
3 The Reinforcement Learning Problem

In this chapter we introduce the problem that we try to solve in the rest of the book. For us, this problem defines the field of reinforcement learning: any method that is suited to solving this problem we consider to be a reinforcement learning method.

Our objective in this chapter is to describe the reinforcement learning problem in a broad sense. We try to convey the wide range of possible applications that can be framed as reinforcement learning tasks. We also describe mathematically idealized forms of the reinforcement learning problem for which precise theoretical statements can be made. We introduce key elements of the problem's mathematical structure, such as value functions and Bellman equations. As in all of artificial intelligence, there is a tension between breadth of applicability and mathematical tractability. In this chapter we introduce this tension and discuss some of the trade-offs and challenges that it implies.

3.1 The Agent–Environment Interface

The reinforcement learning problem is meant to be a straightforward framing of the problem of learning from interaction to achieve a goal. The learner and decision-maker is called the *agent*. The thing it interacts with, comprising everything outside the agent, is called the *environment*. These interact continually, the agent selecting actions and the environment responding to those actions and presenting new situations to the agent.¹ The environment also gives rise to rewards, special numerical

1. We use the terms *agent*, *environment*, and *action* instead of the engineers' terms *controller*, *controlled system* (or *plant*), and *control signal* because they are meaningful to a wider audience.

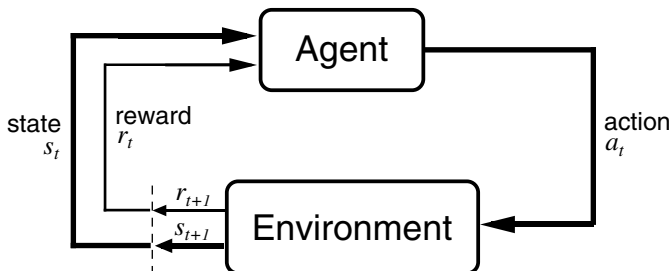


Figure 3.1 The agent–environment interaction in reinforcement learning.

values that the agent tries to maximize over time. A complete specification of an environment defines a *task*, one instance of the reinforcement learning problem.

More specifically, the agent and environment interact at each of a sequence of discrete time steps, $t = 0, 1, 2, 3, \dots$.² At each time step t , the agent receives some representation of the environment’s *state*, $s_t \in \mathcal{S}$, where \mathcal{S} is the set of possible states, and on that basis selects an *action*, $a_t \in \mathcal{A}(s_t)$, where $\mathcal{A}(s_t)$ is the set of actions available in state s_t . One time step later, in part as a consequence of its action, the agent receives a numerical *reward*, $r_{t+1} \in \mathfrak{R}$, and finds itself in a new state, s_{t+1} .³ Figure 3.1 diagrams the agent–environment interaction.

At each time step, the agent implements a mapping from states to probabilities of selecting each possible action. This mapping is called the agent’s *policy* and is denoted π_t , where $\pi_t(s, a)$ is the probability that $a_t = a$ if $s_t = s$. Reinforcement learning methods specify how the agent changes its policy as a result of its experience. The agent’s goal, roughly speaking, is to maximize the total amount of reward it receives over the long run.

This framework is abstract and flexible and can be applied to many different problems in many different ways. For example, the time steps need not refer to fixed intervals of real time; they can refer to arbitrary successive stages of decision-making and acting. The actions can be low-level controls, such as the voltages applied to the motors of a robot arm, or high-level decisions, such as whether or not to have lunch or to go to graduate school. Similarly, the states can take a wide variety of forms.

2. We restrict attention to discrete time to keep things as simple as possible, even though many of the ideas can be extended to the continuous-time case (e.g., see Bertsekas and Tsitsiklis, 1996; Werbos, 1992; Doya, 1996).

3. We use r_{t+1} instead of r_t to denote the immediate reward due to the action taken at time t because it emphasizes that the next reward and the next state, s_{t+1} , are jointly determined.

They can be completely determined by low-level sensations, such as direct sensor readings, or they can be more high-level and abstract, such as symbolic descriptions of objects in a room. Some of what makes up a state could be based on memory of past sensations or even be entirely mental or subjective. For example, an agent could be in “the state” of not being sure where an object is, or of having just been “surprised” in some clearly defined sense. Similarly, some actions might be totally mental or computational. For example, some actions might control what an agent chooses to think about, or where it focuses its attention. In general, actions can be any decisions we want to learn how to make, and the states can be anything we can know that might be useful in making them.

In particular, the boundary between agent and environment is not often the same as the physical boundary of a robot’s or animal’s body. Usually, the boundary is drawn closer to the agent than that. For example, the motors and mechanical linkages of a robot and its sensing hardware should usually be considered parts of the environment rather than parts of the agent. Similarly, if we apply the framework to a person or animal, the muscles, skeleton, and sensory organs should be considered part of the environment. Rewards, too, presumably are computed inside the physical bodies of natural and artificial learning systems, but are considered external to the agent.

The general rule we follow is that anything that cannot be changed arbitrarily by the agent is considered to be outside of it and thus part of its environment. We do not assume that everything in the environment is unknown to the agent. For example, the agent often knows quite a bit about how its rewards are computed as a function of its actions and the states in which they are taken. But we always consider the reward computation to be external to the agent because it defines the task facing the agent and thus must be beyond its ability to change arbitrarily. In fact, in some cases the agent may know *everything* about how its environment works and still face a difficult reinforcement learning task, just as we may know exactly how a puzzle like Rubik’s cube works, but still be unable to solve it. The agent–environment boundary represents the limit of the agent’s *absolute control*, not of its knowledge.

The agent–environment boundary can be located at different places for different purposes. In a complicated robot, many different agents may be operating at once, each with its own boundary. For example, one agent may make high-level decisions which form part of the states faced by a lower-level agent that implements the high-level decisions. In practice, the agent–environment boundary is determined once one has selected particular states, actions, and rewards, and thus has identified a specific decision-making task of interest.

The reinforcement learning framework is a considerable abstraction of the problem of goal-directed learning from interaction. It proposes that whatever the details

of the sensory, memory, and control apparatus, and whatever objective one is trying to achieve, any problem of learning goal-directed behavior can be reduced to three signals passing back and forth between an agent and its environment: one signal to represent the choices made by the agent (the actions), one signal to represent the basis on which the choices are made (the states), and one signal to define the agent's goal (the rewards). This framework may not be sufficient to represent all decision-learning problems usefully, but it has proved to be widely useful and applicable.

Of course, the particular states and actions vary greatly from application to application, and how they are represented can strongly affect performance. In reinforcement learning, as in other kinds of learning, such representational choices are at present more art than science. In this book we offer some advice and examples regarding good ways of representing states and actions, but our primary focus is on general principles for learning how to behave once the representations have been selected.

