the choice of representation is not that important; many choices will work. Complex domains such as shopping on the Internet or driving a car in traffic require more general and flexible representations. This chapter shows how to create these representations, concentrating on general concepts—such as *Events, Time, Physical Objects*, and *Beliefs*—that occur in many different domains. Representing these abstract concepts is sometimes called **ontological engineering**.

ONTOLOGICAL ENGINEERING

The prospect of representing *everything* in the world is daunting. Of course, we won't actually write a complete description of everything—that would be far too much for even a 1000-page textbook—but we will leave placeholders where new knowledge for any domain can fit in. For example, we will define what it means to be a physical object, and the details of different types of objects—robots, televisions, books, or whatever—can be filled in later. This is analogous to the way that designers of an object-oriented programming framework (such as the Java Swing graphical framework) define general concepts like *Window*, expecting users to

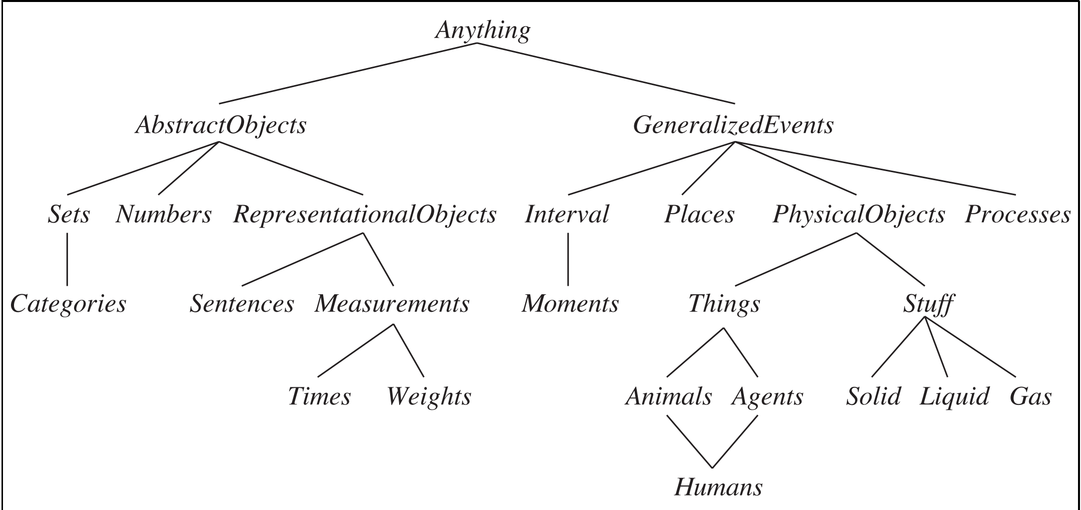

Figure 12.1 The upper ontology of the world, showing the topics to be covered later in the chapter. Each link indicates that the lower concept is a specialization of the upper one. Specializations are not necessarily disjoint; a human is both an animal and an agent, for example. We will see in Section 12.3.3 why physical objects come under generalized events.

use these to define more specific concepts like *SpreadsheetWindow*. The general framework of concepts is called an **upper ontology** because of the convention of drawing graphs with the general concepts at the top and the more specific concepts below them, as in Figure 12.1.

UPPER ONTOLOGY

Before considering the ontology further, we should state one important caveat. We have elected to use first-order logic to discuss the content and organization of knowledge, although certain aspects of the real world are hard to capture in FOL. The principal difficulty is that most generalizations have exceptions or hold only to a degree. For example, although "tomatoes are red" is a useful rule, some tomatoes are green, yellow, or orange. Similar exceptions can be found to almost all the rules in this chapter. The ability to handle exceptions and uncertainty is extremely important, but is orthogonal to the task of understanding the general ontology. For this reason, we delay the discussion of exceptions until Section 12.5 of this chapter, and the more general topic of reasoning with uncertainty until Chapter 13.

Of what use is an upper ontology? Consider the ontology for circuits in Section 8.4.2. It makes many simplifying assumptions: time is omitted completely; signals are fixed and do not propagate; the structure of the circuit remains constant. A more general ontology would consider signals at particular times, and would include the wire lengths and propagation delays. This would allow us to simulate the timing properties of the circuit, and indeed such simulations are often carried out by circuit designers. We could also introduce more interesting classes of gates, for example, by describing the technology (TTL, CMOS, and so on) as well as the input–output specification. If we wanted to discuss reliability or diagnosis, we would include the possibility that the structure of the circuit or the properties of the gates might change spontaneously. To account for stray capacitances, we would need to represent where the wires are on the board.

If we look at the wumpus world, similar considerations apply. Although we do represent time, it has a simple structure: Nothing happens except when the agent acts, and all changes are instantaneous. A more general ontology, better suited for the real world, would allow for simultaneous changes extended over time. We also used a Pit predicate to say which squares have pits. We could have allowed for different kinds of pits by having several individuals belonging to the class of pits, each having different properties. Similarly, we might want to allow for other animals besides wumpuses. It might not be possible to pin down the exact species from the available percepts, so we would need to build up a biological taxonomy to help the agent predict the behavior of cave-dwellers from scanty clues.

For any special-purpose ontology, it is possible to make changes like these to move toward greater generality. An obvious question then arises: do all these ontologies converge on a general-purpose ontology? After centuries of philosophical and computational investigation, the answer is "Maybe." In this section, we present one general-purpose ontology that synthesizes ideas from those centuries. Two major characteristics of general-purpose ontologies distinguish them from collections of special-purpose ontologies:

- A general-purpose ontology should be applicable in more or less any special-purpose domain (with the addition of domain-specific axioms). This means that no representational issue can be finessed or brushed under the carpet.
- In any sufficiently demanding domain, different areas of knowledge must be *unified*, because reasoning and problem solving could involve several areas simultaneously. A robot circuit-repair system, for instance, needs to reason about circuits in terms of electrical connectivity and physical layout, and about time, both for circuit timing analysis and estimating labor costs. The sentences describing time therefore must be capable of being combined with those describing spatial layout and must work equally well for nanoseconds and minutes and for angstroms and meters.

We should say up front that the enterprise of general ontological engineering has so far had only limited success. None of the top AI applications (as listed in Chapter 1) make use of a shared ontology—they all use special-purpose knowledge engineering. Social/political considerations can make it difficult for competing parties to agree on an ontology. As Tom Gruber (2004) says, "Every ontology is a treaty—a social agreement—among people with some common motive in sharing." When competing concerns outweigh the motivation for sharing, there can be no common ontology. Those ontologies that do exist have been created along four routes:

1. By a team of trained ontologist/logicians, who architect the ontology and write axioms. The CYC system was mostly built this way (Lenat and Guha, 1990).
2. By importing categories, attributes, and values from an existing database or databases. DBPEDIA was built by importing structured facts from Wikipedia (Bizer *et al.*, 2007).
3. By parsing text documents and extracting information from them. TEXTRUNNER was built by reading a large corpus of Web pages (Banko and Etzioni, 2008).
4. By enticing unskilled amateurs to enter commonsense knowledge. The OPENMIND system was built by volunteers who proposed facts in English (Singh *et al.*, 2002; Chklovski and Gil, 2005).

12.2 Categories and Objects

CATEGORY

The organization of objects into **categories** is a vital part of knowledge representation. Although interaction with the world takes place at the level of individual objects, *much reasoning takes place at the level of categories.* For example, a shopper would normally have the goal of buying a basketball, rather than a *particular* basketball such as BB_9. Categories also serve to make predictions about objects once they are classified. One infers the presence of certain objects from perceptual input, infers category membership from the perceived properties of the objects, and then uses category information to make predictions about the objects. For example, from its green and yellow mottled skin, one-foot diameter, ovoid shape, red flesh, black seeds, and presence in the fruit aisle, one can infer that an object is a watermelon; from this, one infers that it would be useful for fruit salad.

REIFICATION

There are two choices for representing categories in first-order logic: predicates and objects. That is, we can use the predicate $Basketball(b)$, or we can **reify**[1] the category as an object, $Basketballs$. We could then say $Member(b, Basketballs)$, which we will abbreviate as $b \in Basketballs$, to say that b is a member of the category of basketballs. We say $Subset(Basketballs, Balls)$, abbreviated as $Basketballs \subset Balls$, to say that $Basketballs$ is a **subcategory** of $Balls$. We will use subcategory, subclass, and subset interchangeably.

SUBCATEGORY

INHERITANCE

Categories serve to organize and simplify the knowledge base through **inheritance**. If we say that all instances of the category $Food$ are edible, and if we assert that $Fruit$ is a subclass of $Food$ and $Apples$ is a subclass of $Fruit$, then we can infer that every apple is edible. We say that the individual apples **inherit** the property of edibility, in this case from their membership in the $Food$ category.

TAXONOMY

Subclass relations organize categories into a **taxonomy**, or **taxonomic hierarchy**. Taxonomies have been used explicitly for centuries in technical fields. The largest such taxonomy organizes about 10 million living and extinct species, many of them beetles,[2] into a single hierarchy; library science has developed a taxonomy of all fields of knowledge, encoded as the Dewey Decimal system; and tax authorities and other government departments have developed extensive taxonomies of occupations and commercial products. Taxonomies are also an important aspect of general commonsense knowledge.

First-order logic makes it easy to state facts about categories, either by relating objects to categories or by quantifying over their members. Here are some types of facts, with examples of each:

- An object is a member of a category.
  $BB_9 \in Basketballs$
- A category is a subclass of another category.
  $Basketballs \subset Balls$
- All members of a category have some properties.
  $(x \in Basketballs) \Rightarrow Spherical(x)$

[1] Turning a proposition into an object is called **reification**, from the Latin word *res*, or thing. John McCarthy proposed the term "thingification," but it never caught on.

[2] The famous biologist J. B. S. Haldane deduced "An inordinate fondness for beetles" on the part of the Creator.

- Members of a category can be recognized by some properties.
  $Orange(x) \land Round(x) \land Diameter(x) = 9.5'' \land x \in Balls \;\Rightarrow\; x \in Basketballs$
- A category as a whole has some properties.
  $Dogs \in DomesticatedSpecies$

Notice that because $Dogs$ is a category and is a member of $DomesticatedSpecies$, the latter must be a category of categories. Of course there are exceptions to many of the above rules (punctured basketballs are not spherical); we deal with these exceptions later.

Although subclass and member relations are the most important ones for categories, we also want to be able to state relations between categories that are not subclasses of each other. For example, if we just say that $Males$ and $Females$ are subclasses of $Animals$, then we have not said that a male cannot be a female. We say that two or more categories are **disjoint** if they have no members in common. And even if we know that males and females are disjoint, we will not know that an animal that is not a male must be a female, unless we say that males and females constitute an **exhaustive decomposition** of the animals. A disjoint exhaustive decomposition is known as a **partition**. The following examples illustrate these three concepts:

DISJOINT

EXHAUSTIVE DECOMPOSITION

PARTITION

$$\begin{array}{l} Disjoint(\{Animals,\ Vegetables\}) \\ ExhaustiveDecomposition(\{Americans, Canadians, Mexicans\}, \\ \qquad\qquad\qquad NorthAmericans) \\ Partition(\{Males, Females\}, Animals)\ . \end{array}$$

(Note that the $ExhaustiveDecomposition$ of $NorthAmericans$ is not a $Partition$, because some people have dual citizenship.) The three predicates are defined as follows:

$$\begin{array}{l} Disjoint(s) \;\Leftrightarrow\; (\forall\, c_1, c_2\;\; c_1 \in s \land c_2 \in s \land c_1 \neq c_2 \;\Rightarrow\; Intersection(c_1, c_2) = \{\,\}) \\ ExhaustiveDecomposition(s, c) \;\Leftrightarrow\; (\forall\, i\;\; i \in c \;\Leftrightarrow\; \exists\, c_2\;\; c_2 \in s \land i \in c_2) \\ Partition(s, c) \;\Leftrightarrow\; Disjoint(s) \land ExhaustiveDecomposition(s, c)\ . \end{array}$$

Categories can also be *defined* by providing necessary and sufficient conditions for membership. For example, a bachelor is an unmarried adult male:

$$x \in Bachelors \;\Leftrightarrow\; Unmarried(x) \land x \in Adults \land x \in Males\ .$$

As we discuss in the sidebar on natural kinds on page 443, strict logical definitions for categories are neither always possible nor always necessary.

12.2.1 Physical composition

The idea that one object can be part of another is a familiar one. One's nose is part of one's head, Romania is part of Europe, and this chapter is part of this book. We use the general $PartOf$ relation to say that one thing is part of another. Objects can be grouped into $PartOf$ hierarchies, reminiscent of the $Subset$ hierarchy:

$$\begin{array}{l} PartOf(Bucharest, Romania) \\ PartOf(Romania, EasternEurope) \\ PartOf(EasternEurope, Europe) \\ PartOf(Europe, Earth)\ . \end{array}$$

The $PartOf$ relation is transitive and reflexive; that is,

$$PartOf(x,y) \land PartOf(y,z) \Rightarrow PartOf(x,z)\ .$$
$$PartOf(x,x)\ .$$

Therefore, we can conclude $PartOf(Bucharest, Earth)$.

COMPOSITE OBJECT

Categories of **composite objects** are often characterized by structural relations among parts. For example, a biped has two legs attached to a body:

$$\begin{aligned} Biped(a) \quad \Rightarrow \quad & \exists\, l_1, l_2, b \;\; Leg(l_1) \land Leg(l_2) \land Body(b) \;\land \\ & PartOf(l_1,a) \land PartOf(l_2,a) \land PartOf(b,a) \;\land \\ & Attached(l_1,b) \land Attached(l_2,b) \;\land \\ & l_1 \neq l_2 \land [\forall\, l_3 \;\; Leg(l_3) \land PartOf(l_3,a) \Rightarrow (l_3 = l_1 \lor l_3 = l_2)]\ . \end{aligned}$$

The notation for "exactly two" is a little awkward; we are forced to say that there are two legs, that they are not the same, and that if anyone proposes a third leg, it must be the same as one of the other two. In Section 12.5.2, we describe a formalism called description logic makes it easier to represent constraints like "exactly two."

We can define a $PartPartition$ relation analogous to the $Partition$ relation for categories. (See Exercise 12.8.) An object is composed of the parts in its $PartPartition$ and can be viewed as deriving some properties from those parts. For example, the mass of a composite object is the sum of the masses of the parts. Notice that this is not the case with categories, which have no mass, even though their elements might.

BUNCH

It is also useful to define composite objects with definite parts but no particular structure. For example, we might want to say "The apples in this bag weigh two pounds." The temptation would be to ascribe this weight to the *set* of apples in the bag, but this would be a mistake because the set is an abstract mathematical concept that has elements but does not have weight. Instead, we need a new concept, which we will call a **bunch**. For example, if the apples are $Apple_1$, $Apple_2$, and $Apple_3$, then

$$BunchOf(\{Apple_1, Apple_2, Apple_3\})$$

denotes the composite object with the three apples as parts (not elements). We can then use the bunch as a normal, albeit unstructured, object. Notice that $BunchOf(\{x\}) = x$. Furthermore, $BunchOf(Apples)$ is the composite object consisting of all apples—not to be confused with $Apples$, the category or set of all apples.

