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 will 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 will be fleshed 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, mouth, and other body parts 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. We will make the general assumption that every agent can perceive its own actions (but not always the effects).

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.* If we can specify the agent's choice of action for every possible

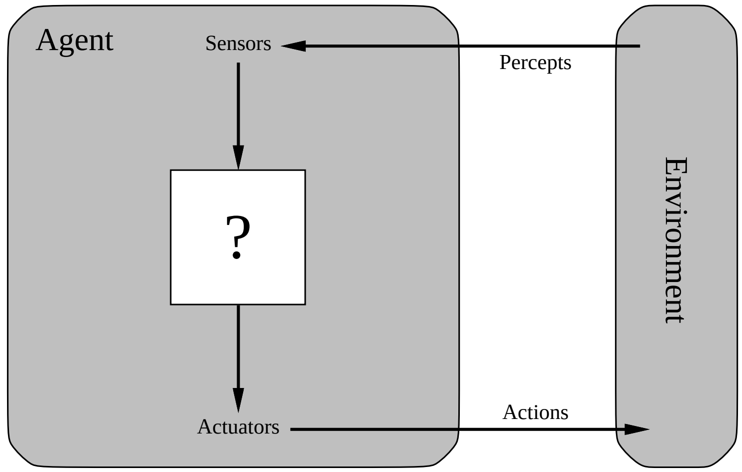

Figure 2.1 Agents interact with environments through sensors and actuators.

percept sequence, then 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 on the agent architecture.

AGENT PROGRAM

To illustrate these ideas, we will 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. A simple agent program for this agent function is given later in the chapter, in Figure 2.8.

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*

[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'll see later in this chapter that it can be very intelligent.

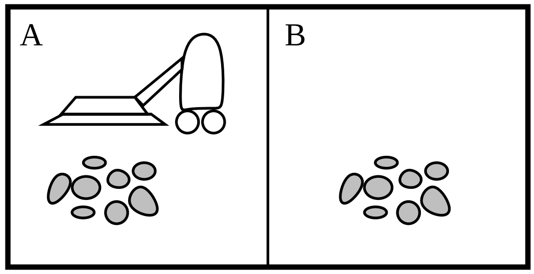

Figure 2.2 A vacuum-cleaner world with just two locations.

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

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

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.

Before closing this section, we will remark 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.

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? As a first approximation, we will say that the right action is the one that will cause the agent to be most successful. Therefore, we will need some way to measure success. Together with the description of the environment and the sensors and actuators of the agent, this will provide a complete specification of the task facing the agent. Given this, we can define more precisely what it means to be rational.

Performance measures

PERFORMANCE MEASURE

A **performance measure** embodies the criterion for success of an 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. Obviously, there is not one fixed measure suitable for all agents. We could ask the agent for a subjective opinion of how happy it is with its own performance, but some agents would be unable to answer, and others would delude themselves.[2] Therefore, we will insist on an objective performance measure, typically one imposed by the designer who is constructing the agent.

Consider 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.*

The selection of a performance measure is not always easy. 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 will leave these questions as an exercise for the diligent reader.

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.

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[2] Human agents in particular are notorious for "sour grapes"—believing they did not really want something after not getting it, as in, "Oh well, never mind, I didn't want that stupid Nobel prize anyway."

DEFINITION OF A RATIONAL AGENT

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

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

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

- The performance measure awards one point for each clean square at each time step, over a "lifetime" of 1000 time steps.
- The "geography" of the environment is known *a priori* (Figure 2.2) but the dirt distribution and the initial location of the agent are not. Clean squares stay clean and sucking cleans the current square. The $Left$ and $Right$ actions move the agent left and right except when this would take the agent outside the environment, in which case the agent remains where it is.
- The only available actions are $Left$, $Right$, $Suck$, and $NoOp$ (do nothing).
- 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 2.4 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 it 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 2.4 asks you to design agents for these cases.

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,[3] 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

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

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.