Example 3.1: Bioreactor Suppose reinforcement learning is being applied to determine moment-by-moment temperatures and stirring rates for a bioreactor (a large vat of nutrients and bacteria used to produce useful chemicals). The actions in such an application might be target temperatures and target stirring rates that are passed to lower-level control systems that, in turn, directly activate heating elements and motors to attain the targets. The states are likely to be thermocouple and other sensory readings, perhaps filtered and delayed, plus symbolic inputs representing the ingredients in the vat and the target chemical. The rewards might be moment-by-moment measures of the rate at which the useful chemical is produced by the bioreactor. Notice that here each state is a list, or vector, of sensor readings and symbolic inputs, and each action is a vector consisting of a target temperature and a stirring rate. It is typical of reinforcement learning tasks to have states and actions with such structured representations. Rewards, on the other hand, are always single numbers. ■

Example 3.2: Pick-and-Place Robot Consider using reinforcement learning to control the motion of a robot arm in a repetitive pick-and-place task. If we want to learn movements that are fast and smooth, the learning agent will have to control the motors directly and have low-latency information about the current positions and velocities of the mechanical linkages. The actions in this case might be the voltages applied to each motor at each joint, and the states might be the latest readings of joint angles and velocities. The reward might be +1 for each object successfully picked up and placed. To encourage smooth movements, on each time step a small, negative reward can be given as a function of the moment-to-moment “jerkiness” of the motion. ■

Example 3.3: Recycling Robot A mobile robot has the job of collecting empty soda cans in an office environment. It has sensors for detecting cans, and an arm and gripper that can pick them up and place them in an onboard bin; it runs on a rechargeable battery. The robot’s control system has components for interpreting sensory information, for navigating, and for controlling the arm and gripper. High-level decisions about how to search for cans are made by a reinforcement learning agent based on the current charge level of the battery. This agent has to decide whether the robot should (1) actively search for a can for a certain period of time, (2) remain stationary and wait for someone to bring it a can, or (3) head back to its home base to recharge its battery. This decision has to be made either periodically or whenever certain events occur, such as finding an empty can. The agent therefore has three actions, and its state is determined by the state of the battery. The rewards might be zero most of the time, but then become positive when the robot secures an empty can, or large and negative if the battery runs all the way down. In this example, the reinforcement learning agent is not the entire robot. The states it monitors describe conditions within the robot itself, not conditions of the robot’s external environment. The agent’s environment therefore includes the rest of the robot, which might contain other complex decision-making systems, as well as the robot’s external environment. ■

Exercise 3.1 Devise three example tasks of your own that fit into the reinforcement learning framework, identifying for each its states, actions, and rewards. Make the three examples as *different* from each other as possible. The framework is abstract and flexible and can be applied in many different ways. Stretch its limits in some way in at least one of your examples.

Exercise 3.2 Is the reinforcement learning framework adequate to usefully represent *all* goal-directed learning tasks? Can you think of any clear exceptions?

Exercise 3.3 Consider the problem of driving. You could define the actions in terms of the accelerator, steering wheel, and brake, that is, where your body meets the machine. Or you could define them farther out—say, where the rubber meets the road, considering your actions to be tire torques. Or you could define them farther in—say, where your brain meets your body, the actions being muscle twitches to control your limbs. Or you could go to a really high level and say that your actions are your choices of *where* to drive. What is the right level, the right place to draw the line between agent and environment? On what basis is one location of the line to be preferred over another? Is there any fundamental reason for preferring one location over another, or is it a free choice?

3.2 Goals and Rewards

In reinforcement learning, the purpose or goal of the agent is formalized in terms of a special reward signal passing from the environment to the agent. At each time step, the reward is a simple number, $r_t \in \mathbb{R}$. Informally, the agent's goal is to maximize the total amount of reward it receives. This means maximizing not immediate reward, but cumulative reward in the long run.

The use of a reward signal to formalize the idea of a goal is one of the most distinctive features of reinforcement learning. Although this way of formulating goals might at first appear limiting, in practice it has proved to be flexible and widely applicable. The best way to see this is to consider examples of how it has been, or could be, used. For example, to make a robot learn to walk, researchers have provided reward on each time step proportional to the robot's forward motion. In making a robot learn how to escape from a maze, the reward is often zero until it escapes, when it becomes $+1$. Another common approach in maze learning is to give a reward of -1 for every time step that passes prior to escape; this encourages the agent to escape as quickly as possible. To make a robot learn to find and collect empty soda cans for recycling, one might give it a reward of zero most of the time, and then a reward of $+1$ for each can collected (and confirmed as empty). One might also want to give the robot negative rewards when it bumps into things or when somebody yells at it. For an agent to learn to play checkers or chess, the natural rewards are $+1$ for winning, -1 for losing, and 0 for drawing and for all nonterminal positions.

You can see what is happening in all of these examples. The agent always learns to maximize its reward. If we want it to do something for us, we must provide rewards to it in such a way that in maximizing them the agent will also achieve our goals. It is thus critical that the rewards we set up truly indicate what we want accomplished. In particular, the reward signal is not the place to impart to the agent prior knowledge about *how* to achieve what we want it to do.⁴ For example, a chess-playing agent should be rewarded only for actually winning, not for achieving subgoals such as taking its opponent's pieces or gaining control of the center of the board. If achieving these sorts of subgoals were rewarded, then the agent might find a way to achieve them without achieving the real goal. For example, it might find a way to take the opponent's pieces even at the cost of losing the game. The reward signal is your way

4. Better places for imparting this kind of prior knowledge are the initial policy or value function, or in influences on these. See Lin (1992), Maclin and Shavlik (1994), and Clouse (1996).

of communicating to the agent *what* you want it to achieve, not *how* you want it achieved.

Newcomers to reinforcement learning are sometimes surprised that the rewards—which define of the goal of learning—are computed in the environment rather than in the agent. Certainly most ultimate goals for animals are recognized by computations occurring inside their bodies, for example, by sensors for recognizing food, hunger, pain, and pleasure. Nevertheless, as we discussed in the previous section, one can redraw the agent–environment interface in such a way that these parts of the body are considered to be outside of the agent (and thus part of the agent’s environment). For example, if the goal concerns a robot’s internal energy reservoirs, then these are considered to be part of the environment; if the goal concerns the positions of the robot’s limbs, then these too are considered to be part of the environment—that is, the agent’s boundary is drawn at the interface between the limbs and their control systems. These things are considered internal to the robot but external to the learning agent. For our purposes, it is convenient to place the boundary of the learning agent not at the limit of its physical body, but at the limit of its control.

The reason we do this is that the agent’s ultimate goal should be something over which it has imperfect control: it should not be able, for example, to simply *decree* that the reward has been received in the same way that it might arbitrarily change its actions. Therefore, we place the reward source outside of the agent. This does not preclude the agent from defining for itself a kind of internal reward, or a sequence of internal rewards. Indeed, this is exactly what many reinforcement learning methods do.

3.3 Returns

So far we have been imprecise regarding the objective of learning. We have said that the agent’s goal is to maximize the reward it receives in the long run. How might this be formally defined? If the sequence of rewards received after time step t is denoted $r_{t+1}, r_{t+2}, r_{t+3}, \dots$, then what precise aspect of this sequence do we wish to maximize? In general, we seek to maximize the *expected return*, where the return, R_t , is defined as some specific function of the reward sequence. In the simplest case the return is the sum of the rewards:

$$R_t = r_{t+1} + r_{t+2} + r_{t+3} + \dots + r_T, \quad (3.1)$$

where T is a final time step. This approach makes sense in applications in which there is a natural notion of final time step, that is, when the agent–environment interaction

breaks naturally into subsequences, which we call *episodes*,⁵ such as plays of a game, trips through a maze, or any sort of repeated interactions. Each episode ends in a special state called the *terminal state*, followed by a reset to a standard starting state or to a sample from a standard distribution of starting states. Tasks with episodes of this kind are called *episodic tasks*. In episodic tasks we sometimes need to distinguish the set of all nonterminal states, denoted \mathcal{S} , from the set of all states plus the terminal state, denoted \mathcal{S}^+ .