We can define $BunchOf$ in terms of the $PartOf$ relation. Obviously, each element of s is part of $BunchOf(s)$:

$$\forall\, x \;\; x \in s \Rightarrow PartOf(x, BunchOf(s))\ .$$

Furthermore, $BunchOf(s)$ *is the smallest object satisfying this condition.* In other words, $BunchOf(s)$ must be part of any object that has all the elements of s as parts:

$$\forall\, y \;\; [\forall\, x \;\; x \in s \Rightarrow PartOf(x,y)] \Rightarrow PartOf(BunchOf(s), y)\ .$$

LOGICAL MINIMIZATION

These axioms are an example of a general technique called **logical minimization**, which means defining an object as the smallest one satisfying certain conditions.

NATURAL KINDS

Some categories have strict definitions: an object is a triangle if and only if it is a polygon with three sides. On the other hand, most categories in the real world have no clear-cut definition; these are called **natural kind** categories. For example, tomatoes tend to be a dull scarlet; roughly spherical; with an indentation at the top where the stem was; about two to four inches in diameter; with a thin but tough skin; and with flesh, seeds, and juice inside. There is, however, variation: some tomatoes are yellow or orange, unripe tomatoes are green, some are smaller or larger than average, and cherry tomatoes are uniformly small. Rather than having a complete definition of tomatoes, we have a set of features that serves to identify objects that are clearly typical tomatoes, but might not be able to decide for other objects. (Could there be a tomato that is fuzzy like a peach?)

This poses a problem for a logical agent. The agent cannot be sure that an object it has perceived is a tomato, and even if it were sure, it could not be certain which of the properties of typical tomatoes this one has. This problem is an inevitable consequence of operating in partially observable environments.

One useful approach is to separate what is true of all instances of a category from what is true only of typical instances. So in addition to the category $Tomatoes$, we will also have the category $Typical(Tomatoes)$. Here, the $Typical$ function maps a category to the subclass that contains only typical instances:

$$Typical(c) \subseteq c\ .$$

Most knowledge about natural kinds will actually be about their typical instances:

$$x \in Typical(Tomatoes)\ \Rightarrow\ Red(x) \land Round(x)\ .$$

Thus, we can write down useful facts about categories without exact definitions. The difficulty of providing exact definitions for most natural categories was explained in depth by Wittgenstein (1953). He used the example of *games* to show that members of a category shared "family resemblances" rather than necessary and sufficient characteristics: what strict definition encompasses chess, tag, solitaire, and dodgeball?

The utility of the notion of strict definition was also challenged by Quine (1953). He pointed out that even the definition of "bachelor" as an unmarried adult male is suspect; one might, for example, question a statement such as "the Pope is a bachelor." While not strictly *false*, this usage is certainly *infelicitous* because it induces unintended inferences on the part of the listener. The tension could perhaps be resolved by distinguishing between logical definitions suitable for internal knowledge representation and the more nuanced criteria for felicitous linguistic usage. The latter may be achieved by "filtering" the assertions derived from the former. It is also possible that failures of linguistic usage serve as feedback for modifying internal definitions, so that filtering becomes unnecessary.

12.2.2 Measurements

MEASURE

In both scientific and commonsense theories of the world, objects have height, mass, cost, and so on. The values that we assign for these properties are called **measures**. Ordinary quantitative measures are quite easy to represent. We imagine that the universe includes abstract "measure objects," such as the *length* that is the length of this line segment: $\vdash\!\!\relbar\!\!\relbar\!\!\relbar\!\!\relbar\!\!\relbar\!\!\relbar\!\!\relbar\!\!\dashv$. We can call this length 1.5 inches or 3.81 centimeters. Thus, the same length has different names in our language.We represent the length with a **units function** that takes a number as argument. (An alternative scheme is explored in Exercise 12.9.) If the line segment is called L_1, we can write

UNITS FUNCTION

$$Length(L_1) = Inches(1.5) = Centimeters(3.81)\ .$$

Conversion between units is done by equating multiples of one unit to another:

$$Centimeters(2.54 \times d) = Inches(d)\ .$$

Similar axioms can be written for pounds and kilograms, seconds and days, and dollars and cents. Measures can be used to describe objects as follows:

$$\begin{array}{l} Diameter(Basketball_{12}) = Inches(9.5)\ . \\ ListPrice(Basketball_{12}) = \$(19)\ . \\ d \in Days\ \Rightarrow\ Duration(d) = Hours(24)\ . \end{array}$$

Note that $\$(1)$ is *not* a dollar bill! One can have two dollar bills, but there is only one object named $\$(1)$. Note also that, while $Inches(0)$ and $Centimeters(0)$ refer to the same zero length, they are not identical to other zero measures, such as $Seconds(0)$.

Simple, quantitative measures are easy to represent. Other measures present more of a problem, because they have no agreed scale of values. Exercises have difficulty, desserts have deliciousness, and poems have beauty, yet numbers cannot be assigned to these qualities. One might, in a moment of pure accountancy, dismiss such properties as useless for the purpose of logical reasoning; or, still worse, attempt to impose a numerical scale on beauty. This would be a grave mistake, because it is unnecessary. The most important aspect of measures is not the particular numerical values, but the fact that measures can be *ordered*.

Although measures are not numbers, we can still compare them, using an ordering symbol such as $>$. For example, we might well believe that Norvig's exercises are tougher than Russell's, and that one scores less on tougher exercises:

$$\begin{array}{l} e_1 \in Exercises \land e_2 \in Exercises \land Wrote(Norvig, e_1) \land Wrote(Russell, e_2)\ \Rightarrow \\ \qquad Difficulty(e_1) > Difficulty(e_2)\ . \\ e_1 \in Exercises \land e_2 \in Exercises \land Difficulty(e_1) > Difficulty(e_2)\ \Rightarrow \\ \qquad ExpectedScore(e_1) < ExpectedScore(e_2)\ . \end{array}$$

This is enough to allow one to decide which exercises to do, even though no numerical values for difficulty were ever used. (One does, however, have to discover who wrote which exercises.) These sorts of monotonic relationships among measures form the basis for the field of **qualitative physics**, a subfield of AI that investigates how to reason about physical systems without plunging into detailed equations and numerical simulations. Qualitative physics is discussed in the historical notes section.

12.2.3 Objects: Things and stuff

The real world can be seen as consisting of primitive objects (e.g., atomic particles) and composite objects built from them. By reasoning at the level of large objects such as apples and cars, we can overcome the complexity involved in dealing with vast numbers of primitive objects individually. There is, however, a significant portion of reality that seems to defy any obvious **individuation**—division into distinct objects. We give this portion the generic name **stuff**. For example, suppose I have some butter and an aardvark in front of me. I can say there is one aardvark, but there is no obvious number of "butter-objects," because any part of a butter-object is also a butter-object, at least until we get to very small parts indeed. This is the major distinction between *stuff* and *things*. If we cut an aardvark in half, we do not get two aardvarks (unfortunately).

INDIVIDUATION

STUFF

The English language distinguishes clearly between *stuff* and *things*. We say "an aardvark," but, except in pretentious California restaurants, one cannot say "a butter." Linguists distinguish between **count nouns**, such as aardvarks, holes, and theorems, and **mass nouns**, such as butter, water, and energy. Several competing ontologies claim to handle this distinction. Here we describe just one; the others are covered in the historical notes section.

COUNT NOUNS

MASS NOUN

To represent *stuff* properly, we begin with the obvious. We need to have as objects in our ontology at least the gross "lumps" of *stuff* we interact with. For example, we might recognize a lump of butter as the one left on the table the night before; we might pick it up, weigh it, sell it, or whatever. In these senses, it is an object just like the aardvark. Let us call it $Butter_3$. We also define the category $Butter$. Informally, its elements will be all those things of which one might say "It's butter," including $Butter_3$. With some caveats about very small parts that we w omit for now, any part of a butter-object is also a butter-object:

$$b \in Butter \land PartOf(p, b) \;\Rightarrow\; p \in Butter \,.$$

We can now say that butter melts at around 30 degrees centigrade:

$$b \in Butter \;\Rightarrow\; MeltingPoint(b, Centigrade(30)) \,.$$

We could go on to say that butter is yellow, is less dense than water, is soft at room temperature, has a high fat content, and so on. On the other hand, butter has no particular size, shape, or weight. We can define more specialized categories of butter such as $UnsaltedButter$, which is also a kind of *stuff*. Note that the category $PoundOfButter$, which includes as members all butter-objects weighing one pound, is not a kind of *stuff*. If we cut a pound of butter in half, we do not, alas, get two pounds of butter.

INTRINSIC

What is actually going on is this: some properties are **intrinsic**: they belong to the very substance of the object, rather than to the object as a whole. When you cut an instance of *stuff* in half, the two pieces retain the intrinsic properties—things like density, boiling point, flavor, color, ownership, and so on. On the other hand, their **extrinsic** properties—weight, length, shape, and so on—are not retained under subdivision. A category of objects that includes in its definition only *intrinsic* properties is then a substance, or mass noun; a class that includes *any* extrinsic properties in its definition is a count noun. The category $Stuff$ is the most general substance category, specifying no intrinsic properties. The category $Thing$ is the most general discrete object category, specifying no extrinsic properties.

EXTRINSIC

12.3 Events

In Section 10.4.2, we showed how situation calculus represents actions and their effects. Situation calculus is limited in its applicability: it was designed to describe a world in which actions are discrete, instantaneous, and happen one at a time. Consider a continuous action, such as filling a bathtub. Situation calculus can say that the tub is empty before the action and full when the action is done, but it can't talk about what happens *during* the action. It also can't describe two actions happening at the same time—such as brushing one's teeth while waiting for the tub to fill. To handle such cases we introduce an alternative formalism known as **event calculus**, which is based on points of time rather than on situations.[3]

EVENT CALCULUS

Event calculus reifies fluents and events. The fluent $At(Shankar, Berkeley)$ is an object that refers to the fact of Shankar being in Berkeley, but does not by itself say anything about whether it is true. To assert that a fluent is actually true at some point in time we use the predicate T, as in $T(At(Shankar, Berkeley), t)$.

Events are described as instances of event categories.[4] The event E_1 of Shankar flying from San Francisco to Washington, D.C. is described as

$$E_1 \in Flyings \land Flyer(E_1, Shankar) \land Origin(E_1, SF) \land Destination(E_1, DC)\,.$$

If this is too verbose, we can define an alternative three-argument version of the category of flying events and say

$$E_1 \in Flyings(Shankar, SF, DC)\,.$$

We then use $Happens(E_1, i)$ to say that the event E_1 took place over the time interval i, and we say the same thing in functional form with $Extent(E_1) = i$. We represent time intervals by a (start, end) pair of times; that is, $i = (t_1, t_2)$ is the time interval that starts at t_1 and ends at t_2. The complete set of predicates for one version of the event calculus is

$T(f, t)$	Fluent f is true at time t
$Happens(e, i)$	Event e happens over the time interval i
$Initiates(e, f, t)$	Event e causes fluent f to start to hold at time t
$Terminates(e, f, t)$	Event e causes fluent f to cease to hold at time t
$Clipped(f, i)$	Fluent f ceases to be true at some point during time interval i
$Restored(f, i)$	Fluent f becomes true sometime during time interval i

We assume a distinguished event, $Start$, that describes the initial state by saying which fluents are initiated or terminated at the start time. We define T by saying that a fluent holds at a point in time if the fluent was initiated by an event at some time in the past and was not made false (clipped) by an intervening event. A fluent does not hold if it was terminated by an event and

[3] The terms "event" and "action" may be used interchangeably. Informally, "action" connotes an agent while "event" connotes the possibility of agentless actions.

[4] Some versions of event calculus do not distinguish event categories from instances of the categories.

not made true (restored) by another event. Formally, the axioms are:

$$\begin{aligned}&\mathit{Happens}(e,(t_1,t_2)) \land \mathit{Initiates}(e,f,t_1) \land \neg \mathit{Clipped}(f,(t_1,t)) \land t_1 < t \;\Rightarrow\\ &\qquad T(f,t)\\ &\mathit{Happens}(e,(t_1,t_2)) \land \mathit{Terminates}(e,f,t_1) \land \neg \mathit{Restored}(f,(t_1,t)) \land t_1 < t \;\Rightarrow\\ &\qquad \neg T(f,t)\end{aligned}$$

where *Clipped* and *Restored* are defined by

$$\begin{aligned}&\mathit{Clipped}(f,(t_1,t_2)) \;\Leftrightarrow\\ &\quad \exists\, e,t,t_3 \;\; \mathit{Happens}(e,(t,t_3)) \land t_1 \le t < t_2 \land \mathit{Terminates}(e,f,t)\\ &\mathit{Restored}(f,(t_1,t_2)) \;\Leftrightarrow\\ &\quad \exists\, e,t,t_3 \;\; \mathit{Happens}(e,(t,t_3)) \land t_1 \le t < t_2 \land \mathit{Initiates}(e,f,t)\end{aligned}$$

It is convenient to extend T to work over intervals as well as time points; a fluent holds over an interval if it holds on every point within the interval:

$$T(f,(t_1,t_2)) \;\Leftrightarrow\; [\forall\, t \;\; (t_1 \le t < t_2) \;\Rightarrow\; T(f,t)]$$

Fluents and actions are defined with domain-specific axioms that are similar to successor-state axioms. For example, we can say that the only way a wumpus-world agent gets an arrow is at the start, and the only way to use up an arrow is to shoot it:

$$\begin{aligned}&\mathit{Initiates}(e, \mathit{HaveArrow}(a), t) \;\Leftrightarrow\; e = \mathit{Start}\\ &\mathit{Terminates}(e, \mathit{HaveArrow}(a), t) \;\Leftrightarrow\; e \in \mathit{Shootings}(a)\end{aligned}$$

By reifying events we make it possible to add any amount of arbitrary information about them. For example, we can say that Shankar's flight was bumpy with $\mathit{Bumpy}(E_1)$. In an ontology where events are n-ary predicates, there would be no way to add extra information like this; moving to an $n+1$-ary predicate isn't a scalable solution.

We can extend event calculus to make it possible to represent simultaneous events (such as two people being necessary to ride a seesaw), exogenous events (such as the wind blowing and changing the location of an object), continuous events (such as the level of water in the bathtub continuously rising) and other complications.

12.3.1 Processes

DISCRETE EVENTS

The events we have seen so far are what we call **discrete events**—they have a definite structure. Shankar's trip has a beginning, middle, and end. If interrupted halfway, the event would be something different—it would not be a trip from San Francisco to Washington, but instead a trip from San Francisco to somewhere over Kansas. On the other hand, the category of events denoted by *Flyings* has a different quality. If we take a small interval of Shankar's flight, say, the third 20-minute segment (while he waits anxiously for a bag of peanuts), that event is still a member of *Flyings*. In fact, this is true for any subinterval.