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

INFORMATION GATHERING

EXPLORATION

LEARNING

Our definition requires a rational agent not only to gather information, but also to **learn** as much as possible from what it perceives. The agent's initial configuration could reflect some prior knowledge of the environment, but as the agent gains experience this may be modified and augmented. There are extreme cases in which the environment is completely known *a priori*. In such cases, the agent need not perceive or learn; it simply acts correctly. Of course, such agents are very 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 on 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 a entomologist moves the caterpillar a few inches away while the sphex is doing the check, it will revert back 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.

Successful agents split the task of computing the agent function into three different periods: when the agent is being designed, some of the computation is done by its designers; when it is deliberating on its next action, the agent does more computation; and as it learns from experience, it does even more computation to decide how to modify its behavior.

AUTONOMY

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

2.3 THE NATURE OF ENVIRONMENTS

TASK ENVIRONMENTS

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.

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 will group all these together under the heading of the **task environment**. For the acronymically minded, we call this the **PEAS** (**P**erformance, **E**nvironment, **A**ctuators, **S**ensors) description. In designing an agent, the first step must always be to specify the task environment as fully as possible.

The vacuum world was a simple example; let us consider a more complex problem: an automated taxi driver. We will use this example throughout the rest of the chapter. We should point out, before the reader becomes alarmed, that a fully automated taxi is currently somewhat beyond the capabilities of existing technology. (See page 27 for a description of an existing driving robot, or look at recent proceedings of the conferences on Intelligent Transportation Systems.) 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.

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 and/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 there will be tradeoffs involved.

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,

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.

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** available to an automated taxi will be more or less the same as 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.

To achieve its goals in the driving environment, the taxi will need to know where it is, what else is on the road, and how fast it is going. Its basic **sensors** should therefore include one or more controllable TV cameras, the speedometer, and the odometer. To control the vehicle properly, especially on curves, it should have an accelerometer; it will also need to know the mechanical state of the vehicle, so it will need the usual array of engine and electrical system sensors. It might have instruments that are not available to the average human driver: a satellite global positioning system (GPS) to give it accurate position information with respect to an electronic map, and infrared or sonar sensors to detect distances to other cars and obstacles. 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 2.5. It may come as a surprise to some readers that we include in our list of agent types 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 conveyer belt will be parts of a kind that it knows about, and that there are only two actions (accept or reject).

Agent Type	Performance Measure	Environment	Actuators	Sensors
Medical diagnosis system	Healthy patient, minimize costs, lawsuits	Patient, hospital, staff	Display 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 categorization of scene	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	Maximize purity, yield, safety	Refinery, operators	Valves, pumps, heaters, displays	Temperature, pressure, chemical sensors
Interactive English tutor	Maximize student's score on test	Set of students, testing agency	Display exercises, suggestions, corrections	Keyboard entry

Figure 2.5 Examples of agent types and their PEAS descriptions.

SOFTWARE AGENTS
SOFTBOTS

In contrast, some **software agents** (or software robots or **softbots**) exist in rich, unlimited domains. Imagine a softbot designed to fly a flight simulator for a large commercial airplane. The simulator is a very detailed, complex environment including other aircraft and ground operations, and the software agent must choose from a wide variety of actions in real time. Or imagine a softbot designed to scan Internet news sources and show the interesting items to its customers. To do well, it will need some natural language processing abilities, it will need to learn what each customer 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 agents.

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, 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

◇ **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.[4] 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.

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. If the environment is partially observable, however, then it could *appear* to be stochastic. This is particularly true if the environment is complex, making it hard to keep track of all the unobserved aspects. Thus, it is often better to think of an environment as deterministic or stochastic *from the point of view of the agent*. 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 2.12). If the environment is deterministic except for the actions of other agents, we say that the environment is **strategic**.

STRATEGIC

EPISODIC
SEQUENTIAL

◇ **Episodic** vs. **sequential**.[5]
In an episodic task environment, the agent's experience is divided into atomic episodes. Each episode consists of the agent perceiving and then performing a single action. Crucially, the next episode does not depend on the actions taken in previous episodes. In episodic environments, the choice of action in each episode depends only on the episode itself. 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

[4] The first edition of this book used the terms **accessible** and **inaccessible** instead of **fully** and **partially observable**; **nondeterministic** instead of **stochastic**; and **nonepisodic** instead of **sequential**. The new terminology is more consistent with established usage.