On the other hand, in many cases the agent–environment interaction does not break naturally into identifiable episodes, but goes on continually without limit. For example, this would be the natural way to formulate a continual process-control task, or an application to a robot with a long life span. We call these *continuing tasks*. The return formulation (3.1) is problematic for continuing tasks because the final time step would be $T = \infty$, and the return, which is what we are trying to maximize, could itself easily be infinite. (For example, suppose the agent receives a reward of +1 at each time step.) Thus, in this book we usually use a definition of return that is slightly more complex conceptually but much simpler mathematically.

The additional concept that we need is that of *discounting*. According to this approach, the agent tries to select actions so that the sum of the discounted rewards it receives over the future is maximized. In particular, it chooses a_t to maximize the expected *discounted return*:

$$R_t = r_{t+1} + \gamma r_{t+2} + \gamma^2 r_{t+3} + \cdots = \sum_{k=0}^{\infty} \gamma^k r_{t+k+1}, \quad (3.2)$$

where γ is a parameter, $0 \leq \gamma \leq 1$, called the *discount rate*.

The discount rate determines the present value of future rewards: a reward received k time steps in the future is worth only γ^{k-1} times what it would be worth if it were received immediately. If $\gamma < 1$, the infinite sum has a finite value as long as the reward sequence $\{r_k\}$ is bounded. If $\gamma = 0$, the agent is “myopic” in being concerned only with maximizing immediate rewards: its objective in this case is to learn how to choose a_t so as to maximize only r_{t+1} . If each of the agent’s actions happened to influence only the immediate reward, not future rewards as well, then a myopic agent could maximize (3.2) by separately maximizing each immediate reward. But in general, acting to maximize immediate reward can reduce access to future rewards so that the return may actually be reduced. As γ approaches 1, the objective takes future rewards into account more strongly: the agent becomes more farsighted.

5. Episodes are often called “trials” in the literature.

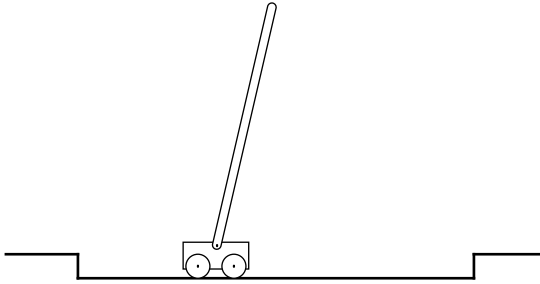


Figure 3.2 The pole-balancing task.

Example 3.4: Pole-Balancing Figure 3.2 shows a task that served as an early illustration of reinforcement learning. The objective here is to apply forces to a cart moving along a track so as to keep a pole hinged to the cart from falling over. A failure is said to occur if the pole falls past a given angle from vertical or if the cart reaches an end of the track. The pole is reset to vertical after each failure. This task could be treated as episodic, where the natural episodes are the repeated attempts to balance the pole. The reward in this case could be $+1$ for every time step on which failure did not occur, so that the return at each time would be the number of steps until failure. Alternatively, we could treat pole-balancing as a continuing task, using discounting. In this case the reward would be -1 on each failure and zero at all other times. The return at each time would then be related to $-\gamma^k$, where k is the number of time steps before failure. In either case, the return is maximized by keeping the pole balanced for as long as possible. ■

Exercise 3.4 Suppose you treated pole-balancing as an episodic task but also used discounting, with all rewards zero except for -1 upon failure. What then would the return be at each time? How does this return differ from that in the discounted, continuing formulation of this task?

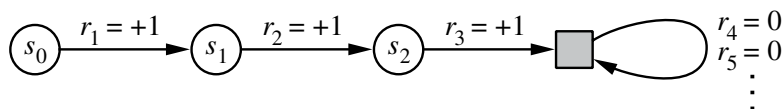
Exercise 3.5 Imagine that you are designing a robot to run a maze. You decide to give it a reward of $+1$ for escaping from the maze and a reward of zero at all other times. The task seems to break down naturally into episodes—the successive runs through the maze—so you decide to treat it as an episodic task, where the goal is to maximize expected total reward (3.1). After running the learning agent for a while, you find that it is showing no improvement in escaping from the maze. What is going wrong? Have you effectively communicated to the agent what you want it to achieve?

3.4 Unified Notation for Episodic and Continuing Tasks

In the preceding section we described two kinds of reinforcement learning tasks, one in which the agent–environment interaction naturally breaks down into a sequence of separate episodes (episodic tasks), and one in which it does not (continuing tasks). The former case is mathematically easier because each action affects only the finite number of rewards subsequently received during the episode. In this book we consider sometimes one kind of problem and sometimes the other, but often both. It is therefore useful to establish one notation that enables us to talk precisely about both cases simultaneously.

To be precise about episodic tasks requires some additional notation. Rather than one long sequence of time steps, we need to consider a series of episodes, each of which consists of a finite sequence of time steps. We number the time steps of each episode starting anew from zero. Therefore, we have to refer not just to s_t , the state at time t , but to $s_{t,i}$, the state at time t of episode i (and similarly for $a_{t,i}$, $r_{t,i}$, $\pi_{t,i}$, T_i , etc.). However, it turns out that when we discuss episodic tasks we will almost never have to distinguish between different episodes. We will almost always be considering a particular single episode, or stating something that is true for all episodes. Accordingly, in practice we will almost always abuse notation slightly by dropping the explicit reference to episode number. That is, we will write s_t to refer to $s_{t,i}$, and so on.

We need one other convention to obtain a single notation that covers both episodic and continuing tasks. We have defined the return as a sum over a finite number of terms in one case (3.1) and as a sum over an infinite number of terms in the other (3.2). These can be unified by considering episode termination to be the entering of a special *absorbing state* that transitions only to itself and that generates only rewards of zero. For example, consider the state transition diagram:



Here the solid square represents the special absorbing state corresponding to the end of an episode. Starting from s_0 , we get the reward sequence $+1, +1, +1, 0, 0, 0, \dots$. Summing these, we get the same return whether we sum over the first T rewards

(here $T = 3$) or over the full infinite sequence. This remains true even if we introduce discounting. Thus, we can define the return, in general, according to (3.2), using the convention of omitting episode numbers when they are not needed, and including the possibility that $\gamma = 1$ if the sum remains finite (e.g., because all episodes terminate). Alternatively, we can also write the return as

$$R_t = \sum_{k=0}^T \gamma^k r_{t+k+1}, \quad (3.3)$$

including the possibility that $T = \infty$ or $\gamma = 1$ (but not both⁶). We use these conventions throughout the rest of the book to simplify notation and to express the close parallels between episodic and continuing tasks.

★ 3.5 The Markov Property

In the reinforcement learning framework, the agent makes its decisions as a function of a signal from the environment called the environment's *state*. In this section we discuss what is required of the state signal, and what kind of information we should and should not expect it to provide. In particular, we formally define a property of environments and their state signals that is of particular interest, called the Markov property.

In this book, by “the state” we mean whatever information is available to the agent. We assume that the state is given by some preprocessing system that is nominally part of the environment. We do not address the issues of constructing, changing, or learning the state signal in this book. We take this approach not because we consider state representation to be unimportant, but in order to focus fully on the decision-making issues. In other words, our main concern is not with designing the state signal, but with deciding what action to take as a function of whatever state signal is available.