PROCESS

LIQUID EVENT

Categories of events with this property are called **process** categories or **liquid event** categories. Any process e that happens over an interval also happens over any subinterval:

$$(e \in \mathit{Processes}) \land \mathit{Happens}(e,(t_1,t_4)) \land (t_1 < t_2 < t_3 < t_4) \;\Rightarrow\; \mathit{Happens}(e,(t_2,t_3))\,.$$

The distinction between liquid and nonliquid events is exactly analogous to the difference between substances, or *stuff*, and individual objects, or *things*. In fact, some have called liquid events **temporal substances**, whereas substances like butter are **spatial substances**.

TEMPORAL SUBSTANCE

SPATIAL SUBSTANCE

12.3.2 Time intervals

Event calculus opens us up to the possibility of talking about time, and time intervals. We will consider two kinds of time intervals: moments and extended intervals. The distinction is that only moments have zero duration:

$$\begin{array}{l} Partition(\{Moments, ExtendedIntervals\}, Intervals) \\ i \in Moments \;\Leftrightarrow\; Duration(i) = Seconds(0)\ . \end{array}$$

Next we invent a time scale and associate points on that scale with moments, giving us absolute times. The time scale is arbitrary; we measure it in seconds and say that the moment at midnight (GMT) on January 1, 1900, has time 0. The functions *Begin* and *End* pick out the earliest and latest moments in an interval, and the function $Time$ delivers the point on the time scale for a moment. The function $Duration$ gives the difference between the end time and the start time.

$$\begin{array}{l} Interval(i) \;\Rightarrow\; Duration(i) = (Time(End(i)) - Time(Begin(i)))\ . \\ Time(Begin(AD1900)) = Seconds(0)\ . \\ Time(Begin(AD2001)) = Seconds(3187324800)\ . \\ Time(End(AD2001)) = Seconds(3218860800)\ . \\ Duration(AD2001) = Seconds(31536000)\ . \end{array}$$

To make these numbers easier to read, we also introduce a function $Date$, which takes six arguments (hours, minutes, seconds, day, month, and year) and returns a time point:

$$\begin{array}{l} Time(Begin(AD2001)) = Date(0, 0, 0, 1, Jan, 2001) \\ Date(0, 20, 21, 24, 1, 1995) = Seconds(3000000000)\ . \end{array}$$

Two intervals $Meet$ if the end time of the first equals the start time of the second. The complete set of interval relations, as proposed by Allen (1983), is shown graphically in Figure 12.2 and logically below:

$$\begin{array}{lcl} Meet(i,j) & \Leftrightarrow & End(i) = Begin(j) \\ Before(i,j) & \Leftrightarrow & End(i) < Begin(j) \\ After(j,i) & \Leftrightarrow & Before(i,j) \\ During(i,j) & \Leftrightarrow & Begin(j) < Begin(i) < End(i) < End(j) \\ Overlap(i,j) & \Leftrightarrow & Begin(i) < Begin(j) < End(i) < End(j) \\ Begins(i,j) & \Leftrightarrow & Begin(i) = Begin(j) \\ Finishes(i,j) & \Leftrightarrow & End(i) = End(j) \\ Equals(i,j) & \Leftrightarrow & Begin(i) = Begin(j) \land End(i) = End(j) \end{array}$$

These all have their intuitive meaning, with the exception of *Overlap*: we tend to think of overlap as symmetric (if *i* overlaps *j* then *j* overlaps *i*), but in this definition, $Overlap(i,j)$ only holds if *i* begins before *j*. To say that the reign of Elizabeth II immediately followed that of George VI, and the reign of Elvis overlapped with the 1950s, we can write the following:

$$\begin{array}{l} Meets(ReignOf(GeorgeVI), ReignOf(ElizabethII))\ . \\ Overlap(Fifties, ReignOf(Elvis))\ . \\ Begin(Fifties) = Begin(AD1950)\ . \\ End(Fifties) = End(AD1959)\ . \end{array}$$

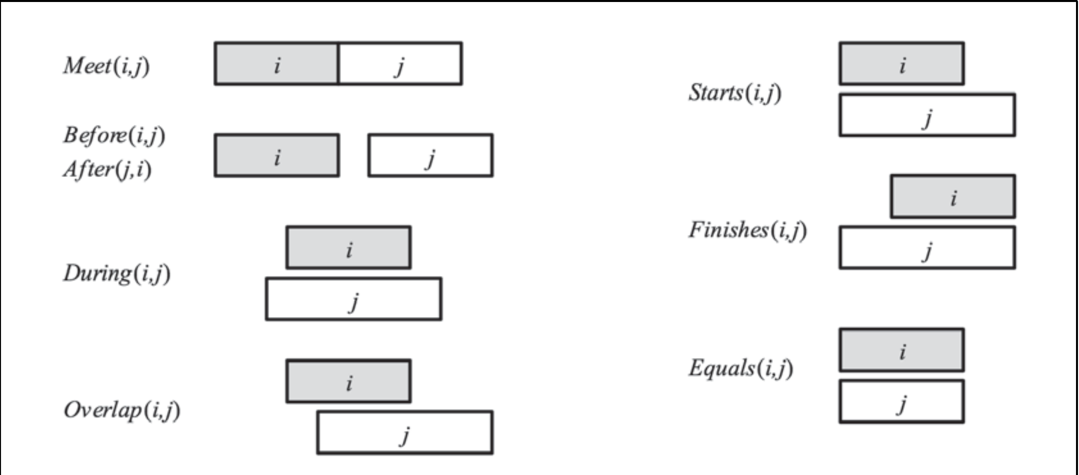

Figure 12.2 Predicates on time intervals.

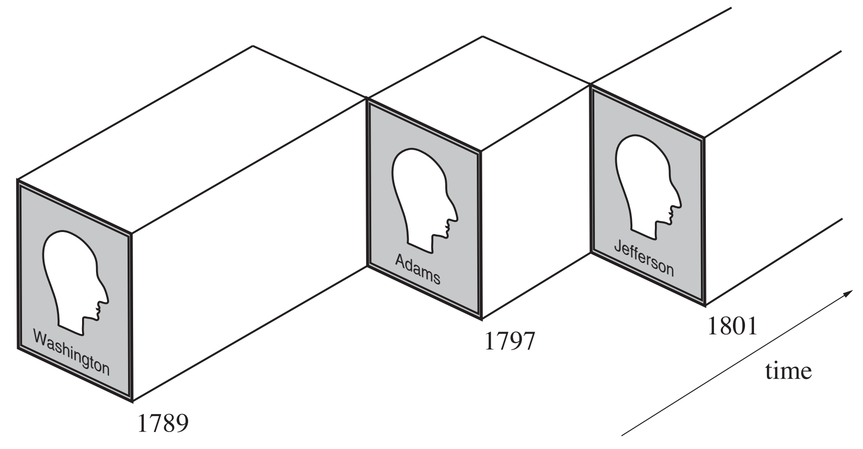

Figure 12.3 A schematic view of the object $President(USA)$ for the first 15 years of its existence.

12.3.3 Fluents and objects

Physical objects can be viewed as generalized events, in the sense that a physical object is a chunk of space–time. For example, USA can be thought of as an event that began in, say, 1776 as a union of 13 states and is still in progress today as a union of 50. We can describe the changing properties of USA using state fluents, such as $Population(USA)$. A property of the USA that changes every four or eight years, barring mishaps, is its president. One might propose that $President(USA)$ is a logical term that denotes a different object at different times. Unfortunately, this is not possible, because a term denotes exactly one object in a given model structure. (The term $President(USA, t)$ can denote different objects, depending on the value of t, but our ontology keeps time indices separate from fluents.) The only possibility is that $President(USA)$ denotes a single object that consists of different people at different times. It is the object that is George Washington from 1789 to 1797, John Adams from 1797 to 1801, and so on, as in Figure 12.3. To say that George Washington was president throughout 1790, we can write

$$T(Equals(President(USA), GeorgeWashington), AD1790) .$$

We use the function symbol $Equals$ rather than the standard logical predicate $=$, because we cannot have a predicate as an argument to T, and because the interpretation is *not* that $GeorgeWashington$ and $President(USA)$ are logically identical in 1790; logical identity is not something that can change over time. The identity is between the subevents of each object that are defined by the period 1790.

12.4 Mental Events and Mental Objects

The agents we have constructed so far have beliefs and can deduce new beliefs. Yet none of them has any knowledge *about* beliefs or *about* deduction. Knowledge about one's own knowledge and reasoning processes is useful for controlling inference. For example, suppose Alice asks "what is the square root of 1764" and Bob replies "I don't know." If Alice insists "think harder," Bob should realize that with some more thought, this question can in fact be answered. On the other hand, if the question were "Is your mother sitting down right now?" then Bob should realize that thinking harder is unlikely to help. Knowledge about the knowledge of other agents is also important; Bob should realize that his mother knows whether she is sitting or not, and that asking her would be a way to find out.

What we need is a model of the mental objects that are in someone's head (or something's knowledge base) and of the mental processes that manipulate those mental objects. The model does not have to be detailed. We do not have to be able to predict how many milliseconds it will take for a particular agent to make a deduction. We will be happy just to be able to conclude that mother knows whether or not she is sitting.

PROPOSITIONAL ATTITUDE

We begin with the **propositional attitudes** that an agent can have toward mental objects: attitudes such as $Believes$, $Knows$, $Wants$, $Intends$, and $Informs$. The difficulty is that these attitudes do not behave like "normal" predicates. For example, suppose we try to assert that Lois knows that Superman can fly:

$$Knows(Lois, CanFly(Superman)) .$$

One minor issue with this is that we normally think of $CanFly(Superman)$ as a sentence, but here it appears as a term. That issue can be patched up just be reifying $CanFly(Superman)$; making it a fluent. A more serious problem is that, if it is true that Superman is Clark Kent, then we must conclude that Lois knows that Clark can fly:

$$\begin{aligned}&(Superman = Clark) \land Knows(Lois, CanFly(Superman))\\&\quad \models Knows(Lois, CanFly(Clark)) .\end{aligned}$$

This is a consequence of the fact that equality reasoning is built into logic. Normally that is a good thing; if our agent knows that $2 + 2 = 4$ and $4 < 5$, then we want our agent to know

REFERENTIAL TRANSPARENCY

that $2 + 2 < 5$. This property is called **referential transparency**—it doesn't matter what term a logic uses to refer to an object, what matters is the object that the term names. But for propositional attitudes like *believes* and *knows*, we would like to have referential opacity—the terms used *do* matter, because not all agents know which terms are co-referential.

MODAL LOGIC

Modal logic is designed to address this problem. Regular logic is concerned with a single modality, the modality of truth, allowing us to express "*P* is true." Modal logic includes special modal operators that take sentences (rather than terms) as arguments. For example, "*A* knows *P*" is represented with the notation $\mathbf{K}_A P$, where **K** is the modal operator for knowledge. It takes two arguments, an agent (written as the subscript) and a sentence. The syntax of modal logic is the same as first-order logic, except that sentences can also be formed with modal operators.

POSSIBLE WORLD

ACCESSIBILITY RELATIONS

The semantics of modal logic is more complicated. In first-order logic a **model** contains a set of objects and an interpretation that maps each name to the appropriate object, relation, or function. In modal logic we want to be able to consider both the possibility that Superman's secret identity is Clark and that it isn't. Therefore, we will need a more complicated model, one that consists of a collection of **possible worlds** rather than just one true world. The worlds are connected in a graph by **accessibility relations**, one relation for each modal operator. We say that world w_1 is accessible from world w_0 with respect to the modal operator $\mathbf{K}_A$ if everything in w_1 is consistent with what A knows in w_0, and we write this as $Acc(\mathbf{K}_A, w_0, w_1)$. In diagrams such as Figure 12.4 we show accessibility as an arrow between possible worlds. As an example, in the real world, Bucharest is the capital of Romania, but for an agent that did not know that, other possible worlds are accessible, including ones where the capital of Romania is Sibiu or Sofia. Presumably a world where $2 + 2 = 5$ would not be accessible to any agent.

In general, a knowledge atom $\mathbf{K}_A P$ is true in world w if and only if P is true in every world accessible from w. The truth of more complex sentences is derived by recursive application of this rule and the normal rules of first-order logic. That means that modal logic can be used to reason about nested knowledge sentences: what one agent knows about another agent's knowledge. For example, we can say that, even though Lois doesn't know whether Superman's secret identity is Clark Kent, she does know that Clark knows:

$$\mathbf{K}_{Lois}[\mathbf{K}_{Clark} Identity(Superman, Clark) \lor \mathbf{K}_{Clark} \neg Identity(Superman, Clark)]$$

Figure 12.4 shows some possible worlds for this domain, with accessibility relations for Lois and Superman.

In the TOP-LEFT diagram, it is common knowledge that Superman knows his own identity, and neither he nor Lois has seen the weather report. So in w_0 the worlds w_0 and w_2 are accessible to Superman; maybe rain is predicted, maybe not. For Lois all four worlds are accessible from each other; she doesn't know anything about the report or if Clark is Superman. But she does know that Superman knows whether he is Clark, because in every world that is accessible to Lois, either Superman knows I, or he knows $\neg I$. Lois does not know which is the case, but either way she knows Superman knows.

In the TOP-RIGHT diagram it is common knowledge that Lois has seen the weather report. So in w_4 she knows rain is predicted and in w_6 she knows rain is not predicted.

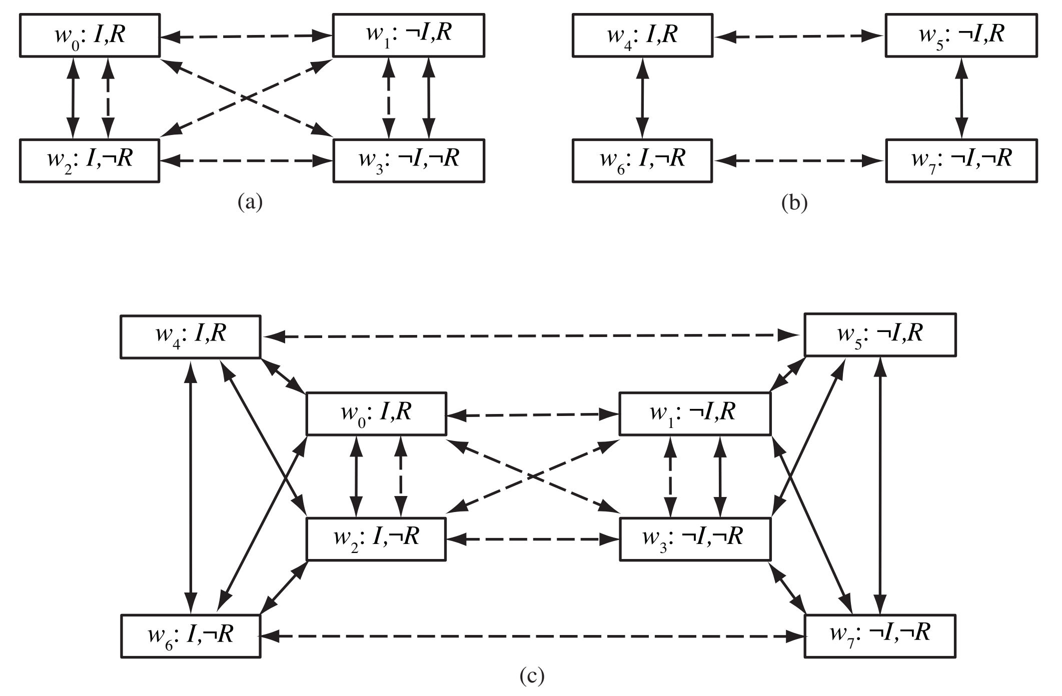

Figure 12.4 Possible worlds with accessibility relations $\mathbf{K}_{Superman}$ (solid arrows) and $\mathbf{K}_{Lois}$ (dotted arrows). The proposition R means "the weather report for tomorrow is rain" and I means "Superman's secret identity is Clark Kent." All worlds are accessible to themselves; the arrows from a world to itself are not shown.