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

part is defective. In sequential environments, on the other hand, the current decision could affect all future decisions. 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 can be applied to the *state* of the environment, to the way *time* is handled, and to the *percepts* and *actions* of the agent. For example, a discrete-state environment such as a chess game has a finite number of distinct states. 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.

SINGLE AGENT
MULTIAGENT

◇ **Single agent** vs. **multiagent**.
The distinction between single-agent and multiagent environments 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 a stochastically behaving object, 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 arising in multiagent environments are often

COMPETITIVE
COOPERATIVE

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

Figure 2.6 Examples of task environments and their characteristics.

quite different from those in single-agent environments; for example, **communication** often emerges as a rational behavior in multiagent environments; in some partially observable competitive environments, **stochastic behavior** is rational because it avoids the pitfalls of predictability.

As one might expect, the hardest case is *partially observable*, *stochastic*, *sequential*, *dynamic*, *continuous*, and *multiagent*. It also turns out that most real situations are so complex that whether they are *really* deterministic is a moot point. For practical purposes, they must be treated as stochastic. Taxi driving is hard in all these senses.

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 have listed chess as fully observable; strictly speaking, this is false because certain rules about castling, *en passant* capture, and draws by repetition require remembering some facts about the game history that are not observable as part of the board state. These exceptions to observability are of course minor compared to those faced by the taxi driver, the English tutor, or the medical diagnosis system.

Some other 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 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 2.7 to 2.12 take you through the process of developing an environment class and evaluating various agents therein.

ENVIRONMENT CLASS

ENVIRONMENT GENERATOR

2.4 THE STRUCTURE OF AGENTS

So far we have talked about agents by describing *behavior*—the action that is performed after any given sequence of percepts. Now, we will have to bite the bullet and talk about how the insides work. The job of AI is to design the **agent program** that implements the agent function mapping 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**:

AGENT PROGRAM

ARCHITECTURE

$$agent = architecture + program \ .$$

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

Agent programs

The agent programs that we will 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.[6] 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

[6] 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
  static: percepts, a sequence, initially empty
          table, a table of actions, indexed by percept sequences, initially fully specified

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

Figure 2.7 The TABLE-DRIVEN-AGENT program is invoked for each new percept and returns an action each time. It keeps track of the percept sequence using its own private data structure.

perept as input because nothing more is available from the environment; if the agent's actions depend on the entire percept sequence, the agent will have to remember the percepts.

