

2

INTELLIGENT AGENTS

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

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

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

2.1 AGENTS AND ENVIRONMENTS

ENVIRONMENT

SENSOR

ACTUATOR

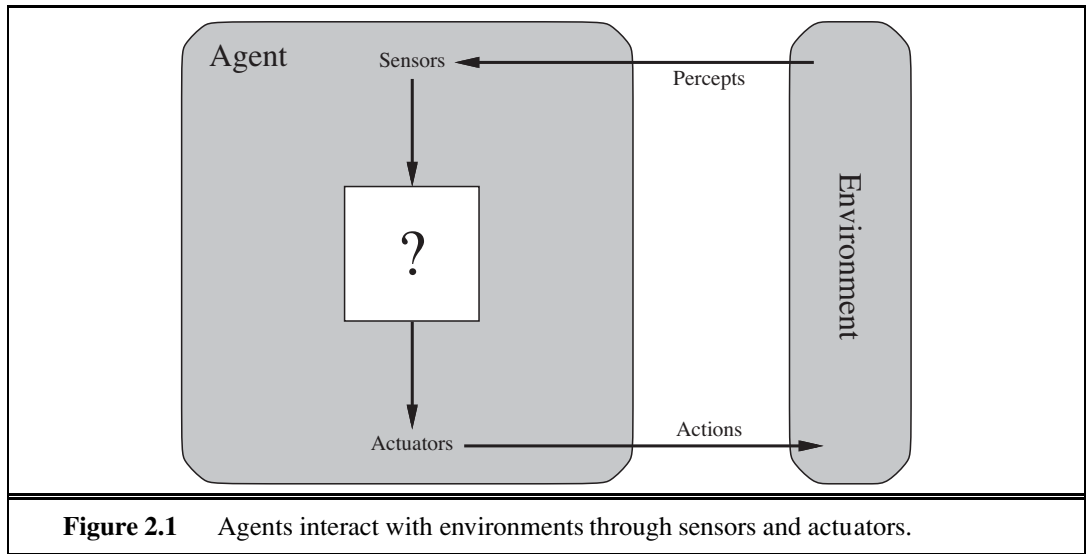
An **agent** is anything that can be viewed as perceiving its **environment** through **sensors** and acting upon that environment through **actuators**. This simple idea is illustrated in Figure 2.1. A human agent has eyes, ears, and other organs for sensors and hands, legs, vocal tract, and so on for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

PERCEPT

PERCEPT SEQUENCE



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



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

AGENT FUNCTION

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

AGENT PROGRAM

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

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



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

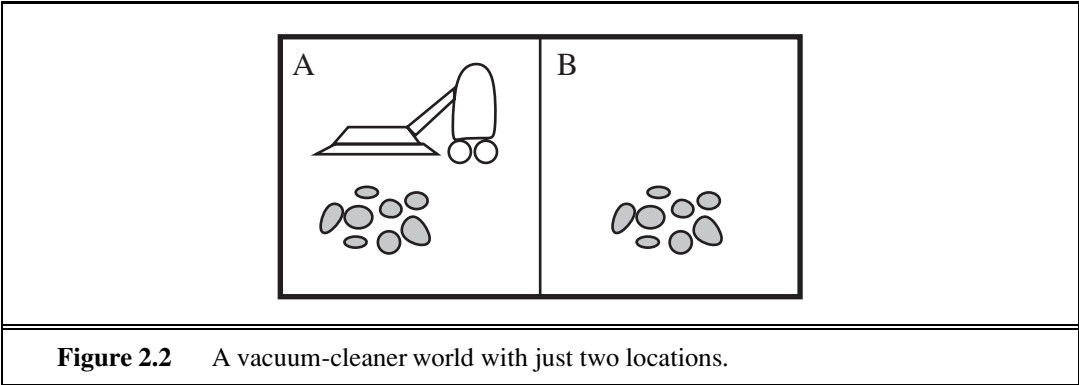


Figure 2.2 A vacuum-cleaner world with just two locations.

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

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

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

2.2 GOOD BEHAVIOR: THE CONCEPT OF RATIONALITY

RATIONAL AGENT

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

PERFORMANCE
MEASURE

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

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

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



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

2.2.1 Rationality

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

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

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

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

DEFINITION OF A
RATIONAL AGENT

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

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

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

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

2.2.2 Omniscience, learning, and autonomy

OMNISCIENCE

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

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

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

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

INFORMATION
GATHERING
EXPLORATION

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

LEARNING

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

AUTONOMY

2.3 THE NATURE OF ENVIRONMENTS

TASK ENVIRONMENT

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

2.3.1 Specifying the task environment

PEAS

In our discussion of the rationality of the simple vacuum-cleaner agent, we had to specify the performance measure, the environment, and the agent’s actuators and sensors. We group all these under the heading of the **task environment**. For the acronymically minded, we call this the **PEAS** (Performance, Environment, Actuators, Sensors) description. In designing an agent, the first step must always be to specify the task environment as fully as possible.