Superman does not know the report, but he knows that Lois knows, because in every world that is accessible to him, either she knows R or she knows $\neg R$.

In the BOTTOM diagram we represent the scenario where it is common knowledge that Superman knows his identity, and Lois might or might not have seen the weather report. We represent this by combining the two top scenarios, and adding arrows to show that Superman does not know which scenario actually holds. Lois does know, so we don't need to add any arrows for her. In w_0 Superman still knows I but not R, and now he does not know whether Lois knows R. From what Superman knows, he might be in w_0 or w_2, in which case Lois does not know whether R is true, or he could be in w_4, in which case she knows R, or w_6, in which case she knows $\neg R$.

There are an infinite number of possible worlds, so the trick is to introduce just the ones you need to represent what you are trying to model. A new possible world is needed to talk about different possible facts (e.g., rain is predicted or not), or to talk about different states of knowledge (e.g., does Lois know that rain is predicted). That means two possible worlds, such as w_4 and w_0 in Figure 12.4, might have the same base facts about the world, but differ in their accessibility relations, and therefore in facts about knowledge.

Modal logic solves some tricky issues with the interplay of quantifiers and knowledge. The English sentence "Bond knows that someone is a spy" is ambiguous. The first reading is that there is a particular someone who Bond knows is a spy; we can write this as

$$\exists\, x \;\; \mathbf{K}_{Bond} Spy(x)\,,$$

which in modal logic means that there is an x that, in all accessible worlds, Bond knows to be a spy. The second reading is that Bond just knows that there is at least one spy:

$$\mathbf{K}_{Bond} \exists\, x \;\; Spy(x)\,.$$

The modal logic interpretation is that in each accessible world there is an x that is a spy, but it need not be the same x in each world.

Now that we have a modal operator for knowledge, we can write axioms for it. First, we can say that agents are able to draw deductions; if an agent knows P and knows that P implies Q, then the agent knows Q:

$$(\mathbf{K}_a P \wedge \mathbf{K}_a (P \;\Rightarrow\; Q)) \;\Rightarrow\; \mathbf{K}_a Q\,.$$

From this (and a few other rules about logical identities) we can establish that $\mathbf{K}_A(P \vee \neg P)$ is a tautology; every agent knows every proposition P is either true or false. On the other hand, $(\mathbf{K}_A P) \vee (\mathbf{K}_A \neg P)$ is not a tautology; in general, there will be lots of propositions that an agent does not know to be true and does not know to be false.

It is said (going back to Plato) that knowledge is justified true belief. That is, if it is true, if you believe it, and if you have an unassailably good reason, then you know it. That means that if you know something, it must be true, and we have the axiom:

$$\mathbf{K}_a P \;\Rightarrow\; P\,.$$

Furthermore, logical agents should be able to introspect on their own knowledge. If they know something, then they know that they know it:

$$\mathbf{K}_a P \;\Rightarrow\; \mathbf{K}_a(\mathbf{K}_a P)\,.$$

LOGICAL OMNISCIENCE

We can define similar axioms for belief (often denoted by **B**) and other modalities. However, one problem with the modal logic approach is that it assumes **logical omniscience** on the part of agents. That is, if an agent knows a set of axioms, then it knows all consequences of those axioms. This is on shaky ground even for the somewhat abstract notion of knowledge, but it seems even worse for belief, because belief has more connotation of referring to things that are physically represented in the agent, not just potentially derivable. There have been attempts to define a form of limited rationality for agents; to say that agents believe those assertions that can be derived with the application of no more than k reasoning steps, or no more than s seconds of computation. These attempts have been generally unsatisfactory.

12.5 REASONING SYSTEMS FOR CATEGORIES

Categories are the primary building blocks of large-scale knowledge representation schemes. This section describes systems specially designed for organizing and reasoning with categories. There are two closely related families of systems: **semantic networks** provide graphical aids for visualizing a knowledge base and efficient algorithms for inferring properties of an object on the basis of its category membership; and **description logics** provide a formal language for constructing and combining category definitions and efficient algorithms for deciding subset and superset relationships between categories.

12.5.1 Semantic networks

EXISTENTIAL GRAPHS

In 1909, Charles S. Peirce proposed a graphical notation of nodes and edges called **existential graphs** that he called "the logic of the future." Thus began a long-running debate between advocates of "logic" and advocates of "semantic networks." Unfortunately, the debate obscured the fact that semantics networks—at least those with well-defined semantics—*are* a form of logic. The notation that semantic networks provide for certain kinds of sentences is often more convenient, but if we strip away the "human interface" issues, the underlying concepts—objects, relations, quantification, and so on—are the same.

There are many variants of semantic networks, but all are capable of representing individual objects, categories of objects, and relations among objects. A typical graphical notation displays object or category names in ovals or boxes, and connects them with labeled links. For example, Figure 12.5 has a $MemberOf$ link between $Mary$ and $FemalePersons$, corresponding to the logical assertion $Mary \in FemalePersons$; similarly, the $SisterOf$ link between $Mary$ and $John$ corresponds to the assertion $SisterOf(Mary, John)$. We can connect categories using $SubsetOf$ links, and so on. It is such fun drawing bubbles and arrows that one can get carried away. For example, we know that persons have female persons as mothers, so can we draw a $HasMother$ link from $Persons$ to $FemalePersons$? The answer is no, because $HasMother$ is a relation between a person and his or her mother, and categories do not have mothers.[5]

For this reason, we have used a special notation—the double-boxed link—in Figure 12.5. This link asserts that

$$\forall x \;\; x \in Persons \;\Rightarrow\; [\forall y \;\; HasMother(x, y) \;\Rightarrow\; y \in FemalePersons] .$$

We might also want to assert that persons have two legs—that is,

$$\forall x \;\; x \in Persons \;\Rightarrow\; Legs(x, 2) .$$

As before, we need to be careful not to assert that a category has legs; the single-boxed link in Figure 12.5 is used to assert properties of every member of a category.

The semantic network notation makes it convenient to perform **inheritance** reasoning of the kind introduced in Section 12.2. For example, by virtue of being a person, Mary inherits the property of having two legs. Thus, to find out how many legs Mary has, the inheritance algorithm follows the $MemberOf$ link from $Mary$ to the category she belongs to, and then follows $SubsetOf$ links up the hierarchy until it finds a category for which there is a boxed $Legs$ link—in this case, the $Persons$ category. The simplicity and efficiency of this inference

[5] Several early systems failed to distinguish between properties of members of a category and properties of the category as a whole. This can lead directly to inconsistencies, as pointed out by Drew McDermott (1976) in his article "Artificial Intelligence Meets Natural Stupidity." Another common problem was the use of IsA links for both subset and membership relations, in correspondence with English usage: "a cat is a mammal" and "Fifi is a cat." See Exercise 12.22 for more on these issues.

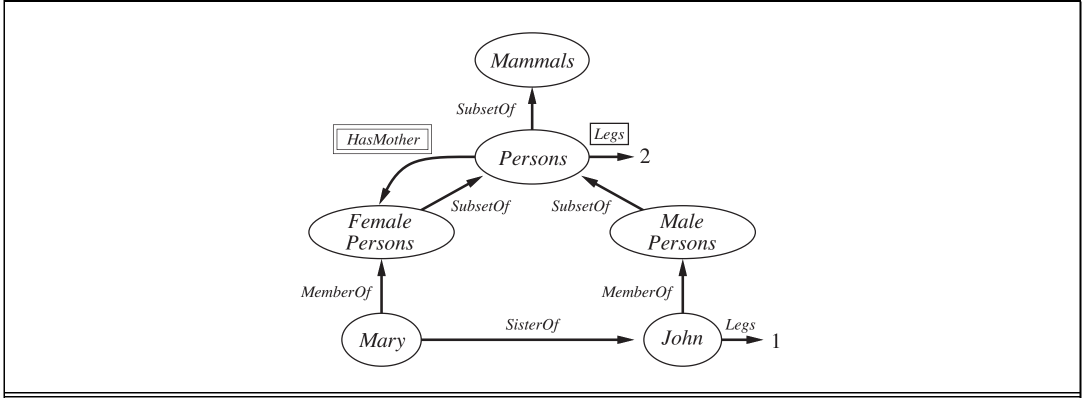

Figure 12.5 A semantic network with four objects (John, Mary, 1, and 2) and four categories. Relations are denoted by labeled links.

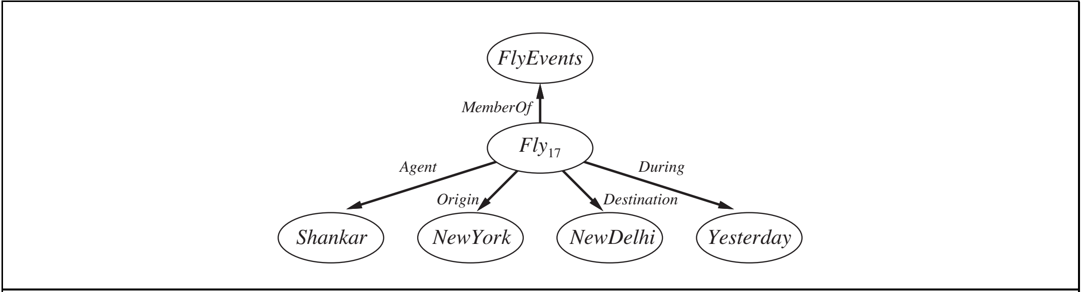

Figure 12.6 A fragment of a semantic network showing the representation of the logical assertion $Fly(Shankar, NewYork, NewDelhi, Yesterday)$.

mechanism, compared with logical theorem proving, has been one of the main attractions of semantic networks.

MULTIPLE INHERITANCE

Inheritance becomes complicated when an object can belong to more than one category or when a category can be a subset of more than one other category; this is called **multiple inheritance**. In such cases, the inheritance algorithm might find two or more conflicting values answering the query. For this reason, multiple inheritance is banned in some **object-oriented programming** (OOP) languages, such as Java, that use inheritance in a class hierarchy. It is usually allowed in semantic networks, but we defer discussion of that until Section 12.6.

The reader might have noticed an obvious drawback of semantic network notation, compared to first-order logic: the fact that links between bubbles represent only *binary* relations. For example, the sentence $Fly(Shankar, NewYork, NewDelhi, Yesterday)$ cannot be asserted directly in a semantic network. Nonetheless, we *can* obtain the effect of n-ary assertions by reifying the proposition itself as an event belonging to an appropriate event category. Figure 12.6 shows the semantic network structure for this particular event. Notice that the restriction to binary relations forces the creation of a rich ontology of reified concepts.

Reification of propositions makes it possible to represent every ground, function-free atomic sentence of first-order logic in the semantic network notation. Certain kinds of universally quantified sentences can be asserted using inverse links and the singly boxed and doubly boxed arrows applied to categories, but that still leaves us a long way short of full first-order logic. Negation, disjunction, nested function symbols, and existential quantification are all missing. Now it is *possible* to extend the notation to make it equivalent to first-order logic—as in Peirce's existential graphs—but doing so negates one of the main advantages of semantic networks, which is the simplicity and transparency of the inference processes. Designers can build a large network and still have a good idea about what queries will be efficient, because (a) it is easy to visualize the steps that the inference procedure will go through and (b) in some cases the query language is so simple that difficult queries cannot be posed. In cases where the expressive power proves to be too limiting, many semantic network systems provide for **procedural attachment** to fill in the gaps. Procedural attachment is a technique whereby a query about (or sometimes an assertion of) a certain relation results in a call to a special procedure designed for that relation rather than a general inference algorithm.

DEFAULT VALUE

One of the most important aspects of semantic networks is their ability to represent **default values** for categories. Examining Figure 12.5 carefully, one notices that John has one leg, despite the fact that he is a person and all persons have two legs. In a strictly logical KB, this would be a contradiction, but in a semantic network, the assertion that all persons have two legs has only default status; that is, a person is assumed to have two legs unless this is contradicted by more specific information. The default semantics is enforced naturally by the inheritance algorithm, because it follows links upwards from the object itself (John in this case) and stops as soon as it finds a value. We say that the default is **overridden** by the more specific value. Notice that we could also override the default number of legs by creating a category of $OneLeggedPersons$, a subset of $Persons$ of which $John$ is a member.

OVERRIDING

We can retain a strictly logical semantics for the network if we say that the $Legs$ assertion for $Persons$ includes an exception for John:

$$\forall x \;\; x \in Persons \land x \neq John \;\Rightarrow\; Legs(x, 2) \, .$$

For a *fixed* network, this is semantically adequate but will be much less concise than the network notation itself if there are lots of exceptions. For a network that will be updated with more assertions, however, such an approach fails—we really want to say that any persons as yet unknown with one leg are exceptions too. Section 12.6 goes into more depth on this issue and on default reasoning in general.

12.5.2 Description logics

DESCRIPTION LOGIC

The syntax of first-order logic is designed to make it easy to say things about objects. **Description logics** are notations that are designed to make it easier to describe definitions and properties of categories. Description logic systems evolved from semantic networks in response to pressure to formalize what the networks mean while retaining the emphasis on taxonomic structure as an organizing principle.

SUBSUMPTION

CLASSIFICATION

The principal inference tasks for description logics are **subsumption** (checking if one category is a subset of another by comparing their definitions) and **classification** (checking whether an object belongs to a category).. Some systems also include **consistency** of a category definition—whether the membership criteria are logically satisfiable.

$$
\begin{array}{rcl}
Concept & \rightarrow & \textbf{Thing} \mid ConceptName \\
 & \mid & \textbf{And}(Concept, \ldots) \\
 & \mid & \textbf{All}(RoleName, Concept) \\
 & \mid & \textbf{AtLeast}(Integer, RoleName) \\
 & \mid & \textbf{AtMost}(Integer, RoleName) \\
 & \mid & \textbf{Fills}(RoleName, IndividualName, \ldots) \\
 & \mid & \textbf{SameAs}(Path, Path) \\
 & \mid & \textbf{OneOf}(IndividualName, \ldots) \\
Path & \rightarrow & [RoleName, \ldots]
\end{array}
$$

Figure 12.7 The syntax of descriptions in a subset of the CLASSIC language.