Certainly the state signal should include immediate sensations such as sensory measurements, but it can contain much more than that. State representations can be highly processed versions of original sensations, or they can be complex structures

6. Ways to formulate tasks that are both continuing and undiscounted are subjects of current research (e.g., Mahadevan, 1996; Schwartz, 1993; Tadepalli and Ok, 1994). Some of the ideas are discussed in Section 6.7.

built up over time from the sequence of sensations. For example, we can move our eyes over a scene, with only a tiny spot corresponding to the fovea visible in detail at any one time, yet build up a rich and detailed representation of a scene. Or, more obviously, we can look at an object, then look away, and know that it is still there. We can hear the word “yes” and consider ourselves to be in totally different states depending on the question that came before and which is no longer audible. At a more mundane level, a control system can measure position at two different times to produce a state representation including information about velocity. In all of these cases the state is constructed and maintained on the basis of immediate sensations together with the previous state or some other memory of past sensations. In this book, we do not explore how that is done, but certainly it can be and has been done. There is no reason to restrict the state representation to immediate sensations; in typical applications we should expect the state representation to be able to inform the agent of more than that.

On the other hand, the state signal should not be expected to inform the agent of everything about the environment, or even everything that would be useful to it in making decisions. If the agent is playing blackjack, we should not expect it to know what the next card in the deck is. If the agent is answering the phone, we should not expect it to know in advance who the caller is. If the agent is a paramedic called to a road accident, we should not expect it to know immediately the internal injuries of an unconscious victim. In all of these cases there is hidden state information in the environment, and that information would be useful if the agent knew it, but the agent cannot know it because it has never received any relevant sensations. In short, we don’t fault an agent for not knowing something that matters, but only for having known something and then forgotten it!

What we would like, ideally, is a state signal that summarizes past sensations compactly, yet in such a way that all relevant information is retained. This normally requires more than the immediate sensations, but never more than the complete history of all past sensations. A state signal that succeeds in retaining all relevant information is said to be *Markov*, or to have *the Markov property* (we define this formally below). For example, a checkers position—the current configuration of all the pieces on the board—would serve as a Markov state because it summarizes everything important about the complete sequence of positions that led to it. Much of the information about the sequence is lost, but all that really matters for the future of the game is retained. Similarly, the current position and velocity of a cannonball is all that matters for its future flight. It doesn’t matter how that position and velocity came about. This is sometimes also referred to as an “independence of path” property because all that matters is in the current state signal; its meaning is independent of the “path,” or history, of signals that have led up to it.

We now formally define the Markov property for the reinforcement learning problem. To keep the mathematics simple, we assume here that there are a finite number of states and reward values. This enables us to work in terms of sums and probabilities rather than integrals and probability densities, but the argument can easily be extended to include continuous states and rewards. Consider how a general environment might respond at time $t + 1$ to the action taken at time t . In the most general, causal case this response may depend on everything that has happened earlier. In this case the dynamics can be defined only by specifying the complete probability distribution:

$$\Pr \{s_{t+1} = s', r_{t+1} = r \mid s_t, a_t, r_t, s_{t-1}, a_{t-1}, \dots, r_1, s_0, a_0\}, \quad (3.4)$$

for all s', r , and all possible values of the past events: $s_t, a_t, r_t, \dots, r_1, s_0, a_0$. If the state signal has the *Markov property*, on the other hand, then the environment's response at $t + 1$ depends only on the state and action representations at t , in which case the environment's dynamics can be defined by specifying only

$$\Pr \{s_{t+1} = s', r_{t+1} = r \mid s_t, a_t\}, \quad (3.5)$$

for all s', r, s_t , and a_t . In other words, a state signal has the Markov property, and is a Markov state, if and only if (3.5) is equal to (3.4) for all s', r , and histories, $s_t, a_t, r_t, \dots, r_1, s_0, a_0$. In this case, the environment and task as a whole are also said to have the Markov property.

If an environment has the Markov property, then its one-step dynamics (3.5) enable us to predict the next state and expected next reward given the current state and action. One can show that, by iterating this equation, one can predict all future states and expected rewards from knowledge only of the current state as well as would be possible given the complete history up to the current time. It also follows that Markov states provide the best possible basis for choosing actions. That is, the best policy for choosing actions as a function of a Markov state is just as good as the best policy for choosing actions as a function of complete histories.

Even when the state signal is non-Markov, it is still appropriate to think of the state in reinforcement learning as an approximation to a Markov state. In particular, we always want the state to be a good basis for predicting future rewards and for selecting actions. In cases in which a model of the environment is learned (see Chapter 9), we also want the state to be a good basis for predicting subsequent states. Markov states provide an unsurpassed basis for doing all of these things. To the extent that the state approaches the ability of Markov states in these ways, one will obtain better performance from reinforcement learning systems. For all of these reasons, it is useful to think of the state at each time step as an approximation to a Markov state, although one should remember that it may not fully satisfy the Markov property.

The Markov property is important in reinforcement learning because decisions and values are assumed to be functions only of the current state. In order for these to be effective and informative, the state representation must be informative. All of the theory presented in this book assumes Markov state signals. This means that not all the theory strictly applies to cases in which the Markov property does not strictly apply. However, the theory developed for the Markov case still helps us to understand the behavior of the algorithms, and the algorithms can be successfully applied to many tasks with states that are not strictly Markov. A full understanding of the theory of the Markov case is an essential foundation for extending it to the more complex and realistic non-Markov case. Finally, we note that the assumption of Markov state representations is not unique to reinforcement learning but is also present in most if not all other approaches to artificial intelligence.

Example 3.5: Pole-Balancing State In the pole-balancing task introduced earlier, a state signal would be Markov if it specified exactly, or made it possible to reconstruct exactly, the position and velocity of the cart along the track, the angle between the cart and the pole, and the rate at which this angle is changing (the angular velocity). In an idealized cart–pole system, this information would be sufficient to exactly predict the future behavior of the cart and pole, given the actions taken by the controller. In practice, however, it is never possible to know this information exactly because any real sensor would introduce some distortion and delay in its measurements. Furthermore, in any real cart–pole system there are always other effects, such as the bending of the pole, the temperatures of the wheel and pole bearings, and various forms of backlash, that slightly affect the behavior of the system. These factors would cause violations of the Markov property if the state signal were only the positions and velocities of the cart and the pole.

However, often the positions and velocities serve quite well as states. Some early studies of learning to solve the pole-balancing task used a coarse state signal that divided cart positions into three regions: right, left, and middle (and similar rough quantizations of the other three intrinsic state variables). This distinctly non-Markov state was sufficient to allow the task to be solved easily by reinforcement learning methods. In fact, this coarse representation may have facilitated rapid learning by forcing the learning agent to ignore fine distinctions that would not have been useful in solving the task. ■

Example 3.6: Draw Poker In draw poker, each player is dealt a hand of five cards. There is a round of betting, in which each player exchanges some of his cards for new ones, and then there is a final round of betting. At each round, each player must

match or exceed the highest bets of the other players, or else drop out (fold). After the second round of betting, the player with the best hand who has not folded is the winner and collects all the bets.

The state signal in draw poker is different for each player. Each player knows the cards in his own hand, but can only guess at those in the other players' hands. A common mistake is to think that a Markov state signal should include the contents of all the players' hands and the cards remaining in the deck. In a fair game, however, we assume that the players are in principle unable to determine these things from their past observations. If a player did know them, then she could predict some future events (such as the cards one could exchange for) *better* than by remembering all past observations.

In addition to knowledge of one's own cards, the state in draw poker should include the bets and the numbers of cards drawn by the other players. For example, if one of the other players drew three new cards, you may suspect he retained a pair and adjust your guess of the strength of his hand accordingly. The players' bets also influence your assessment of their hands. In fact, much of your past history with these particular players is part of the Markov state. Does Ellen like to bluff, or does she play conservatively? Does her face or demeanor provide clues to the strength of her hand? How does Joe's play change when it is late at night, or when he has already won a lot of money?