We will describe the agent programs via 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 represents explicitly the agent function that the agent program embodies. To build a rational agent in 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 small amount of code rather than from a large number of table entries. 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.

```
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.

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

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

We then explain in general terms how to convert all these into *learning agents*.

Simple reflex agents

SIMPLE REFLEX AGENT

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

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**,[7] written as

CONDITION–ACTION RULE

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

Humans also have many such connections, some of which are learned responses (as for driving) and some of which are innate reflexes (such as blinking when something approaches the eye). In the course of the book, we will see 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–

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

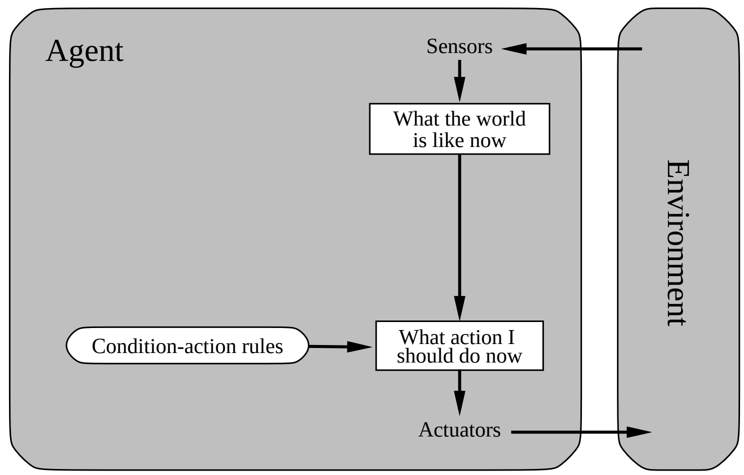


Figure 2.9 Schematic diagram of a simple reflex agent.

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

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

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 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 very 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—the current video image—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 (for ever) if it happens to start in square A, and moving $Right$ fails (for ever) 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, it will clean it and the cleaning 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.

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.

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 reflex agent with internal state, showing how the current percept is combined with the old internal state to generate the updated description

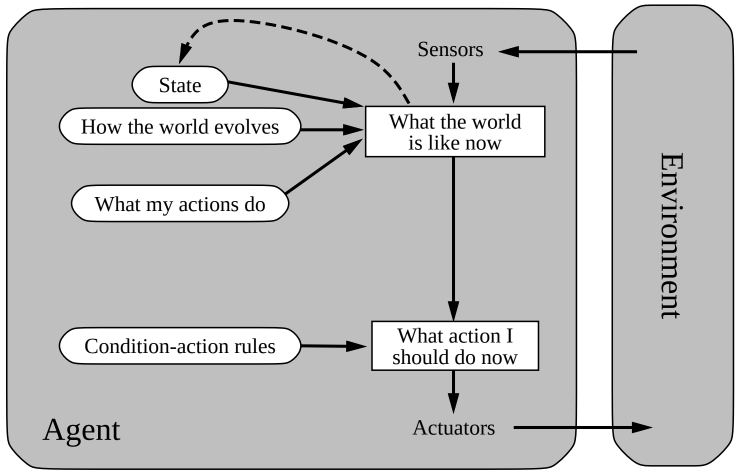


Figure 2.11 A model-based reflex agent.

function REFLEX-AGENT-WITH-STATE(*percept*) **returns** an action
  static: *state*, a description of the current world state
    rules, a set of condition–action rules
    action, the most recent action, initially none

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

of the current state. The agent program is shown in Figure 2.12. The interesting part is the function UPDATE-STATE, which is responsible for creating the new internal state description. As well as interpreting the new percept in the light of existing knowledge about the state, it uses information about how the world evolves to keep track of the unseen parts of the world, and also must know about what the agent's actions do to the state of the world. Detailed examples appear in Chapters 10 and 17.

Goal-based agents

Knowing 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

GOAL

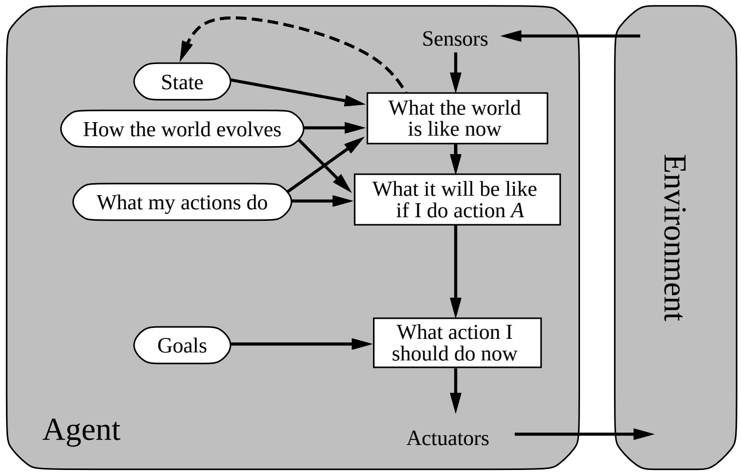


Figure 2.13 A model-based, goal-based agent. It keeps track of the world state as well as a set of goals it is trying to achieve, and chooses an action that will (eventually) lead to the achievement of its goals.

program can combine this with information about the results of possible actions (the same information as was used to update internal state in the reflex agent) in order to choose actions that achieve the goal. Figure 2.13 shows the goal-based agent's structure.

Sometimes goal-based action selection is straightforward, when goal satisfaction results immediately from a single action. Sometimes it will be more tricky, when the agent has to consider long sequences of twists and turns to find a way to achieve the goal. **Search** (Chapters 3 to 6) and **planning** (Chapters 11 and 12) are the subfields of AI devoted to finding action sequences that achieve the agent's goals.