The CLASSIC language (Borgida *et al.*, 1989) is a typical description logic. The syntax of CLASSIC descriptions is shown in Figure 12.7.[6] For example, to say that bachelors are unmarried adult males we would write

$$Bachelor = And(Unmarried, Adult, Male)\ .$$

The equivalent in first-order logic would be

$$Bachelor(x) \Leftrightarrow Unmarried(x) \land Adult(x) \land Male(x)\ .$$

Notice that the description logic has an an algebra of operations on predicates, which of course we can't do in first-order logic. Any description in CLASSIC can be translated into an equivalent first-order sentence, but some descriptions are more straightforward in CLASSIC. For example, to describe the set of men with at least three sons who are all unemployed and married to doctors, and at most two daughters who are all professors in physics or math departments, we would use

$$
\begin{array}{l}
And(Man, AtLeast(3, Son), AtMost(2, Daughter), \\
\qquad All(Son, And(Unemployed, Married, All(Spouse, Doctor))), \\
\qquad All(Daughter, And(Professor, Fills(Department, Physics, Math))))\ .
\end{array}
$$

We leave it as an exercise to translate this into first-order logic.

Perhaps the most important aspect of description logics is their emphasis on tractability of inference. A problem instance is solved by describing it and then asking if it is subsumed by one of several possible solution categories. In standard first-order logic systems, predicting the solution time is often impossible. It is frequently left to the user to engineer the representation to detour around sets of sentences that seem to be causing the system to take several weeks to solve a problem. The thrust in description logics, on the other hand, is to ensure that subsumption-testing can be solved in time polynomial in the size of the descriptions.[7]

[6] Notice that the language does *not* allow one to simply state that one concept, or category, is a subset of another. This is a deliberate policy: subsumption between categories must be derivable from some aspects of the descriptions of the categories. If not, then something is missing from the descriptions.

[7] CLASSIC provides efficient subsumption testing in practice, but the worst-case run time is exponential.

This sounds wonderful in principle, until one realizes that it can only have one of two consequences: either hard problems cannot be stated at all, or they require exponentially large descriptions! However, the tractability results do shed light on what sorts of constructs cause problems and thus help the user to understand how different representations behave. For example, description logics usually lack *negation* and *disjunction*. Each forces first-order logical systems to go through a potentially exponential case analysis in order to ensure completeness. CLASSIC allows only a limited form of disjunction in the $Fills$ and $OneOf$ constructs, which permit disjunction over explicitly enumerated individuals but not over descriptions. With disjunctive descriptions, nested definitions can lead easily to an exponential number of alternative routes by which one category can subsume another.

12.6 Reasoning with Default Information

In the preceding section, we saw a simple example of an assertion with default status: people have two legs. This default can be overridden by more specific information, such as that Long John Silver has one leg. We saw that the inheritance mechanism in semantic networks implements the overriding of defaults in a simple and natural way. In this section, we study defaults more generally, with a view toward understanding the *semantics* of defaults rather than just providing a procedural mechanism.

12.6.1 Circumscription and default logic

We have seen two examples of reasoning processes that violate the **monotonicity** property of logic that was proved in Chapter 7.[8] In this chapter we saw that a property inherited by all members of a category in a semantic network could be overridden by more specific information for a subcategory. In Section 9.4.5, we saw that under the closed-world assumption, if a proposition α is not mentioned in KB then $KB \models \neg\alpha$, but $KB \wedge \alpha \models \alpha$.

Simple introspection suggests that these failures of monotonicity are widespread in commonsense reasoning. It seems that humans often "jump to conclusions." For example, when one sees a car parked on the street, one is normally willing to believe that it has four wheels even though only three are visible. Now, probability theory can certainly provide a conclusion that the fourth wheel exists with high probability, yet, for most people, the possibility of the car's not having four wheels *does not arise unless some new evidence presents itself*. Thus, it seems that the four-wheel conclusion is reached *by default*, in the absence of any reason to doubt it. If new evidence arrives—for example, if one sees the owner carrying a wheel and notices that the car is jacked up—then the conclusion can be retracted. This kind of reasoning is said to exhibit **nonmonotonicity**, because the set of beliefs does not grow monotonically over time as new evidence arrives. **Nonmonotonic logics** have been devised with modified notions of truth and entailment in order to capture such behavior. We will look at two such logics that have been studied extensively: circumscription and default logic.

NONMONOTONICITY

NONMONOTONIC LOGIC

[8] Recall that monotonicity requires all entailed sentences to remain entailed after new sentences are added to the KB. That is, if $KB \models \alpha$ then $KB \wedge \beta \models \alpha$.

CIRCUMSCRIPTION

Circumscription can be seen as a more powerful and precise version of the closed-world assumption. The idea is to specify particular predicates that are assumed to be "as false as possible"—that is, false for every object except those for which they are known to be true. For example, suppose we want to assert the default rule that birds fly. We would introduce a predicate, say $Abnormal_1(x)$, and write

$$Bird(x) \land \neg Abnormal_1(x) \;\Rightarrow\; Flies(x)\ .$$

If we say that $Abnormal_1$ is to be **circumscribed**, a circumscriptive reasoner is entitled to assume $\neg Abnormal_1(x)$ unless $Abnormal_1(x)$ is known to be true. This allows the conclusion $Flies(Tweety)$ to be drawn from the premise $Bird(Tweety)$, but the conclusion no longer holds if $Abnormal_1(Tweety)$ is asserted.

MODEL PREFERENCE

Circumscription can be viewed as an example of a **model preference** logic. In such logics, a sentence is entailed (with default status) if it is true in all *preferred* models of the KB, as opposed to the requirement of truth in *all* models in classical logic. For circumscription, one model is preferred to another if it has fewer abnormal objects.[9] Let us see how this idea works in the context of multiple inheritance in semantic networks. The standard example for which multiple inheritance is problematic is called the "Nixon diamond." It arises from the observation that Richard Nixon was both a Quaker (and hence by default a pacifist) and a Republican (and hence by default not a pacifist). We can write this as follows:

$$\begin{aligned}&Republican(Nixon) \land Quaker(Nixon)\ .\\&Republican(x) \land \neg Abnormal_2(x) \;\Rightarrow\; \neg Pacifist(x)\ .\\&Quaker(x) \land \neg Abnormal_3(x) \;\Rightarrow\; Pacifist(x)\ .\end{aligned}$$

If we circumscribe $Abnormal_2$ and $Abnormal_3$, there are two preferred models: one in which $Abnormal_2(Nixon)$ and $Pacifist(Nixon)$ hold and one in which $Abnormal_3(Nixon)$ and $\neg Pacifist(Nixon)$ hold. Thus, the circumscriptive reasoner remains properly agnostic as to whether Nixon was a pacifist. If we wish, in addition, to assert that religious beliefs take precedence over political beliefs, we can use a formalism called **prioritized circumscription** to give preference to models where $Abnormal_3$ is minimized.

PRIORITIZED CIRCUMSCRIPTION

DEFAULT LOGIC

DEFAULT RULES

Default logic is a formalism in which **default rules** can be written to generate contingent, nonmonotonic conclusions. A default rule looks like this:

$$Bird(x) : Flies(x)/Flies(x)\ .$$

This rule means that if $Bird(x)$ is true, and if $Flies(x)$ is consistent with the knowledge base, then $Flies(x)$ may be concluded by default. In general, a default rule has the form

$$P : J_1, \ldots, J_n/C$$

where P is called the prerequisite, C is the conclusion, and J_i are the justifications—if any one of them can be proven false, then the conclusion cannot be drawn. Any variable that

[9] For the closed-world assumption, one model is preferred to another if it has fewer true atoms—that is, preferred models are **minimal** models. There is a natural connection between the closed-world assumption and definite-clause KBs, because the fixed point reached by forward chaining on definite-clause KBs is the unique minimal model. See page 258 for more on this point.

appears in J_i or C must also appear in P. The Nixon-diamond example can be represented in default logic with one fact and two default rules:

$$Republican(Nixon) \wedge Quaker(Nixon) .$$
$$Republican(x) : \neg Pacifist(x) / \neg Pacifist(x) .$$
$$Quaker(x) : Pacifist(x) / Pacifist(x) .$$

EXTENSION

To interpret what the default rules mean, we define the notion of an **extension** of a default theory to be a maximal set of consequences of the theory. That is, an extension S consists of the original known facts and a set of conclusions from the default rules, such that no additional conclusions can be drawn from S and the justifications of every default conclusion in S are consistent with S. As in the case of the preferred models in circumscription, we have two possible extensions for the Nixon diamond: one wherein he is a pacifist and one wherein he is not. Prioritized schemes exist in which some default rules can be given precedence over others, allowing some ambiguities to be resolved.

Since 1980, when nonmonotonic logics were first proposed, a great deal of progress has been made in understanding their mathematical properties. There are still unresolved questions, however. For example, if "Cars have four wheels" is false, what does it mean to have it in one's knowledge base? What is a good set of default rules to have? If we cannot decide, for each rule separately, whether it belongs in our knowledge base, then we have a serious problem of nonmodularity. Finally, how can beliefs that have default status be used to make decisions? This is probably the hardest issue for default reasoning. Decisions often involve tradeoffs, and one therefore needs to compare the *strengths* of belief in the outcomes of different actions, and the *costs* of making a wrong decision. In cases where the same kinds of decisions are being made repeatedly, it is possible to interpret default rules as "threshold probability" statements. For example, the default rule "My brakes are always OK" really means "The probability that my brakes are OK, given no other information, is sufficiently high that the optimal decision is for me to drive without checking them." When the decision context changes—for example, when one is driving a heavily laden truck down a steep mountain road—the default rule suddenly becomes inappropriate, even though there is no new evidence of faulty brakes. These considerations have led some researchers to consider how to embed default reasoning within probability theory or utility theory.

12.6.2 Truth maintenance systems

We have seen that many of the inferences drawn by a knowledge representation system will have only default status, rather than being absolutely certain. Inevitably, some of these inferred facts will turn out to be wrong and will have to be retracted in the face of new information. This process is called **belief revision.**[10] Suppose that a knowledge base KB contains a sentence P—perhaps a default conclusion recorded by a forward-chaining algorithm, or perhaps just an incorrect assertion—and we want to execute TELL(KB, $\neg P$). To avoid creating a contradiction, we must first execute RETRACT(KB, P). This sounds easy enough.

BELIEF REVISION

[10] Belief revision is often contrasted with **belief update**, which occurs when a knowledge base is revised to reflect a change in the world rather than new information about a fixed world. Belief update combines belief revision with reasoning about time and change; it is also related to the process of **filtering** described in Chapter 15.

Problems arise, however, if any *additional* sentences were inferred from P and asserted in the KB. For example, the implication $P \Rightarrow Q$ might have been used to add Q. The obvious "solution"—retracting all sentences inferred from P—fails because such sentences may have other justifications besides P. For example, if R and $R \Rightarrow Q$ are also in the KB, then Q does not have to be removed after all. **Truth maintenance systems**, or TMSs, are designed to handle exactly these kinds of complications.

TRUTH MAINTENANCE SYSTEM

One simple approach to truth maintenance is to keep track of the order in which sentences are told to the knowledge base by numbering them from P_1 to P_n. When the call RETRACT(KB, P_i) is made, the system reverts to the state just before P_i was added, thereby removing both P_i and any inferences that were derived from P_i. The sentences P_{i+1} through P_n can then be added again. This is simple, and it guarantees that the knowledge base will be consistent, but retracting P_i requires retracting and reasserting $n - i$ sentences as well as undoing and redoing all the inferences drawn from those sentences. For systems to which many facts are being added—such as large commercial databases—this is impractical.

JTMS

JUSTIFICATION

A more efficient approach is the justification-based truth maintenance system, or **JTMS**. In a JTMS, each sentence in the knowledge base is annotated with a **justification** consisting of the set of sentences from which it was inferred. For example, if the knowledge base already contains $P \Rightarrow Q$, then TELL(P) will cause Q to be added with the justification $\{P,\ P \Rightarrow Q\}$. In general, a sentence can have any number of justifications. Justifications make retraction efficient. Given the call RETRACT(P), the JTMS will delete exactly those sentences for which P is a member of every justification. So, if a sentence Q had the single justification $\{P,\ P \Rightarrow Q\}$, it would be removed; if it had the additional justification $\{P,\ P \vee R \Rightarrow Q\}$, it would still be removed; but if it also had the justification $\{R,\ P \vee R \Rightarrow Q\}$, then it would be spared. In this way, the time required for retraction of P depends only on the number of sentences derived from P rather than on the number of other sentences added since P entered the knowledge base.

The JTMS assumes that sentences that are considered once will probably be considered again, so rather than deleting a sentence from the knowledge base entirely when it loses all justifications, we merely mark the sentence as being *out* of the knowledge base. If a subsequent assertion restores one of the justifications, then we mark the sentence as being back *in*. In this way, the JTMS retains all the inference chains that it uses and need not rederive sentences when a justification becomes valid again.

In addition to handling the retraction of incorrect information, TMSs can be used to speed up the analysis of multiple hypothetical situations. Suppose, for example, that the Romanian Olympic Committee is choosing sites for the swimming, athletics, and equestrian events at the 2048 Games to be held in Romania. For example, let the first hypothesis be $Site(Swimming, Pitesti)$, $Site(Athletics, Bucharest)$, and $Site(Equestrian, Arad)$. A great deal of reasoning must then be done to work out the logistical consequences and hence the desirability of this selection. If we want to consider $Site(Athletics, Sibiu)$ instead, the TMS avoids the need to start again from scratch. Instead, we simply retract $Site(Athletics, Bucharest)$ and assert $Site(Athletics, Sibiu)$ and the TMS takes care of the necessary revisions. Inference chains generated from the choice of Bucharest can be reused with Sibiu, provided that the conclusions are the same.

ATMS

An assumption-based truth maintenance system, or **ATMS**, makes this type of context-switching between hypothetical worlds particularly efficient. In a JTMS, the maintenance of justifications allows you to move quickly from one state to another by making a few retractions and assertions, but at any time only one state is represented. An ATMS represents *all* the states that have ever been considered at the same time. Whereas a JTMS simply labels each sentence as being *in* or *out*, an ATMS keeps track, for each sentence, of which assumptions would cause the sentence to be true. In other words, each sentence has a label that consists of a set of assumption sets. The sentence holds just in those cases in which all the assumptions in one of the assumption sets hold.

EXPLANATION

ASSUMPTION

Truth maintenance systems also provide a mechanism for generating **explanations**. Technically, an explanation of a sentence P is a set of sentences E such that E entails P. If the sentences in E are already known to be true, then E simply provides a sufficient basis for proving that P must be the case. But explanations can also include **assumptions**—sentences that are not known to be true, but would suffice to prove P if they were true. For example, one might not have enough information to prove that one's car won't start, but a reasonable explanation might include the assumption that the battery is dead. This, combined with knowledge of how cars operate, explains the observed nonbehavior. In most cases, we will prefer an explanation E that is minimal, meaning that there is no proper subset of E that is also an explanation. An ATMS can generate explanations for the "car won't start" problem by making assumptions (such as "gas in car" or "battery dead") in any order we like, even if some assumptions are contradictory. Then we look at the label for the sentence "car won't start" to read off the sets of assumptions that would justify the sentence.