Although everything ever observed about the other players may have an effect on the probabilities that they are holding various kinds of hands, in practice this is far too much to remember and analyze, and most of it will have no clear effect on one's predictions and decisions. Very good poker players are adept at remembering just the key clues, and at sizing up new players quickly, but no one remembers everything that is relevant. As a result, the state representations people use to make their poker decisions are undoubtedly non-Markov, and the decisions themselves are presumably imperfect. Nevertheless, people still make very good decisions in such tasks. We conclude that the inability to have access to a *perfect* Markov state representation is probably not a severe problem for a reinforcement learning agent. ■

Exercise 3.6: Broken Vision System Imagine that you are a vision system. When you are first turned on, an image floods into your camera. You can see lots of things, but not all things. You can't see objects that are occluded, and of course you can't see objects that are behind you. After seeing that first scene, do you have access to the Markov state of the environment? Suppose your camera were broken and you received no images at all, all day. Would you have access to the Markov state then?

3.6 Markov Decision Processes

A reinforcement learning task that satisfies the Markov property is called a *Markov decision process*, or *MDP*. If the state and action spaces are finite, then it is called a *finite Markov decision process (finite MDP)*. Finite MDPs are particularly important to the theory of reinforcement learning. We treat them extensively throughout this book; they are all you need to understand 90% of modern reinforcement learning.

A particular finite MDP is defined by its state and action sets and by the one-step dynamics of the environment. Given any state and action, s and a , the probability of each possible next state, s' , is

$$\mathcal{P}_{ss'}^a = \Pr \{s_{t+1} = s' \mid s_t = s, a_t = a\}. \quad (3.6)$$

These quantities are called *transition probabilities*. Similarly, given any current state and action, s and a , together with any next state, s' , the expected value of the next reward is

$$\mathcal{R}_{ss'}^a = E \{r_{t+1} \mid s_t = s, a_t = a, s_{t+1} = s'\}. \quad (3.7)$$

These quantities, $\mathcal{P}_{ss'}^a$ and $\mathcal{R}_{ss'}^a$, completely specify the most important aspects of the dynamics of a finite MDP (only information about the distribution of rewards around the expected value is lost). Most of the theory we present in the rest of this book implicitly assumes the environment is a finite MDP.

Example 3.7: Recycling Robot MDP The recycling robot (Example 3.3) can be turned into a simple example of an MDP by simplifying it and providing some more details. (Our aim is to produce a simple example, not a particularly realistic one.) Recall that the agent makes a decision at times determined by external events (or by other parts of the robot's control system). At each such time the robot decides whether it should (1) actively search for a can, (2) remain stationary and wait for someone to bring it a can, or (3) go back to home base to recharge its battery. Suppose the environment works as follows. The best way to find cans is to actively search for them, but this runs down the robot's battery, whereas waiting does not. Whenever the robot is searching, the possibility exists that its battery will become depleted. In this case the robot must shut down and wait to be rescued (producing a low reward).

The agent makes its decisions solely as a function of the energy level of the battery. It can distinguish two levels, high and low, so that the state set is $\mathcal{S} = \{\text{high}, \text{low}\}$. Let us call the possible decisions—the agent's actions—wait, search, and recharge. When the energy level is high, recharging would always be foolish,

Table 3.1 Transition probabilities and expected rewards for the finite MDP of the recycling robot example.

| s | s' | a | $\mathcal{P}_{ss'}^a$ | $\mathcal{R}_{ss'}^a$ |
|------|------|----------|-----------------------|-------------------------------|
| high | high | search | α | $\mathcal{R}^{\text{search}}$ |
| high | low | search | $1 - \alpha$ | $\mathcal{R}^{\text{search}}$ |
| low | high | search | $1 - \beta$ | -3 |
| low | low | search | β | $\mathcal{R}^{\text{search}}$ |
| high | high | wait | 1 | $\mathcal{R}^{\text{wait}}$ |
| high | low | wait | 0 | $\mathcal{R}^{\text{wait}}$ |
| low | high | wait | 0 | $\mathcal{R}^{\text{wait}}$ |
| low | low | wait | 1 | $\mathcal{R}^{\text{wait}}$ |
| low | high | recharge | 1 | 0 |
| low | low | recharge | 0 | 0 |

Note: There is a row for each possible combination of current state, s , next state, s' , and action possible in the current state, $a \in \mathcal{A}(s)$.

so we do not include it in the action set for this state. The agent's action sets are

$$\mathcal{A}(\text{high}) = \{\text{search}, \text{wait}\}$$

$$\mathcal{A}(\text{low}) = \{\text{search}, \text{wait}, \text{recharge}\}.$$

If the energy level is high, then a period of active search can always be completed without risk of depleting the battery. A period of searching that begins with a high energy level leaves the energy level high with probability α and reduces it to low with probability $1 - \alpha$. On the other hand, a period of searching undertaken when the energy level is low leaves it low with probability β and depletes the battery with probability $1 - \beta$. In the latter case, the robot must be rescued, and the battery is then recharged back to high. Each can collected by the robot counts as a unit reward, whereas a reward of -3 results whenever the robot has to be rescued. Let $\mathcal{R}^{\text{search}}$ and $\mathcal{R}^{\text{wait}}$, with $\mathcal{R}^{\text{search}} > \mathcal{R}^{\text{wait}}$, respectively denote the expected number of cans the robot will collect (and hence the expected reward) while searching and while waiting. Finally, to keep things simple, suppose that no cans can be collected during a run home for recharging, and that no cans can be collected on a step in which the battery is depleted. This system is then a finite MDP, and we can write down the transition probabilities and the expected rewards, as in Table 3.1.

A *transition graph* is a useful way to summarize the dynamics of a finite MDP. Figure 3.3 shows the transition graph for the recycling robot example. There are two

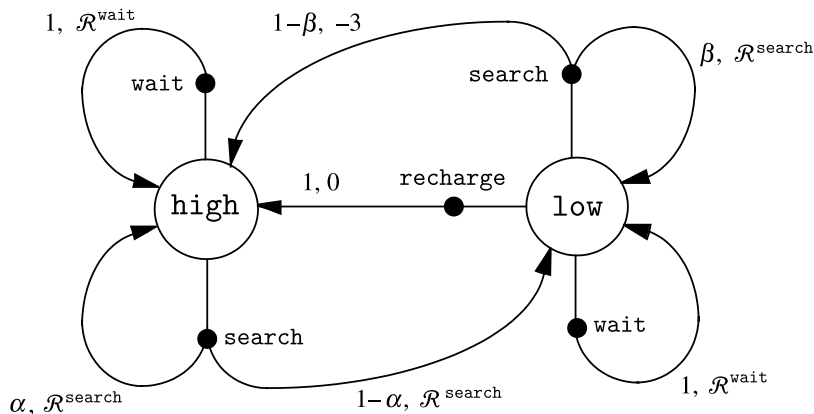


Figure 3.3 Transition graph for the recycling robot example.

kinds of nodes: *state nodes* and *action nodes*. There is a state node for each possible state (a large open circle labeled by the name of the state), and an action node for each state–action pair (a small solid circle labeled by the name of the action and connected by a line to the state node). Starting in state s and taking action a moves you along the line from state node s to action node (s, a) . Then the environment responds with a transition to the next state’s node via one of the arrows leaving action node (s, a) . Each arrow corresponds to a triple (s, s', a) , where s' is the next state, and we label the arrow with the transition probability, $\mathcal{P}_{ss'}^a$, and the expected reward for that transition, $\mathcal{R}_{ss'}^a$. Note that the transition probabilities labeling the arrows leaving an action node always sum to 1. ■

Exercise 3.7 Assuming a finite MDP with a finite number of reward values, write an equation for the transition probabilities and the expected rewards in terms of the joint conditional distribution in (3.5).