Notice that decision making of this kind is fundamentally different from the condition–action rules described earlier, in that it involves consideration of the future—both "What will happen if I do such-and-such?" and "Will that make me happy?" In the reflex agent designs, this information is not explicitly represented, because the built-in rules map directly from percepts to actions. The reflex agent brakes when it sees brake lights. A goal-based agent, in principle, could reason that if the car in front has its brake lights on, it will slow down. Given the way the world usually evolves, the only action that will achieve the goal of not hitting other cars is to brake.

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

Utility-based agents

Goals alone are not really enough to generate high-quality behavior in most environments. For example, there are many action sequences that will get the taxi to its destination (thereby achieving the goal) but some are quicker, safer, more reliable, or cheaper than others. Goals just provide a crude binary distinction between "happy" and "unhappy" states, whereas a more general performance measure should allow a comparison of different world states according to exactly how happy they would make the agent if they could be achieved. Because "happy" does not sound very scientific, the customary terminology is to say that if one world state is preferred to another, then it has higher **utility** for the agent.[8]

UTILITY

UTILITY FUNCTION

A **utility function** maps a state (or a sequence of states) onto a real number, which describes the associated degree of happiness. A complete specification of the utility function allows rational decisions in two kinds of cases where goals are inadequate. First, when there are conflicting goals, only some of which can be achieved (for example, speed and safety), the utility function specifies the appropriate tradeoff. Second, when there are several goals that the agent can aim for, none of which can be achieved with certainty, utility provides a way in which the likelihood of success can be weighed up against the importance of the goals.

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

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

Learning agents

We have described agent programs with various methods for selecting actions. We have not, so far, explained how the agent programs *come into being*. In his famous early paper, Turing (1950) considers the idea of actually programming his intelligent machines by hand. He estimates how much work this might take and concludes "Some more expeditious method seems desirable." The method he proposes is to build learning machines and then to teach them. In many areas of AI, this is now the preferred method for creating state-of-the-art systems. Learning has another advantage, as we noted earlier: it allows the agent to operate in initially unknown environments and to become more competent than its initial knowledge alone might allow. In this section, we briefly introduce the main ideas of learning agents. In almost every chapter of the book, we will comment on opportunities and methods for learning in particular kinds of agents. Part VI goes into much more depth on the various learning algorithms themselves.

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

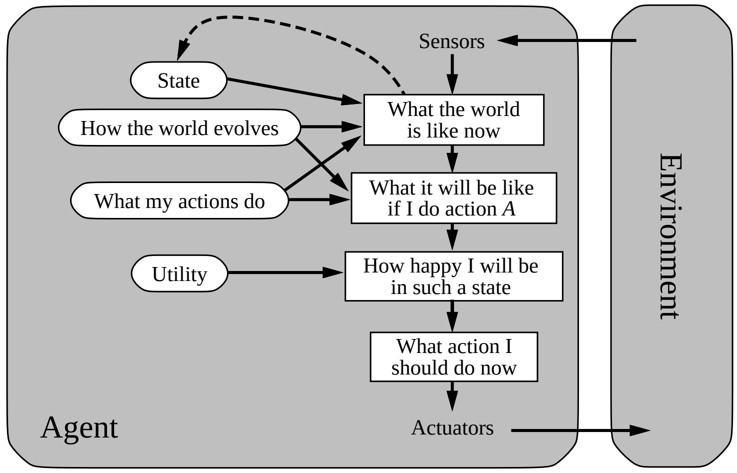


Figure 2.14 A model-based, utility-based agent. It uses a model of the world, along with a utility function that measures its preferences among states of the world. Then it chooses the action that leads to the best expected utility, where expected utility is computed by averaging over all possible outcome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

LEARNING ELEMENT
PERFORMANCE ELEMENT
CRITIC

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

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

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

PROBLEM GENERATOR

The last component of the learning agent is the **problem generator**. It is responsible for suggesting actions that will lead to new and informative experiences. The point is that if the performance element had its way, it would keep doing the actions that are best, given what it knows. But if the agent is willing to explore a little, and do some perhaps suboptimal actions in the short run, it might discover much better actions for the long run. The problem

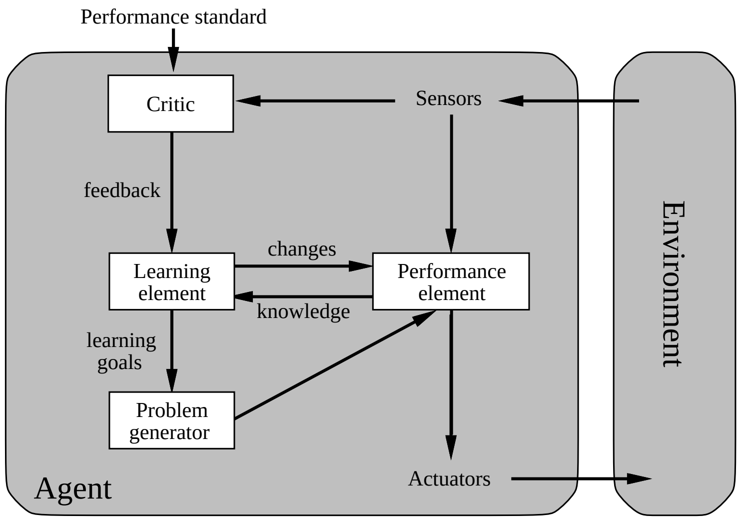


Figure 2.15 A general model of learning agents.