The exact algorithms used to implement truth maintenance systems are a little complicated, and we do not cover them here. The computational complexity of the truth maintenance problem is at least as great as that of propositional inference—that is, NP-hard. Therefore, you should not expect truth maintenance to be a panacea. When used carefully, however, a TMS can provide a substantial increase in the ability of a logical system to handle complex environments and hypotheses.

12.7 The Internet Shopping World

In this final section we put together all we have learned to encode knowledge for a shopping research agent that helps a buyer find product offers on the Internet. The shopping agent is given a product description by the buyer and has the task of producing a list of Web pages that offer such a product for sale, and ranking which offers are best. In some cases the buyer's product description will be precise, as in *Canon Rebel XTi digital camera*, and the task is then to find the store(s) with the best offer. In other cases the description will be only partially specified, as in *digital camera for under $300*, and the agent will have to compare different products.

The shopping agent's environment is the entire World Wide Web in its full complexity—not a toy simulated environment. The agent's percepts are Web pages, but whereas a human

Example Online Store

Select from our fine line of products:

- Computers
- Cameras
- Books
- Videos
- Music

```
<h1>Example Online Store</h1>
<i>Select</i> from our fine line of products:
<ul>
<li> <a href="http://example.com/compu">Computers</a>
<li> <a href="http://example.com/camer">Cameras</a>
<li> <a href="http://example.com/books">Books</a>
<li> <a href="http://example.com/video">Videos</a>
<li> <a href="http://example.com/music">Music</a>
</ul>
```

Figure 12.8 A Web page from a generic online store in the form perceived by the human user of a browser (top), and the corresponding HTML string as perceived by the browser or the shopping agent (bottom). In HTML, characters between < and > are markup directives that specify how the page is displayed. For example, the string `<i>Select</i>` means to switch to italic font, display the word *Select*, and then end the use of italic font. A page identifier such as `http://example.com/books` is called a **uniform resource locator (URL)**. The markup `<a href="`*url*`">`*Books*`</a>` means to create a hypertext link to *url* with the **anchor text** *Books*.

Web user would see pages displayed as an array of pixels on a screen, the shopping agent will perceive a page as a character string consisting of ordinary words interspersed with formatting commands in the HTML markup language. Figure 12.8 shows a Web page and a corresponding HTML character string. The perception problem for the shopping agent involves extracting useful information from percepts of this kind.

Clearly, perception on Web pages is easier than, say, perception while driving a taxi in Cairo. Nonetheless, there are complications to the Internet perception task. The Web page in Figure 12.8 is simple compared to real shopping sites, which may include CSS, cookies, Java, Javascript, Flash, robot exclusion protocols, malformed HTML, sound files, movies, and text that appears only as part of a JPEG image. An agent that can deal with *all* of the Internet is almost as complex as a robot that can move in the real world. We concentrate on a simple agent that ignores most of these complications.

The agent's first task is to collect product offers that are relevant to a query. If the query is "laptops," then a Web page with a review of the latest high-end laptop would be relevant, but if it doesn't provide a way to buy, it isn't an offer. For now, we can say a page is an offer if it contains the words "buy" or "price" or "add to cart" within an HTML link or form on the page. For example, if the page contains a string of the form "`<a ... add to cart ... </a`" then it is an offer. This could be represented in first-order logic, but it is more straightforward to encode it into program code. We show how to do more sophisticated information extraction in Section 22.4.

12.7.1 Following links

The strategy is to start at the home page of an online store and consider all pages that can be reached by following relevant links.[11] The agent will have knowledge of a number of stores, for example:

$$\begin{aligned}
&Amazon \in OnlineStores \land Homepage(Amazon, \text{“}amazon.com\text{”})\ .\\
&Ebay \in OnlineStores \land Homepage(Ebay, \text{“}ebay.com\text{”})\ .\\
&ExampleStore \in OnlineStores \land Homepage(ExampleStore, \text{“}example.com\text{”})\ .
\end{aligned}$$

These stores classify their goods into product categories, and provide links to the major categories from their home page. Minor categories can be reached through a chain of relevant links, and eventually we will reach offers. In other words, a page is relevant to the query if it can be reached by a chain of zero or more relevant category links from a store's home page, and then from one more link to the product offer. We can define relevance:

$$\begin{aligned}
&Relevant(page, query) \Leftrightarrow\\
&\quad \exists\, store, home \;\; store \in OnlineStores \land Homepage(store, home)\\
&\quad \land \exists\, url, url_2 \;\; RelevantChain(home, url_2, query) \land Link(url_2, url)\\
&\qquad \land\, page = Contents(url)\ .
\end{aligned}$$

Here the predicate $Link(from, to)$ means that there is a hyperlink from the *from* URL to the *to* URL. To define what counts as a *RelevantChain*, we need to follow not just any old hyperlinks, but only those links whose associated anchor text indicates that the link is relevant to the product query. For this, we use $LinkText(from, to, text)$ to mean that there is a link between *from* and *to* with *text* as the anchor text. A chain of links between two URLs, *start* and *end*, is relevant to a description d if the anchor text of each link is a relevant category name for d. The existence of the chain itself is determined by a recursive definition, with the empty chain ($start = end$) as the base case:

$$\begin{aligned}
&RelevantChain(start, end, query) \Leftrightarrow (start = end)\\
&\quad \lor (\exists\, u, text \;\; LinkText(start, u, text) \land RelevantCategoryName(query, text)\\
&\qquad \land\, RelevantChain(u, end, query))\ .
\end{aligned}$$

Now we must define what it means for *text* to be a *RelevantCategoryName* for *query*. First, we need to relate strings to the categories they name. This is done using the predicate $Name(s, c)$, which says that string s is a name for category c—for example, we might assert that $Name(\text{“}laptops\text{”}, LaptopComputers)$. Some more examples of the *Name* predicate appear in Figure 12.9(b). Next, we define relevance. Suppose that *query* is "laptops." Then $RelevantCategoryName(query, text)$ is true when one of the following holds:

- The *text* and *query* name the same category—e.g., "notebooks" and "laptops."

[11] An alternative to the link-following strategy is to use an Internet search engine; the technology behind Internet search, information retrieval, will be covered in Section 22.3.

$Books \subset Products$
$MusicRecordings \subset Products$
  $MusicCDs \subset MusicRecordings$
$Electronics \subset Products$
  $DigitalCameras \subset Electronics$
  $StereoEquipment \subset Electronics$
  $Computers \subset Electronics$
    $DesktopComputers \subset Computers$
    $LaptopComputers \subset Computers$
    ...

(a)

$Name(\text{"}books\text{"}, Books)$
$Name(\text{"}music\text{"}, MusicRecordings)$
  $Name(\text{"}CDs\text{"}, MusicCDs)$
$Name(\text{"}electronics\text{"}, Electronics)$
  $Name(\text{"}digital\ cameras\text{"}, DigitalCameras)$
  $Name(\text{"}stereos\text{"}, StereoEquipment)$
  $Name(\text{"}computers\text{"}, Computers)$
    $Name(\text{"}desktops\text{"}, DesktopComputers)$
    $Name(\text{"}laptops\text{"}, LaptopComputers)$
    $Name(\text{"}notebooks\text{"}, LaptopComputers)$
    ...

(b)

Figure 12.9 (a) Taxonomy of product categories. (b) Names for those categories.

- The *text* names a supercategory such as "computers."
- The *text* names a subcategory such as "ultralight notebooks."

The logical definition of $RelevantCategoryName$ is as follows:

$$RelevantCategoryName(query, text) \Leftrightarrow$$
$$\exists\, c_1, c_2 \;\; Name(query, c_1) \wedge Name(text, c_2) \wedge (c_1 \subseteq c_2 \vee c_2 \subseteq c_1)\,. \qquad (12.1)$$

Otherwise, the anchor text is irrelevant because it names a category outside this line, such as "clothes" or "lawn & garden."

To follow relevant links, then, it is essential to have a rich hierarchy of product categories. The top part of this hierarchy might look like Figure 12.9(a). It will not be feasible to list *all* possible shopping categories, because a buyer could always come up with some new desire and manufacturers will always come out with new products to satisfy them (electric kneecap warmers?). Nonetheless, an ontology of about a thousand categories will serve as a very useful tool for most buyers.

In addition to the product hierarchy itself, we also need to have a rich vocabulary of names for categories. Life would be much easier if there were a one-to-one correspondence between categories and the character strings that name them. We have already seen the problem of **synonymy**—two names for the same category, such as "laptop computers" and "laptops." There is also the problem of **ambiguity**—one name for two or more different categories. For example, if we add the sentence

$$Name(\text{"}CDs\text{"}, CertificatesOfDeposit)$$

to the knowledge base in Figure 12.9(b), then "CDs" will name two different categories.

Synonymy and ambiguity can cause a significant increase in the number of paths that the agent has to follow, and can sometimes make it difficult to determine whether a given page is indeed relevant. A much more serious problem is the very broad range of descriptions that a user can type and category names that a store can use. For example, the link might say "laptop" when the knowledge base has only "laptops" or the user might ask for "a computer

I can fit on the tray table of an economy-class airline seat." It is impossible to enumerate in advance all the ways a category can be named, so the agent will have to be able to do additional reasoning in some cases to determine if the *Name* relation holds. In the worst case, this requires full natural language understanding, a topic that we will defer to Chapter 22. In practice, a few simple rules—such as allowing "laptop" to match a category named "laptops"—go a long way. Exercise 12.10 asks you to develop a set of such rules after doing some research into online stores.

Given the logical definitions from the preceding paragraphs and suitable knowledge bases of product categories and naming conventions, are we ready to apply an inference algorithm to obtain a set of relevant offers for our query? Not quite! The missing element is the $Contents(url)$ function, which refers to the HTML page at a given URL. The agent doesn't have the page contents of every URL in its knowledge base; nor does it have explicit rules for deducing what those contents might be. Instead, we can arrange for the right HTTP procedure to be executed whenever a subgoal involves the *Contents* function. In this way, it appears to the inference engine as if the entire Web is inside the knowledge base. This is an example of a general technique called **procedural attachment**, whereby particular predicates and functions can be handled by special-purpose methods.

PROCEDURAL ATTACHMENT

12.7.2 Comparing offers

Let us assume that the reasoning processes of the preceding section have produced a set of offer pages for our "laptops" query. To compare those offers, the agent must extract the relevant information—price, speed, disk size, weight, and so on—from the offer pages. This can be a difficult task with real Web pages, for all the reasons mentioned previously. A common way of dealing with this problem is to use programs called **wrappers** to extract information from a page. The technology of information extraction is discussed in Section 22.4. For now we assume that wrappers exist, and when given a page and a knowledge base, they add assertions to the knowledge base. Typically, a hierarchy of wrappers would be applied to a page: a very general one to extract dates and prices, a more specific one to extract attributes for computer-related products, and if necessary a site-specific one that knows the format of a particular store. Given a page on the example.com site with the text

WRAPPER

```
IBM ThinkBook 970.  Our price:  $399.00
```

followed by various technical specifications, we would like a wrapper to extract information such as the following:

$$\begin{aligned}
&\exists\, c, \mathit{offer}\;\; c \in \mathit{LaptopComputers} \land \mathit{offer} \in \mathit{ProductOffers} \land \\
&\quad \mathit{Manufacturer}(c, \mathit{IBM}) \land \mathit{Model}(c, \mathit{ThinkBook970}) \land \\
&\quad \mathit{ScreenSize}(c, \mathit{Inches}(14)) \land \mathit{ScreenType}(c, \mathit{ColorLCD}) \land \\
&\quad \mathit{MemorySize}(c, \mathit{Gigabytes}(2)) \land \mathit{CPUSpeed}(c, \mathit{GHz}(1.2)) \land \\
&\quad \mathit{OfferedProduct}(\mathit{offer}, c) \land \mathit{Store}(\mathit{offer}, \mathit{GenStore}) \land \\
&\quad \mathit{URL}(\mathit{offer}, \text{``}\texttt{example.com/computers/34356.html}\text{''}) \land \\
&\quad \mathit{Price}(\mathit{offer}, \$(399)) \land \mathit{Date}(\mathit{offer}, \mathit{Today})\,.
\end{aligned}$$

This example illustrates several issues that arise when we take seriously the task of knowledge engineering for commercial transactions. For example, notice that the price is an attribute of the *offer*, not the product itself. This is important because the offer at a given store may change from day to day even for the same individual laptop; for some categories—such as houses and paintings—the same individual object may even be offered simultaneously by different intermediaries at different prices. There are still more complications that we have not handled, such as the possibility that the price depends on the method of payment and on the buyer's qualifications for certain discounts. The final task is to compare the offers that have been extracted. For example, consider these three offers:

A : 1.4 GHz CPU, 2GB RAM, 250 GB disk, \$299 .
B : 1.2 GHz CPU, 4GB RAM, 350 GB disk, \$500 .
C : 1.2 GHz CPU, 2GB RAM, 250 GB disk, \$399 .

C is **dominated** by A; that is, A is cheaper and faster, and they are otherwise the same. In general, X dominates Y if X has a better value on at least one attribute, and is not worse on any attribute. But neither A nor B dominates the other. To decide which is better we need to know how the buyer weighs CPU speed and price against memory and disk space. The general topic of preferences among multiple attributes is addressed in Section 16.4; for now, our shopping agent will simply return a list of all undominated offers that meet the buyer's description. In this example, both A and B are undominated. Notice that this outcome relies on the assumption that everyone prefers cheaper prices, faster processors, and more storage. Some attributes, such as screen size on a notebook, depend on the user's particular preference (portability versus visibility); for these, the shopping agent will just have to ask the user.

The shopping agent we have described here is a simple one; many refinements are possible. Still, it has enough capability that with the right domain-specific knowledge it can actually be of use to a shopper. Because of its declarative construction, it extends easily to more complex applications. The main point of this section is to show that some knowledge representation—in particular, the product hierarchy—is necessary for such an agent, and that once we have some knowledge in this form, the rest follows naturally.

12.8 SUMMARY

By delving into the details of how one represents a variety of knowledge, we hope we have given the reader a sense of how real knowledge bases are constructed and a feeling for the interesting philosophical issues that arise. The major points are as follows:

- Large-scale knowledge representation requires a general-purpose ontology to organize and tie together the various specific domains of knowledge.
- A general-purpose ontology needs to cover a wide variety of knowledge and should be capable, in principle, of handling any domain.
- Building a large, general-purpose ontology is a significant challenge that has yet to be fully realized, although current frameworks seem to be quite robust.
- We presented an **upper ontology** based on categories and the event calculus. We covered categories, subcategories, parts, structured objects, measurements, substances, events, time and space, change, and beliefs.

- Natural kinds cannot be defined completely in logic, but properties of natural kinds can be represented.
- Actions, events, and time can be represented either in situation calculus or in more expressive representations such as event calculus. Such representations enable an agent to construct plans by logical inference.
- We presented a detailed analysis of the Internet shopping domain, exercising the general ontology and showing how the domain knowledge can be used by a shopping agent.
- Special-purpose representation systems, such as **semantic networks** and **description logics**, have been devised to help in organizing a hierarchy of categories. **Inheritance** is an important form of inference, allowing the properties of objects to be deduced from their membership in categories.
- The **closed-world assumption**, as implemented in logic programs, provides a simple way to avoid having to specify lots of negative information. It is best interpreted as a **default** that can be overridden by additional information.
- **Nonmonotonic logics**, such as **circumscription** and **default logic**, are intended to capture default reasoning in general.
- **Truth maintenance systems** handle knowledge updates and revisions efficiently.