3.7 Value Functions

Almost all reinforcement learning algorithms are based on estimating *value functions*—functions of states (or of state–action pairs) that estimate *how good* it is for the agent to be in a given state (or how good it is to perform a given action in a given state). The notion of “how good” here is defined in terms of future rewards that can be expected, or, to be precise, in terms of expected return. Of course the

rewards the agent can expect to receive in the future depend on what actions it will take. Accordingly, value functions are defined with respect to particular policies.

Recall that a policy, π , is a mapping from each state, $s \in \mathcal{S}$, and action, $a \in \mathcal{A}(s)$, to the probability $\pi(s, a)$ of taking action a when in state s . Informally, the *value* of a state s under a policy π , denoted $V^\pi(s)$, is the expected return when starting in s and following π thereafter. For MDPs, we can define $V^\pi(s)$ formally as

$$V^\pi(s) = E_\pi\{R_t \mid s_t = s\} = E_\pi\left\{\sum_{k=0}^{\infty} \gamma^k r_{t+k+1} \mid s_t = s\right\}, \quad (3.8)$$

where $E_\pi\{\cdot\}$ denotes the expected value given that the agent follows policy π . Note that the value of the terminal state, if any, is always zero. We call the function V^π the *state-value function for policy π* .

Similarly, we define the value of taking action a in state s under a policy π , denoted $Q^\pi(s, a)$, as the expected return starting from s , taking the action a , and thereafter following policy π :

$$Q^\pi(s, a) = E_\pi\{R_t \mid s_t = s, a_t = a\} = E_\pi\left\{\sum_{k=0}^{\infty} \gamma^k r_{t+k+1} \mid s_t = s, a_t = a\right\}. \quad (3.9)$$

We call Q^π the *action-value function for policy π* .

The value functions V^π and Q^π can be estimated from experience. For example, if an agent follows policy π and maintains an average, for each state encountered, of the actual returns that have followed that state, then the average will converge to the state's value, $V^\pi(s)$, as the number of times that state is encountered approaches infinity. If separate averages are kept for each action taken in a state, then these averages will similarly converge to the action values, $Q^\pi(s, a)$. We call estimation methods of this kind *Monte Carlo methods* because they involve averaging over random samples of actual returns. These kinds of methods are presented in Chapter 5. Of course, if there are very many states, then it may not be practical to keep separate averages for each state individually. Instead, the agent would have to maintain V^π and Q^π as parameterized functions and adjust the parameters to better match the observed returns. This can also produce accurate estimates, although much depends on the nature of the parameterized function approximator (Chapter 8).

A fundamental property of value functions used throughout reinforcement learning and dynamic programming is that they satisfy particular recursive relationships. For any policy π and any state s , the following consistency condition holds between the value of s and the value of its possible successor states:

$$\begin{aligned}
V^\pi(s) &= E_\pi\{R_t \mid s_t = s\} \\
&= E_\pi\left\{\sum_{k=0}^{\infty} \gamma^k r_{t+k+1} \mid s_t = s\right\} \\
&= E_\pi\left\{r_{t+1} + \gamma \sum_{k=0}^{\infty} \gamma^k r_{t+k+2} \mid s_t = s\right\} \\
&= \sum_a \pi(s, a) \sum_{s'} \mathcal{P}_{ss'}^a \left[\mathcal{R}_{ss'}^a + \gamma E_\pi\left\{\sum_{k=0}^{\infty} \gamma^k r_{t+k+2} \mid s_{t+1} = s'\right\} \right] \\
&= \sum_a \pi(s, a) \sum_{s'} \mathcal{P}_{ss'}^a [\mathcal{R}_{ss'}^a + \gamma V^\pi(s')], \tag{3.10}
\end{aligned}$$

where it is implicit that the actions, a , are taken from the set $\mathcal{A}(s)$, and the next states, s' , are taken from the set \mathcal{S} , or from \mathcal{S}^+ in the case of an episodic problem. Equation (3.10) is the *Bellman equation for V^π* . It expresses a relationship between the value of a state and the values of its successor states. Think of looking ahead from one state to its possible successor states, as suggested by Figure 3.4a. Each open circle represents a state and each solid circle represents a state–action pair. Starting from state s , the root node at the top, the agent could take any of some set of actions—three are shown in Figure 3.4a. From each of these, the environment could respond with one of several next states, s' , along with a reward, r . The Bellman equation (3.10) averages over all the possibilities, weighting each by its probability of occurring. It states that the value of the start state must equal the (discounted) value of the expected next state, plus the reward expected along the way.

The value function V^π is the unique solution to its Bellman equation. We show in subsequent chapters how this Bellman equation forms the basis of a number of

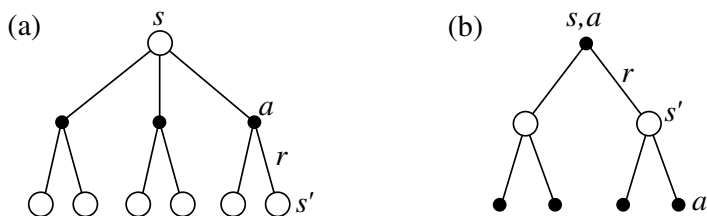


Figure 3.4 Backup diagrams for (a) V^π and (b) Q^π .

ways to compute, approximate, and learn V^π . We call diagrams like those shown in Figure 3.4 *backup diagrams* because they diagram relationships that form the basis of the update or *backup* operations that are at the heart of reinforcement learning methods. These operations transfer value information *back* to a state (or a state–action pair) from its successor states (or state–action pairs). We use backup diagrams throughout the book to provide graphical summaries of the algorithms we discuss. (Note that unlike transition graphs, the state nodes of backup diagrams do not necessarily represent distinct states; for example, a state might be its own successor. We also omit explicit arrowheads because time always flows downward in a backup diagram.)

Example 3.8: Gridworld Figure 3.5a uses a rectangular grid to illustrate value functions for a simple finite MDP. The cells of the grid correspond to the states of the environment. At each cell, four actions are possible: north, south, east, and west, which deterministically cause the agent to move one cell in the corresponding direction on the grid. Actions that would take the agent off the grid leave its location unchanged, but also result in a reward of -1 . Other actions result in a reward of 0 , except those that move the agent out of the special states **A** and **B**. From state **A**, all four actions yield a reward of $+10$ and take the agent to **A'**. From state **B**, all actions yield a reward of $+5$ and take the agent to **B'**.