generator's job is to suggest these exploratory actions. This is what scientists do when they carry out experiments. Galileo did not think that dropping rocks from the top of a tower in Pisa was valuable in itself. He was not trying to break the rocks, nor to modify the brains of unfortunate passers-by. His aim was to modify his own brain, by identifying a better theory of the motion of objects.

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

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

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

In summary, agents have a variety of components, and those components can be represented in many ways within the agent program, so there appears to be great variety among learning methods. There is, however, a single unifying theme. Learning in intelligent agents can be summarized as a process of modification of each component of the agent to bring the components into closer agreement with the available feedback information, thereby improving the overall performance of the agent.

2.5 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, deterministic or stochastic, episodic or sequential, static or dynamic, discrete or continuous, and single-agent or multiagent.
- 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 the construction of 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 in the field and is a central theme in recent texts (Poole *et al.*, 1998; Nilsson, 1998).

CONTROLLER

Chapter 1 traced the roots of the concept of rationality in philosophy and economics. In AI, the concept was of peripheral interest until the mid-1980s, when it began to suffuse many discussions about the proper technical foundations of the field. A paper by Jon Doyle (1983) predicted that rational agent design would come to be seen as the core mission of AI, while other popular topics would spin off to form new disciplines.

Careful attention to the properties of the environment and their consequences for rational agent design is most apparent in the control theory tradition—for example, classical control systems (Dorf and Bishop, 1999) handle fully observable, deterministic environments; stochastic optimal control (Kumar and Varaiya, 1986) handles partially observable, stochastic environments; and hybrid control (Henzinger and Sastry, 1998) deals with environments containing both discrete and continuous elements. The distinction between fully and partially observable environments is also central in the **dynamic programming** literature developed in the field of operations research (Puterman, 1994), which we will discuss in Chapter 17.

Reflex agents were the primary model for psychological behaviorists such as Skinner (1953), who attempted to reduce the psychology of organisms strictly to input/output or stimulus/response mappings. The advance from behaviorism to functionalism in psychology, which was at least partly driven by the application of the computer metaphor to agents (Putnam, 1960; Lewis, 1966), introduced the internal state of the agent into the picture. Most work in AI views the idea of pure reflex agents with state as too simple to provide much leverage, but work by Rosenschein (1985) and Brooks (1986) questioned this assumption (see Chapter 25). In recent years, a great deal of work has gone into finding efficient algorithms for keeping track of complex environments (Hamscher *et al.*, 1992). The Remote Agent program that controlled the Deep Space One spacecraft (described on page 27) is a particularly impressive example (Muscettola *et al.*, 1998; Jonsson *et al.*, 2000).

Goal-based agents are presupposed in everything from Aristotle's view of practical reasoning to McCarthy's early papers on logical AI. Shakey the Robot (Fikes and Nilsson, 1971; Nilsson, 1984) was the first robotic embodiment of a logical, goal-based agent. A full logical analysis of goal-based agents appeared in Genesereth and Nilsson (1987), and a goal-based programming methodology called agent-oriented programming was developed by Shoham (1993).

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

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

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