BIBLIOGRAPHICAL AND HISTORICAL NOTES

Briggs (1985) claims that formal knowledge representation research began with classical Indian theorizing about the grammar of Shastric Sanskrit, which dates back to the first millennium B.C. In the West, the use of definitions of terms in ancient Greek mathematics can be regarded as the earliest instance: Aristotle's *Metaphysics* (literally, what comes after the book on physics) is a near-synonym for *Ontology*. Indeed, the development of technical terminology in any field can be regarded as a form of knowledge representation.

Early discussions of representation in AI tended to focus on "*problem* representation" rather than "*knowledge* representation." (See, for example, Amarel's (1968) discussion of the Missionaries and Cannibals problem.) In the 1970s, AI emphasized the development of "expert systems" (also called "knowledge-based systems") that could, if given the appropriate domain knowledge, match or exceed the performance of human experts on narrowly defined tasks. For example, the first expert system, DENDRAL (Feigenbaum *et al.*, 1971; Lindsay *et al.*, 1980), interpreted the output of a mass spectrometer (a type of instrument used to analyze the structure of organic chemical compounds) as accurately as expert chemists. Although the success of DENDRAL was instrumental in convincing the AI research community of the importance of knowledge representation, the representational formalisms used in DENDRAL are highly specific to the domain of chemistry. Over time, researchers became interested in standardized knowledge representation formalisms and ontologies that could streamline the process of creating new expert systems. In so doing, they ventured into territory previously explored by philosophers of science and of language. The discipline imposed in AI by the need for one's theories to "work" has led to more rapid and deeper progress than was the case when these problems were the exclusive domain of philosophy (although it has at times also led to the repeated reinvention of the wheel).

The creation of comprehensive taxonomies or classifications dates back to ancient times. Aristotle (384–322 B.C.) strongly emphasized classification and categorization schemes. His *Organon*, a collection of works on logic assembled by his students after his death, included a treatise called *Categories* in which he attempted to construct what we would now call an upper ontology. He also introduced the notions of **genus** and **species** for lower-level classification. Our present system of biological classification, including the use of "binomial nomenclature" (classification via genus and species in the technical sense), was invented by the Swedish biologist Carolus Linnaeus, or Carl von Linne (1707–1778). The problems associated with natural kinds and inexact category boundaries have been addressed by Wittgenstein (1953), Quine (1953), Lakoff (1987), and Schwartz (1977), among others.

Interest in larger-scale ontologies is increasing, as documented by the *Handbook on Ontologies* (Staab, 2004). The OPENCYC project (Lenat and Guha, 1990; Matuszek *et al.*, 2006) has released a 150,000-concept ontology, with an upper ontology similar to the one in Figure 12.1 as well as specific concepts like "OLED Display" and "iPhone," which is a type of "cellular phone," which in turn is a type of "consumer electronics," "phone," "wireless communication device," and other concepts. The DBPEDIA project extracts structured data from Wikipedia; specifically from Infoboxes: the boxes of attribute/value pairs that accompany many Wikipedia articles (Wu and Weld, 2008; Bizer *et al.*, 2007). As of mid-2009, DBPEDIA contains 2.6 million concepts, with about 100 facts per concept. The IEEE working group P1600.1 created the Suggested Upper Merged Ontology (SUMO) (Niles and Pease, 2001; Pease and Niles, 2002), which contains about 1000 terms in the upper ontology and links to over 20,000 domain-specific terms. Stoffel *et al.* (1997) describe algorithms for efficiently managing a very large ontology. A survey of techniques for extracting knowledge from Web pages is given by Etzioni *et al.* (2008).

On the Web, representation languages are emerging. RDF (Brickley and Guha, 2004) allows for assertions to be made in the form of relational triples, and provides some means for evolving the meaning of names over time. OWL (Smith *et al.*, 2004) is a description logic that supports inferences over these triples. So far, usage seems to be inversely proportional to representational complexity: the traditional HTML and CSS formats account for over 99% of Web content, followed by the simplest representation schemes, such as microformats (Khare, 2006) and RDFa (Adida and Birbeck, 2008), which use HTML and XHTML markup to add attributes to literal text. Usage of sophisticated RDF and OWL ontologies is not yet widespread, and the full vision of the Semantic Web (Berners-Lee *et al.*, 2001) has not yet been realized. The conferences on *Formal Ontology in Information Systems* (FOIS) contain many interesting papers on both general and domain-specific ontologies.

The taxonomy used in this chapter was developed by the authors and is based in part on their experience in the CYC project and in part on work by Hwang and Schubert (1993) and Davis (1990, 2005). An inspirational discussion of the general project of commonsense knowledge representation appears in Hayes's (1978, 1985b) "Naive Physics Manifesto."

Successful deep ontologies within a specific field include the Gene Ontology project (Consortium, 2008) and CML, the Chemical Markup Language (Murray-Rust *et al.*, 2003).

Doubts about the feasibility of a single ontology for *all* knowledge are expressed by Doctorow (2001), Gruber (2004), Halevy *et al.* (2009), and Smith (2004), who states, "the initial project of building one single ontology ... has ... largely been abandoned."

The event calculus was introduced by Kowalski and Sergot (1986) to handle continuous time, and there have been several variations (Sadri and Kowalski, 1995; Shanahan, 1997) and overviews (Shanahan, 1999; Mueller, 2006). van Lambalgen and Hamm (2005) show how the logic of events maps onto the language we use to talk about events. An alternative to the event and situation calculi is the fluent calculus (Thielscher, 1999). James Allen introduced time intervals for the same reason (Allen, 1984), arguing that intervals were much more natural than situations for reasoning about extended and concurrent events. Peter Ladkin (1986a, 1986b) introduced "concave" time intervals (intervals with gaps; essentially, unions of ordinary "convex" time intervals) and applied the techniques of mathematical abstract algebra to time representation. Allen (1991) systematically investigates the wide variety of techniques available for time representation; van Beek and Manchak (1996) analyze algorithms for temporal reasoning. There are significant commonalities between the event-based ontology given in this chapter and an analysis of events due to the philosopher Donald Davidson (1980). The **histories** in Pat Hayes's (1985a) ontology of liquids and the **chronicles** in McDermott's (1985) theory of plans were also important influences on the field and this chapter.

The question of the ontological status of substances has a long history. Plato proposed that substances were abstract entities entirely distinct from physical objects; he would say $MadeOf(Butter_3, Butter)$ rather than $Butter_3 \in Butter$. This leads to a substance hierarchy in which, for example, $UnsaltedButter$ is a more specific substance than $Butter$. The position adopted in this chapter, in which substances are categories of objects, was championed by Richard Montague (1973). It has also been adopted in the CYC project. Copeland (1993) mounts a serious, but not invincible, attack. The alternative approach mentioned in the chapter, in which butter is one object consisting of all buttery objects in the universe, was proposed originally by the Polish logician Leśniewski (1916). His **mereology** (the name is derived from the Greek word for "part") used the part–whole relation as a substitute for mathematical set theory, with the aim of eliminating abstract entities such as sets. A more readable exposition of these ideas is given by Leonard and Goodman (1940), and Goodman's *The Structure of Appearance* (1977) applies the ideas to various problems in knowledge representation. While some aspects of the mereological approach are awkward—for example, the need for a separate inheritance mechanism based on part–whole relations—the approach gained the support of Quine (1960). Harry Bunt (1985) has provided an extensive analysis of its use in knowledge representation. Casati and Varzi (1999) cover parts, wholes, and the spatial locations.

MEREOLOGY

Mental objects have been the subject of intensive study in philosophy and AI. There are three main approaches. The one taken in this chapter, based on modal logic and possible worlds, is the classical approach from philosophy (Hintikka, 1962; Kripke, 1963; Hughes and Cresswell, 1996). The book *Reasoning about Knowledge* (Fagin *et al.*, 1995) provides a thorough introduction. The second approach is a first-order theory in which mental objects are fluents. Davis (2005) and Davis and Morgenstern (2005) describe this approach. It relies on the possible-worlds formalism, and builds on work by Robert Moore (1980, 1985). The third approach is a **syntactic theory**, in which mental objects are represented by character

SYNTACTIC THEORY

strings. A string is just a complex term denoting a list of symbols, so $CanFly(Clark)$ can be represented by the list of symbols $[C, a, n, F, l, y, (, C, l, a, r, k,)]$. The syntactic theory of mental objects was first studied in depth by Kaplan and Montague (1960), who showed that it led to paradoxes if not handled carefully. Ernie Davis (1990) provides an excellent comparison of the syntactic and modal theories of knowledge.

The Greek philosopher Porphyry (c. 234–305 A.D.), commenting on Aristotle's *Categories*, drew what might qualify as the first semantic network. Charles S. Peirce (1909) developed existential graphs as the first semantic network formalism using modern logic. Ross Quillian (1961), driven by an interest in human memory and language processing, initiated work on semantic networks within AI. An influential paper by Marvin Minsky (1975) presented a version of semantic networks called **frames**; a frame was a representation of an object or category, with attributes and relations to other objects or categories. The question of semantics arose quite acutely with respect to Quillian's semantic networks (and those of others who followed his approach), with their ubiquitous and very vague "IS-A links" Woods's (1975) famous article "What's In a Link?" drew the attention of AI researchers to the need for precise semantics in knowledge representation formalisms. Brachman (1979) elaborated on this point and proposed solutions. Patrick Hayes's (1979) "The Logic of Frames" cut even deeper, claiming that "Most of 'frames' is just a new syntax for parts of first-order logic." Drew McDermott's (1978b) "Tarskian Semantics, or, No Notation without Denotation!" argued that the model-theoretic approach to semantics used in first-order logic should be applied to all knowledge representation formalisms. This remains a controversial idea; notably, McDermott himself has reversed his position in "A Critique of Pure Reason" (McDermott, 1987). Selman and Levesque (1993) discuss the complexity of inheritance with exceptions, showing that in most formulations it is NP-complete.

The development of description logics is the most recent stage in a long line of research aimed at finding useful subsets of first-order logic for which inference is computationally tractable. Hector Levesque and Ron Brachman (1987) showed that certain logical constructs—notably, certain uses of disjunction and negation—were primarily responsible for the intractability of logical inference. Building on the KL-ONE system (Schmolze and Lipkis, 1983), several researchers developed systems that incorporate theoretical complexity analysis, most notably KRYPTON (Brachman *et al.*, 1983) and Classic (Borgida *et al.*, 1989). The result has been a marked increase in the speed of inference and a much better understanding of the interaction between complexity and expressiveness in reasoning systems. Calvanese *et al.* (1999) summarize the state of the art, and Baader *et al.* (2007) present a comprehensive handbook of description logic. Against this trend, Doyle and Patil (1991) have argued that restricting the expressiveness of a language either makes it impossible to solve certain problems or encourages the user to circumvent the language restrictions through nonlogical means.

The three main formalisms for dealing with nonmonotonic inference—circumscription (McCarthy, 1980), default logic (Reiter, 1980), and modal nonmonotonic logic (McDermott and Doyle, 1980)—were all introduced in one special issue of the AI Journal. Delgrande and Schaub (2003) discuss the merits of the variants, given 25 years of hindsight. Answer set programming can be seen as an extension of negation as failure or as a refinement of circumscription; the underlying theory of stable model semantics was introduced by Gelfond and Lifschitz (1988), and the leading answer set programming systems are DLV (Eiter *et al.*, 1998) and SMODELS (Niemelä *et al.*, 2000). The disk drive example comes from the SMODELS user manual (Syrjänen, 2000). Lifschitz (2001) discusses the use of answer set programming for planning. Brewka *et al.* (1997) give a good overview of the various approaches to nonmonotonic logic. Clark (1978) covers the negation-as-failure approach to logic programming and Clark completion. Van Emden and Kowalski (1976) show that every Prolog program without negation has a unique minimal model. Recent years have seen renewed interest in applications of nonmonotonic logics to large-scale knowledge representation systems. The BENINQ systems for handling insurance-benefit inquiries was perhaps the first commercially successful application of a nonmonotonic inheritance system (Morgenstern, 1998). Lifschitz (2001) discusses the application of answer set programming to planning. A variety of nonmonotonic reasoning systems based on logic programming are documented in the proceedings of the conferences on *Logic Programming and Nonmonotonic Reasoning* (LPNMR).

The study of truth maintenance systems began with the TMS (Doyle, 1979) and RUP (McAllester, 1980) systems, both of which were essentially JTMSs. Forbus and de Kleer (1993) explain in depth how TMSs can be used in AI applications. Nayak and Williams (1997) show how an efficient incremental TMS called an ITMS makes it feasible to plan the operations of a NASA spacecraft in real time.

This chapter could not cover *every* area of knowledge representation in depth. The three principal topics omitted are the following:

QUALITATIVE PHYSICS

Qualitative physics: Qualitative physics is a subfield of knowledge representation concerned specifically with constructing a logical, nonnumeric theory of physical objects and processes. The term was coined by Johan de Kleer (1975), although the enterprise could be said to have started in Fahlman's (1974) BUILD, a sophisticated planner for constructing complex towers of blocks. Fahlman discovered in the process of designing it that most of the effort (80%, by his estimate) went into modeling the physics of the blocks world to calculate the stability of various subassemblies of blocks, rather than into planning per se. He sketches a hypothetical naive-physics-like process to explain why young children can solve BUILD-like problems without access to the high-speed floating-point arithmetic used in BUILD's physical modeling. Hayes (1985a) uses "histories"—four-dimensional slices of space-time similar to Davidson's events—to construct a fairly complex naive physics of liquids. Hayes was the first to prove that a bath with the plug in will eventually overflow if the tap keeps running and that a person who falls into a lake will get wet all over. Davis (2008) gives an update to the ontology of liquids that describes the pouring of liquids into containers.

De Kleer and Brown (1985), Ken Forbus (1985), and Benjamin Kuipers (1985) independently and almost simultaneously developed systems that can reason about a physical system based on qualitative abstractions of the underlying equations. Qualitative physics soon developed to the point where it became possible to analyze an impressive variety of complex physical systems (Yip, 1991). Qualitative techniques have been used to construct novel designs for clocks, windshield wipers, and six-legged walkers (Subramanian and Wang, 1994). The collection *Readings in Qualitative Reasoning about Physical Systems* (Weld and de Kleer, 1990) an encyclopedia article by Kuipers (2001), and a handbook article by Davis (2007) introduce to the field.

SPATIAL REASONING

Spatial reasoning: The reasoning necessary to navigate in the wumpus world and shopping world is trivial in comparison to the rich spatial structure of the real world. The earliest serious attempt to capture commonsense reasoning about space appears in the work of Ernest Davis (1986, 1990). The region connection calculus of Cohn *et al.* (1997) supports a form of qualitative spatial reasoning and has led to new kinds of geographical information systems; see also (Davis, 2006). As with qualitative physics, an agent can go a long way, so to speak, without resorting to a full metric representation. When such a representation is necessary, techniques developed in robotics (Chapter 25) can be used.