Suppose the agent selects all four actions with equal probability in all states. Figure 3.5b shows the value function, V^π , for this policy, for the discounted reward case with $\gamma = 0.9$. This value function was computed by solving the system of equations (3.10). Notice the negative values near the lower edge; these are the result of the high probability of hitting the edge of the grid there under the random policy. State **A** is the best state to be in under this policy, but its expected return is less than

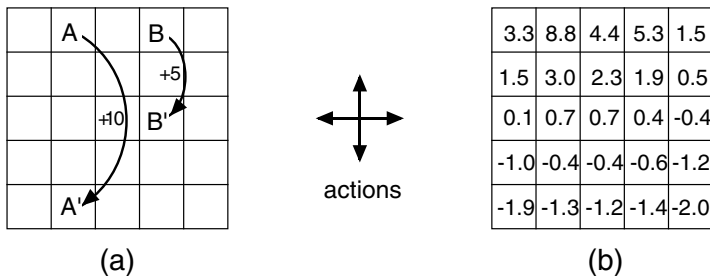


Figure 3.5 Grid example: (a) exceptional reward dynamics; (b) state-value function for the equiprobable random policy.

10, its immediate reward, because from **A** the agent is taken to **A'**, from which it is likely to run into the edge of the grid. State **B**, on the other hand, is valued more than 5, its immediate reward, because from **B** the agent is taken to **B'**, which has a positive value. From **B'** the expected penalty (negative reward) for possibly running into an edge is more than compensated for by the expected gain for possibly stumbling onto **A** or **B**. ■

Example 3.9: Golf To formulate playing a hole of golf as a reinforcement learning task, we count a penalty (negative reward) of -1 for each stroke until the ball is in the hole. The state is the location of the ball. The value of a state is the negative of the number of strokes to the hole from that location. Our actions are how we aim and swing at the ball, of course, and which club we select. Let us take the former as given and consider just the choice of club, which we assume is either a putter or a driver. The upper part of Figure 3.6 shows a possible state-value function, $V^{\text{putt}}(s)$, for the policy that always uses the putter. The terminal state *in-the-hole* has a value of 0. From anywhere on the green we assume we can make a putt; these states have value -1 . Off the green we cannot reach the hole by putting, and the value is greater. If we can reach the green from a state by putting, then that state must have value one less than the green's value, that is, -2 . For simplicity, let us assume we can putt very precisely and deterministically, but with a limited range. This gives us the sharp contour line labeled -2 in the figure; all locations between that line and the green require exactly two strokes to complete the hole. Similarly, any location within putting range of the -2 contour line must have a value of -3 , and so on to get all the contour lines shown in the figure. Putting doesn't get us out of sand traps, so they have a value of $-\infty$. Overall, it takes us six strokes to get from the tee to the hole by putting. ■

Exercise 3.8 What is the Bellman equation for action values, that is, for Q^π ? It must give the action value $Q^\pi(s, a)$ in terms of the action values, $Q^\pi(s', a')$, of possible successors to the state-action pair (s, a) . As a hint, the backup diagram corresponding to this equation is given in Figure 3.4b. Show the sequence of equations analogous to (3.10), but for action values.

Exercise 3.9 The Bellman equation (3.10) must hold for each state for the value function V^π shown in Figure 3.5b. As an example, show numerically that this equation holds for the center state, valued at $+0.7$, with respect to its four neighboring states, valued at $+2.3$, $+0.4$, -0.4 , and $+0.7$. (These numbers are accurate only to one decimal place.)

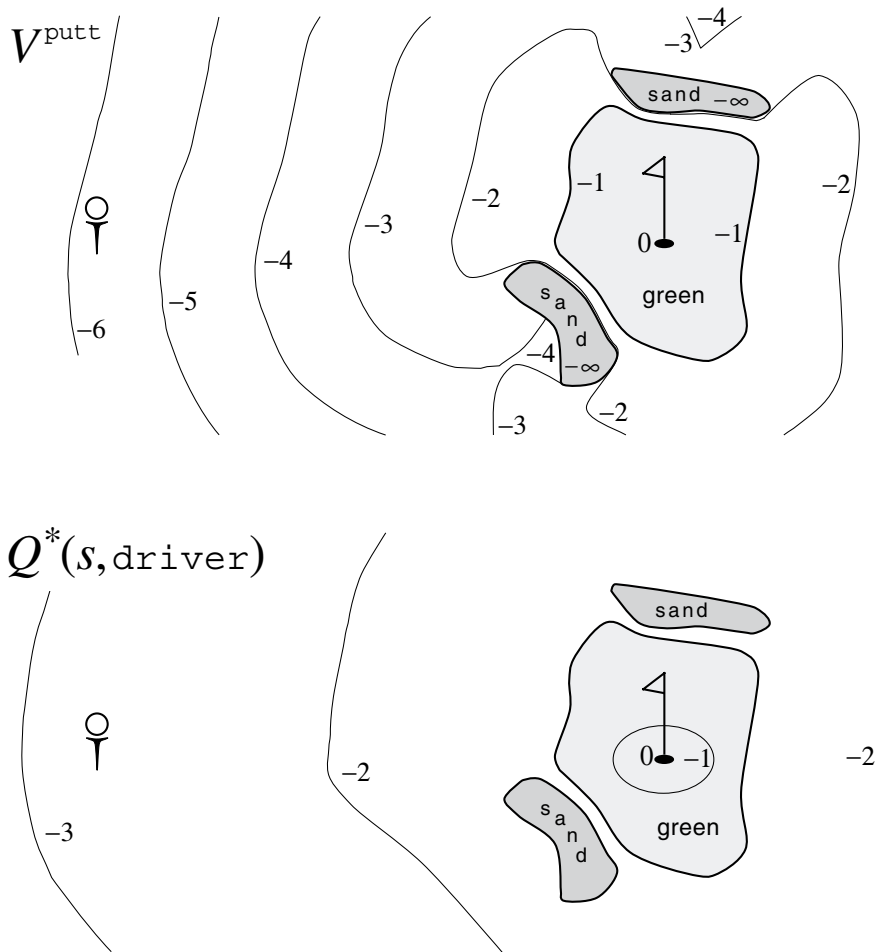
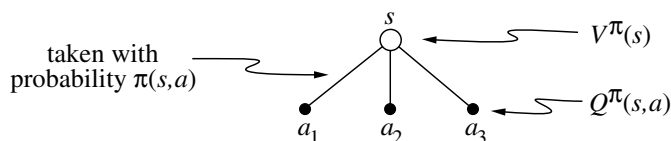


Figure 3.6 A golf example: the state-value function for using the putter (above) and the optimal action-value function for using the driver (below).

Exercise 3.10 In the gridworld example, rewards are positive for goals, negative for running into the edge of the world, and zero the rest of the time. Are the signs of these rewards important, or only the intervals between them? Prove, using (3.2), that adding a constant C to all the rewards adds a constant, K , to the values of all states, and thus does not affect the relative values of any states under any policies. What is K in terms of C and γ ?

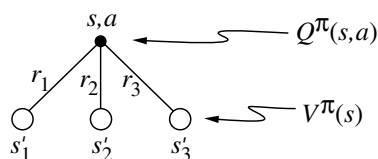
Exercise 3.11 Now consider adding a constant C to all the rewards in an *episodic* task, such as maze running. Would this have any effect, or would it leave the task unchanged as in the continuing task above? Why or why not? Give an example.

Exercise 3.12 The value of a state depends on the values of the actions possible in that state and on how likely each action is to be taken under the current policy. We can think of this in terms of a small backup diagram rooted at the state and considering each possible action:



Give the equation corresponding to this intuition and diagram for the value at the root node, $V^\pi(s)$, in terms of the value at the expected leaf node, $Q^\pi(s_t, a_t)$, given $s_t = s$. This expectation depends on the policy, π . Then give a second equation in which the expected value is written out explicitly in terms of $\pi(s, a)$ such that no expected value notation appears in the equation.