Interest in agents and in agent design has risen rapidly in recent years, partly because of the growth of the Internet and the perceived need for automated and mobile **softbots** (Etzioni and Weld, 1994). Relevant papers are collected in *Readings in Agents* (Huhns and Singh, 1998) and *Foundations of Rational Agency* (Wooldridge and Rao, 1999). *Multiagent Systems* (Weiss, 1999) provides a solid foundation for many aspects of agent design. Conferences devoted to agents include the International Conference on Autonomous Agents, the International Workshop on Agent Theories, Architectures, and Languages, and the International Conference on Multiagent Systems. Finally, *Dung Beetle Ecology* (Hanski and Cambefort, 1991) provides a wealth of interesting information on the behavior of dung beetles.

EXERCISES

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

2.2 Both the performance measure and the utility function measure how well an agent is doing. Explain the difference between the two.

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

- **a**. Can there be more than one agent program that implements a given agent function? Give an example, or show why one is not possible.
- **b**. Are there agent functions that cannot be implemented by any agent program?
- **c**. Given a fixed machine architecture, does each agent program implement exactly one agent function?
- **d**. Given an architecture with n bits of storage, how many different possible agent programs are there?

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

a. Show that the simple vacuum-cleaner agent function described in Figure 2.3 is indeed rational under the assumptions listed on page 36.

b. Describe a rational agent function for the modified performance measure that deducts one point for each movement. Does the corresponding agent program require internal state?

c. Discuss possible agent designs for the cases in which clean squares can become dirty and the geography of the environment is unknown. Does it make sense for the agent to learn from its experience in these cases? If so, what should it learn?

2.5 For each of the following agents, develop a PEAS description of the task environment:

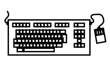
a. Robot soccer player;

b. Internet book-shopping agent;

c. Autonomous Mars rover;

d. Mathematician's theorem-proving assistant.

2.6 For each of the agent types listed in Exercise 2.5, characterize the environment according to the properties given in Section 2.3, and select a suitable agent design.



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

2.7 Implement a performance-measuring environment simulator for the vacuum-cleaner world depicted in Figure 2.2 and specified on page 36. Your implementation should be modular, so that the sensors, actuators, and environment characteristics (size, shape, dirt placement, etc.) can be changed easily. (*Note:* for some choices of programming language and operating system there are already implementations in the online code repository.)

2.8 Implement a simple reflex agent for the vacuum environment in Exercise 2.7. Run the environment simulator with this agent for all possible initial dirt configurations and agent locations. Record the agent's performance score for each configuration and its overall average score.

2.9 Consider a modified version of the vacuum environment in Exercise 2.7, in which the agent is penalized one point for each movement.

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

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

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

2.10 Consider a modified version of the vacuum environment in Exercise 2.7, in which the geography of the environment—its extent, boundaries, and obstacles—is unknown, as is the initial dirt configuration. (The agent can go Up and $Down$ as well as $Left$ and $Right$.)

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

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

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

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

2.11 Repeat Exercise 2.10 for the case in which the location sensor is replaced with a "bump" sensor that detects the agent's attempts to move into an obstacle or to cross the boundaries of the environment. Suppose the bump sensor stops working; how should the agent behave?

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

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

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