PSYCHOLOGICAL REASONING

Psychological reasoning: Psychological reasoning involves the development of a working *psychology* for artificial agents to use in reasoning about themselves and other agents. This is often based on so-called folk psychology, the theory that humans in general are believed to use in reasoning about themselves and other humans. When AI researchers provide their artificial agents with psychological theories for reasoning about other agents, the theories are frequently based on the researchers' description of the logical agents' own design. Psychological reasoning is currently most useful within the context of natural language understanding, where divining the speaker's intentions is of paramount importance.

Minker (2001) collects papers by leading researchers in knowledge representation, summarizing 40 years of work in the field. The proceedings of the international conferences on *Principles of Knowledge Representation and Reasoning* provide the most up-to-date sources for work in this area. *Readings in Knowledge Representation* (Brachman and Levesque, 1985) and *Formal Theories of the Commonsense World* (Hobbs and Moore, 1985) are excellent anthologies on knowledge representation; the former focuses more on historically important papers in representation languages and formalisms, the latter on the accumulation of the knowledge itself. Davis (1990), Stefik (1995), and Sowa (1999) provide textbook introductions to knowledge representation, van Harmelen *et al.* (2007) contributes a handbook, and a special issue of AI Journal covers recent progress (Davis and Morgenstern, 2004). The biennial conference on *Theoretical Aspects of Reasoning About Knowledge* (TARK) covers applications of the theory of knowledge in AI, economics, and distributed systems.

EXERCISES

12.1 Define an ontology in first-order logic for tic-tac-toe. The ontology should contain situations, actions, squares, players, marks (X, O, or blank), and the notion of winning, losing, or drawing a game. Also define the notion of a forced win (or draw): a position from which a player can force a win (or draw) with the right sequence of actions. Write axioms for the domain. (Note: The axioms that enumerate the different squares and that characterize the winning positions are rather long. You need not write these out in full, but indicate clearly what they look like.)

12.2 Figure 12.1 shows the top levels of a hierarchy for everything. Extend it to include as many real categories as possible. A good way to do this is to cover all the things in your everyday life. This includes objects and events. Start with waking up, and proceed in an orderly fashion noting everything that you see, touch, do, and think about. For example, a random sampling produces music, news, milk, walking, driving, gas, Soda Hall, carpet, talking, Professor Fateman, chicken curry, tongue, $7, sun, the daily newspaper, and so on.

You should produce both a single hierarchy chart (on a large sheet of paper) and a listing of objects and categories with the relations satisfied by members of each category. Every object should be in a category, and every category should be in the hierarchy.

12.3 Develop a representational system for reasoning about windows in a window-based computer interface. In particular, your representation should be able to describe:

- The state of a window: minimized, displayed, or nonexistent.
- Which window (if any) is the active window.
- The position of every window at a given time.
- The order (front to back) of overlapping windows.
- The actions of creating, destroying, resizing, and moving windows; changing the state of a window; and bringing a window to the front. Treat these actions as atomic; that is, do not deal with the issue of relating them to mouse actions. Give axioms describing the effects of actions on fluents. You may use either event or situation calculus.

Assume an ontology containing *situations, actions, integers* (for x and y coordinates) and *windows*. Define a language over this ontology; that is, a list of constants, function symbols, and predicates with an English description of each. If you need to add more categories to the ontology (e.g., pixels), you may do so, but be sure to specify these in your write-up. You may (and should) use symbols defined in the text, but be sure to list these explicitly.

12.4 State the following in the language you developed for the previous exercise:

a. In situation S_0, window W_1 is behind W_2 but sticks out on the left and right. Do *not* state exact coordinates for these; describe the *general* situation.

b. If a window is displayed, then its top edge is higher than its bottom edge.

c. After you create a window w, it is displayed.

d. A window can be minimized if it is displayed.

12.5 (Adapted from an example by Doug Lenat.) Your mission is to capture, in logical form, enough knowledge to answer a series of questions about the following simple scenario:

> Yesterday John went to the North Berkeley Safeway supermarket and bought two pounds of tomatoes and a pound of ground beef.

Start by trying to represent the content of the sentence as a series of assertions. You should write sentences that have straightforward logical structure (e.g., statements that objects have certain properties, that objects are related in certain ways, that all objects satisfying one property satisfy another). The following might help you get started:

- Which classes, objects, and relations would you need? What are their parents, siblings and so on? (You will need events and temporal ordering, among other things.)
- Where would they fit in a more general hierarchy?
- What are the constraints and interrelationships among them?
- How detailed must you be about each of the various concepts?

To answer the questions below, your knowledge base must include background knowledge. You'll have to deal with what kind of things are at a supermarket, what is involved with purchasing the things one selects, what the purchases will be used for, and so on. Try to make your representation as general as possible. To give a trivial example: don't say "People buy food from Safeway," because that won't help you with those who shop at another supermarket. Also, don't turn the questions into answers; for example, question (c) asks "Did John buy any meat?"—not "Did John buy a pound of ground beef?"

Sketch the chains of reasoning that would answer the questions. If possible, use a logical reasoning system to demonstrate the sufficiency of your knowledge base. Many of the things you write might be only approximately correct in reality, but don't worry too much; the idea is to extract the common sense that lets you answer these questions at all. A truly complete answer to this question is *extremely* difficult, probably beyond the state of the art of current knowledge representation. But you should be able to put together a consistent set of axioms for the limited questions posed here.

a. Is John a child or an adult? [Adult]
b. Does John now have at least two tomatoes? [Yes]
c. Did John buy any meat? [Yes]
d. If Mary was buying tomatoes at the same time as John, did he see her? [Yes]
e. Are the tomatoes made in the supermarket? [No]
f. What is John going to do with the tomatoes? [Eat them]
g. Does Safeway sell deodorant? [Yes]
h. Did John bring some money or a credit card to the supermarket? [Yes]
i. Does John have less money after going to the supermarket? [Yes]

12.6 Make the necessary additions or changes to your knowledge base from the previous exercise so that the questions that follow can be answered. Include in your report a discussion of your changes, explaining why they were needed, whether they were minor or major, and what kinds of questions would necessitate further changes.

a. Are there other people in Safeway while John is there? [Yes—staff!]
b. Is John a vegetarian? [No]
c. Who owns the deodorant in Safeway? [Safeway Corporation]
d. Did John have an ounce of ground beef? [Yes]
e. Does the Shell station next door have any gas? [Yes]
f. Do the tomatoes fit in John's car trunk? [Yes]

12.7 Represent the following seven sentences using and extending the representations developed in the chapter:

a. Water is a liquid between 0 and 100 degrees.

b. Water boils at 100 degrees.

c. The water in John's water bottle is frozen.

d. Perrier is a kind of water.

e. John has Perrier in his water bottle.

f. All liquids have a freezing point.

g. A liter of water weighs more than a liter of alcohol.

12.8 Write definitions for the following:

a. $ExhaustivePartDecomposition$

b. $PartPartition$

c. $PartwiseDisjoint$

These should be analogous to the definitions for $ExhaustiveDecomposition$, $Partition$, and $Disjoint$. Is it the case that $PartPartition(s, BunchOf(s))$? If so, prove it; if not, give a counterexample and define sufficient conditions under which it does hold.

12.9 An alternative scheme for representing measures involves applying the units function to an abstract length object. In such a scheme, one would write $Inches(Length(L_1)) = 1.5$. How does this scheme compare with the one in the chapter? Issues include conversion axioms, names for abstract quantities (such as "50 dollars"), and comparisons of abstract measures in different units (50 inches is more than 50 centimeters).

12.10 Add sentences to extend the definition of the predicate $Name(s, c)$ so that a string such as "laptop computer" matches the appropriate category names from a variety of stores. Try to make your definition general. Test it by looking at ten online stores, and at the category names they give for three different categories. For example, for the category of laptops, we found the names "Notebooks," "Laptops," "Notebook Computers," "Notebook," "Laptops and Notebooks," and "Notebook PCs." Some of these can be covered by explicit $Name$ facts, while others could be covered by sentences for handling plurals, conjunctions, etc.

12.11 Write event calculus axioms to describe the actions in the wumpus world.

12.12 State the interval-algebra relation that holds between every pair of the following real-world events:

LK: The life of President Kennedy.
IK: The infancy of President Kennedy.
PK: The presidency of President Kennedy.
LJ: The life of President Johnson.
PJ: The presidency of President Johnson.
LO: The life of President Obama.

12.13 Investigate ways to extend the event calculus to handle *simultaneous* events. Is it possible to avoid a combinatorial explosion of axioms?

12.14 Construct a representation for exchange rates between currencies that allows for daily fluctuations.

12.15 Define the predicate $Fixed$, where $Fixed(Location(x))$ means that the location of object x is fixed over time.

12.16 Describe the event of trading something for something else. Describe buying as a kind of trading in which one of the objects traded is a sum of money.

12.17 The two preceding exercises assume a fairly primitive notion of ownership. For example, the buyer starts by *owning* the dollar bills. This picture begins to break down when, for example, one's money is in the bank, because there is no longer any specific collection of dollar bills that one owns. The picture is complicated still further by borrowing, leasing, renting, and bailment. Investigate the various commonsense and legal concepts of ownership, and propose a scheme by which they can be represented formally.

12.18 (Adapted from Fagin *et al.* (1995).) Consider a game played with a deck of just 8 cards, 4 aces and 4 kings. The three players, Alice, Bob, and Carlos, are dealt two cards each. Without looking at them, they place the cards on their foreheads so that the other players can see them. Then the players take turns either announcing that they know what cards are on their own forehead, thereby winning the game, or saying "I don't know." Everyone knows the players are truthful and are perfect at reasoning about beliefs.

a. Game 1. Alice and Bob have both said "I don't know." Carlos sees that Alice has two aces (A-A) and Bob has two kings (K-K). What should Carlos say? (*Hint*: consider all three possible cases for Carlos: A-A, K-K, A-K.)

b. Describe each step of Game 1 using the notation of modal logic.

c. Game 2. Carlos, Alice, and Bob all said "I don't know" on their first turn. Alice holds K-K and Bob holds A-K. What should Carlos say on his second turn?

d. Game 3. Alice, Carlos, and Bob all say "I don't know" on their first turn, as does Alice on her second turn. Alice and Bob both hold A-K. What should Carlos say?

e. Prove that there will always be a winner to this game.

12.19 The assumption of *logical omniscience,* discussed on page 453, is of course not true of any actual reasoners. Rather, it is an *idealization* of the reasoning process that may be more or less acceptable depending on the applications. Discuss the reasonableness of the assumption for each of the following applications of reasoning about knowledge:

a. Partial knowledge adversary games, such as card games. Here one player wants to reason about what his opponent knows about the state of the game.

b. Chess with a clock. Here the player may wish to reason about the limits of his opponent's or his own ability to find the best move in the time available. For instance, if player A has much more time left than player B, then A will sometimes make a move that greatly complicates the situation, in the hopes of gaining an advantage because he has more time to work out the proper strategy.

c. A shopping agent in an environment in which there are costs of gathering information.

d. Reasoning about public key cryptography, which rests on the intractability of certain computational problems.

12.20 Translate the following description logic expression (from page 457) into first-order logic, and comment on the result:

$$\begin{array}{l} \mathit{And}(\mathit{Man}, \mathit{AtLeast}(3, \mathit{Son}), \mathit{AtMost}(2, \mathit{Daughter}), \\ \quad \mathit{All}(\mathit{Son}, \mathit{And}(\mathit{Unemployed}, \mathit{Married}, \mathit{All}(\mathit{Spouse}, \mathit{Doctor}))), \\ \quad \mathit{All}(\mathit{Daughter}, \mathit{And}(\mathit{Professor}, \mathit{Fills}(\mathit{Department}, \mathit{Physics}, \mathit{Math})))) \,. \end{array}$$

12.21 Recall that inheritance information in semantic networks can be captured logically by suitable implication sentences. This exercise investigates the efficiency of using such sentences for inheritance.

a. Consider the information in a used-car catalog such as Kelly's Blue Book—for example, that 1973 Dodge vans are (or perhaps were once) worth $575. Suppose all this information (for 11,000 models) is encoded as logical sentences, as suggested in the chapter. Write down three such sentences, including that for 1973 Dodge vans. How would you use the sentences to find the value of a *particular* car, given a backward-chaining theorem prover such as Prolog?

b. Compare the time efficiency of the backward-chaining method for solving this problem with the inheritance method used in semantic nets.

c. Explain how forward chaining allows a logic-based system to solve the same problem efficiently, assuming that the KB contains only the 11,000 sentences about prices.

d. Describe a situation in which neither forward nor backward chaining on the sentences will allow the price query for an individual car to be handled efficiently.

e. Can you suggest a solution enabling this type of query to be solved efficiently in all cases in logic systems? (*Hint:* Remember that two cars of the same year and model have the same price.)

12.22 One might suppose that the syntactic distinction between unboxed links and singly boxed links in semantic networks is unnecessary, because singly boxed links are always attached to categories; an inheritance algorithm could simply assume that an unboxed link attached to a category is intended to apply to all members of that category. Show that this argument is fallacious, giving examples of errors that would arise.

12.23 One part of the shopping process that was not covered in this chapter is checking for compatibility between items. For example, if a digital camera is ordered, what accessory batteries, memory cards, and cases are compatible with the camera? Write a knowledge base that can determine the compatibility of a set of items and suggest replacements or additional items if the shopper makes a choice that is not compatible. The knowledge base should works with at least one line of products and extend easily to other lines.

12.24 A complete solution to the problem of inexact matches to the buyer's description in shopping is very difficult and requires a full array of natural language processing and information retrieval techniques. (See Chapters 22 and 23.) One small step is to allow the user to specify minimum and maximum values for various attributes. The buyer must use the following grammar for product descriptions:

$$\begin{array}{lcl} \mathit{Description} & \rightarrow & \mathit{Category}\ [\mathit{Connector}\ \mathit{Modifier}]* \\ \mathit{Connector} & \rightarrow & \text{``}\mathit{with}\text{''} \mid \text{``}\mathit{and}\text{''} \mid \text{``,''} \\ \mathit{Modifier} & \rightarrow & \mathit{Attribute} \mid \mathit{Attribute}\ \mathit{Op}\ \mathit{Value} \\ \mathit{Op} & \rightarrow & \text{``}=\text{''} \mid \text{``}>\text{''} \mid \text{``}<\text{''} \end{array}$$

Here, $\mathit{Category}$ names a product category, $\mathit{Attribute}$ is some feature such as "CPU" or "price," and Value is the target value for the attribute. So the query "computer with at least a 2.5 GHz CPU for under \$500" must be re-expressed as "computer with CPU $>$ 2.5 GHz and price $<$ \$500." Implement a shopping agent that accepts descriptions in this language.

12.25 Our description of Internet shopping omitted the all-important step of actually *buying* the product. Provide a formal logical description of buying, using event calculus. That is, define the sequence of events that occurs when a buyer submits a credit-card purchase and then eventually gets billed and receives the product.