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

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

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

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

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

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

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

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

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

SOFTWARE AGENT

SOFTBOT

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

2.3.2 Properties of task environments

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

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

Figure 2.5 Examples of agent types and their PEAS descriptions.

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

FULLY OBSERVABLE
PARTIALLY
OBSERVABLE

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

UNOBSERVABLE

SINGLE AGENT
MULTIAGENT

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

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

COMPETITIVE

COOPERATIVE

DETERMINISTIC

STOCHASTIC

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

UNCERTAIN

NONDETERMINISTIC

EPISODIC

SEQUENTIAL

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

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

STATIC
DYNAMIC

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

SEMIDYNAMIC

DISCRETE
CONTINUOUS

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

KNOWN
UNKNOWN

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

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

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

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

Task Environment	Observable	Agents	Deterministic	Episodic	Static	Discrete
Crossword puzzle	Fully	Single	Deterministic	Sequential	Static	Discrete
Chess with a clock	Fully	Multi	Deterministic	Sequential	Semi	Discrete
Poker	Partially	Multi	Stochastic	Sequential	Static	Discrete
Backgammon	Fully	Multi	Stochastic	Sequential	Static	Discrete
Taxi driving	Partially	Multi	Stochastic	Sequential	Dynamic	Continuous
Medical diagnosis	Partially	Single	Stochastic	Sequential	Dynamic	Continuous
Image analysis	Fully	Single	Deterministic	Episodic	Semi	Continuous
Part-picking robot	Partially	Single	Stochastic	Episodic	Dynamic	Continuous
Refinery controller	Partially	Single	Stochastic	Sequential	Dynamic	Continuous
Interactive English tutor	Partially	Multi	Stochastic	Sequential	Dynamic	Discrete
Figure 2.6 Examples of task environments and their characteristics.						

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

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

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

ENVIRONMENT
GENERATOR

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

2.4 THE STRUCTURE OF AGENTS

AGENT PROGRAM

ARCHITECTURE

So far we have talked about agents by describing *behavior*—the action that is performed after any given sequence of percepts. Now we must bite the bullet and talk about how the insides work. The job of AI is to design an **agent program** that implements the agent function—the mapping from percepts to actions. We assume this program will run on some sort of computing device with physical sensors and actuators—we call this the **architecture**:

$$\text{agent} = \text{architecture} + \text{program} .$$

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

2.4.1 Agent programs

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

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

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

```

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

  append percept to the end of percepts
  action  $\leftarrow$  LOOKUP(percepts, table)
  return action

```

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

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

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

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

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

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

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

```

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

```

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

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

2.4.2 Simple reflex agents

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

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

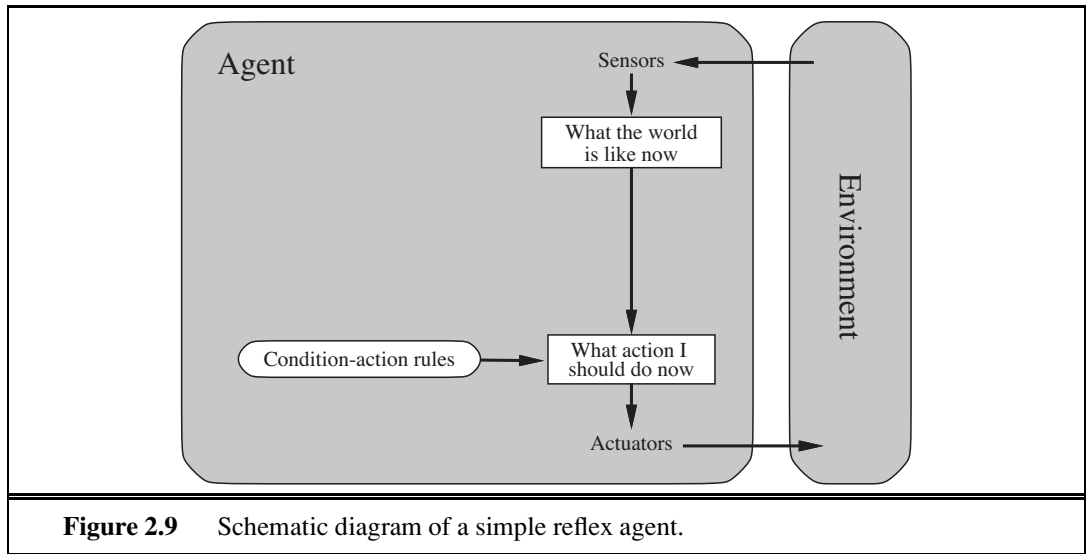
Simple reflex behaviors occur even in more complex environments. Imagine yourself as the driver of the automated taxi. If the car in front brakes and its brake lights come on, then you should notice this and initiate braking. In other words, some processing is done on the visual input to establish the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

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

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

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

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



```

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

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

```

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

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



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

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

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

RANDOMIZATION

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

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

2.4.3 Model-based reflex agents

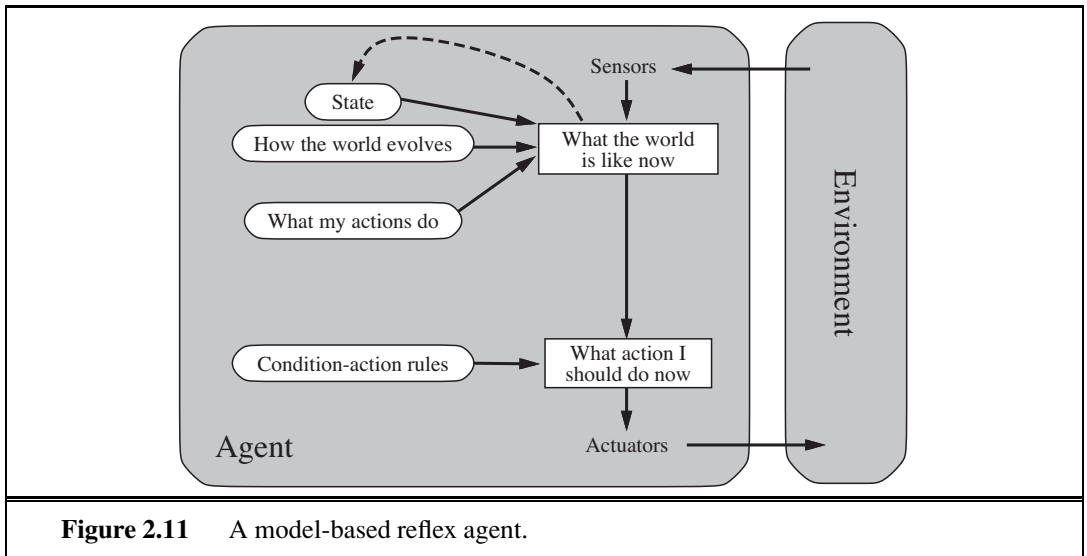
INTERNAL STATE

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

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

MODEL-BASED AGENT

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



function MODEL-BASED-REFLEX-AGENT(*percept*) **returns** an action

persistent: *state*, the agent's current conception of the world state

model, a description of how the next state depends on current state and action

rules, a set of condition–action rules

action, the most recent action, initially none

state \leftarrow UPDATE-STATE(*state*, *action*, *percept*, *model*)

rule \leftarrow RULE-MATCH(*state*, *rules*)

action \leftarrow *rule*.ACTION

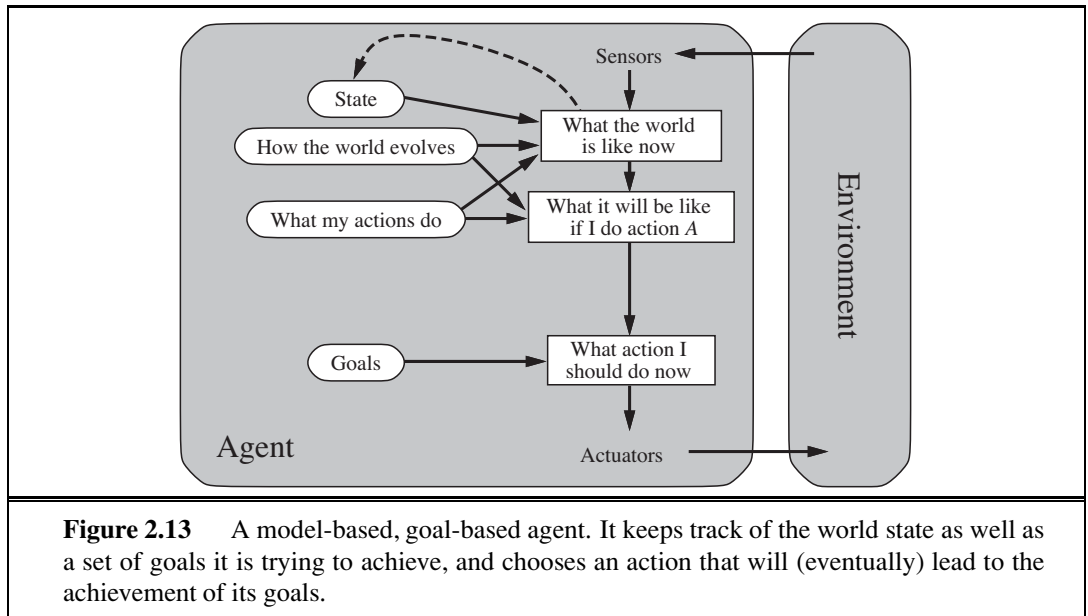
return *action*

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

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

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

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



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

2.4.4 Goal-based agents

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

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

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

2.5 SUMMARY

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

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

BIBLIOGRAPHICAL AND HISTORICAL NOTES

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

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