Exercise 3.13 The value of an action, $Q^\pi(s, a)$, can be divided into two parts, the expected next reward, which does not depend on the policy π , and the expected sum of the remaining rewards, which depends on the next state and the policy. Again we can think of this in terms of a small backup diagram, this one rooted at an action (state–action pair) and branching to the possible next states:



Give the equation corresponding to this intuition and diagram for the action value, $Q^\pi(s, a)$, in terms of the expected next reward, r_{t+1} , and the expected next state value, $V^\pi(s_{t+1})$, given that $s_t = s$ and $a_t = a$. Then give a second equation, writing

out the expected value explicitly in terms of $\mathcal{P}_{ss'}^a$ and $\mathcal{R}_{ss'}^a$, defined respectively by (3.6) and (3.7), such that no expected value notation appears in the equation.

3.8 Optimal Value Functions

Solving a reinforcement learning task means, roughly, finding a policy that achieves a lot of reward over the long run. For finite MDPs, we can precisely define an optimal policy in the following way. Value functions define a partial ordering over policies. A policy π is defined to be better than or equal to a policy π' if its expected return is greater than or equal to that of π' for all states. In other words, $\pi \geq \pi'$ if and only if $V^\pi(s) \geq V^{\pi'}(s)$ for all $s \in \mathcal{S}$. There is always at least one policy that is better than or equal to all other policies. This is an *optimal policy*. Although there may be more than one, we denote all the optimal policies by π^* . They share the same state-value function, called the *optimal state-value function*, denoted V^* , and defined as

$$V^*(s) = \max_{\pi} V^{\pi}(s), \quad (3.11)$$

for all $s \in \mathcal{S}$.

Optimal policies also share the same *optimal action-value function*, denoted Q^* , and defined as

$$Q^*(s, a) = \max_{\pi} Q^{\pi}(s, a), \quad (3.12)$$

for all $s \in \mathcal{S}$ and $a \in \mathcal{A}(s)$. For the state–action pair (s, a) , this function gives the expected return for taking action a in state s and thereafter following an optimal policy. Thus, we can write Q^* in terms of V^* as follows:

$$Q^*(s, a) = E\{r_{t+1} + \gamma V^*(s_{t+1}) \mid s_t = s, a_t = a\}. \quad (3.13)$$

Example 3.10: Optimal Value Functions for Golf The lower part of Figure 3.6 shows the contours of a possible optimal action-value function $Q^*(s, \text{driver})$. These are the values of each state if we first play a stroke with the driver and afterward select either the driver or the putter, whichever is better. The driver enables us to hit the ball farther, but with less accuracy. We can reach the hole in one shot using the driver only if we are already very close; thus the -1 contour for $Q^*(s, \text{driver})$ covers only a small portion of the green. If we have two strokes, however, then we can reach the hole from much farther away, as shown by the -2 contour. In this case we don't have to drive all the way to within the small -1 contour, but only to anywhere on the green; from there we can use the putter. The optimal action-value function gives

the values after committing to a particular *first* action, in this case, to the driver, but afterward using whichever actions are best. The -3 contour is still farther out and includes the starting tee. From the tee, the best sequence of actions is two drives and one putt, sinking the ball in three strokes. ■

Because V^* is the value function for a policy, it must satisfy the self-consistency condition given by the Bellman equation for state values (3.10). Because it is the optimal value function, however, V^* 's consistency condition can be written in a special form without reference to any specific policy. This is the Bellman equation for V^* , or the *Bellman optimality equation*. Intuitively, the Bellman optimality equation expresses the fact that the value of a state under an optimal policy must equal the expected return for the best action from that state:

$$\begin{aligned}
 V^*(s) &= \max_{a \in \mathcal{A}(s)} Q^{\pi^*}(s, a) \\
 &= \max_a E_{\pi^*} \{ R_t \mid s_t = s, a_t = a \} \\
 &= \max_a E_{\pi^*} \left\{ \sum_{k=0}^{\infty} \gamma^k r_{t+k+1} \mid s_t = s, a_t = a \right\} \\
 &= \max_a E_{\pi^*} \left\{ r_{t+1} + \gamma \sum_{k=0}^{\infty} \gamma^k r_{t+k+2} \mid s_t = s, a_t = a \right\} \\
 &= \max_a E \{ r_{t+1} + \gamma V^*(s_{t+1}) \mid s_t = s, a_t = a \} \tag{3.14}
 \end{aligned}$$

$$= \max_a \sum_{s'} \mathcal{P}_{ss'}^a [\mathcal{R}_{ss'}^a + \gamma V^*(s')] . \tag{3.15}$$

The last two equations are two forms of the Bellman optimality equation for V^* . The Bellman optimality equation for Q^* is

$$\begin{aligned}
 Q^*(s, a) &= E \{ r_{t+1} + \gamma \max_{a'} Q^*(s_{t+1}, a') \mid s_t = s, a_t = a \} \\
 &= \sum_{s'} \mathcal{P}_{ss'}^a \left[\mathcal{R}_{ss'}^a + \gamma \max_{a'} Q^*(s', a') \right] .
 \end{aligned}$$

The backup diagrams in Figure 3.7 show graphically the spans of future states and actions considered in the Bellman optimality equations for V^* and Q^* . These are

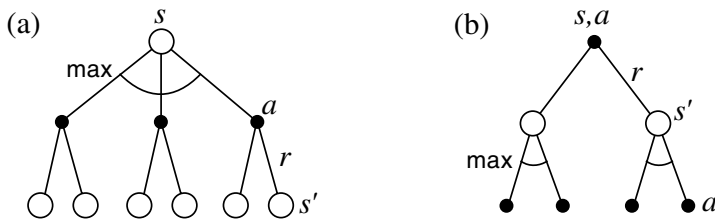


Figure 3.7 Backup diagrams for (a) V^* and (b) Q^*

the same as the backup diagrams for V^π and Q^π except that arcs have been added at the agent's choice points to represent that the maximum over that choice is taken rather than the expected value given some policy. Figure 3.7a graphically represents the Bellman optimality equation (3.15).

For finite MDPs, the Bellman optimality equation (3.15) has a unique solution independent of the policy. The Bellman optimality equation is actually a system of equations, one for each state, so if there are N states, then there are N equations in N unknowns. If the dynamics of the environment are known ($\mathcal{R}_{ss'}^a$ and $\mathcal{P}_{ss'}^a$), then in principle one can solve this system of equations for V^* using any one of a variety of methods for solving systems of nonlinear equations. One can solve a related set of equations for Q^* .

Once one has V^* , it is relatively easy to determine an optimal policy. For each state s , there will be one or more actions at which the maximum is attained in the Bellman optimality equation. Any policy that assigns nonzero probability only to these actions is an optimal policy. You can think of this as a one-step search. If you have the optimal value function, V^* , then the actions that appear best after a one-step search will be optimal actions. Another way of saying this is that any policy that is *greedy* with respect to the optimal value function V^* is an optimal policy. The term *greedy* is used in computer science to describe any search or decision procedure that selects alternatives based only on local or immediate considerations, without considering the possibility that such a selection may prevent future access to even better alternatives. Consequently, it describes policies that select actions based only on their short-term consequences. The beauty of V^* is that if one uses it to evaluate the short-term consequences of actions—specifically, the one-step consequences—then a greedy policy is actually optimal in the long-term sense in which we are interested because V^* already takes into account the reward consequences of all possible future behavior. By means of V^* , the optimal expected long-term return is turned into a quantity that is locally and immediately

available for each state. Hence, a one-step-ahead search yields the long-term optimal actions.

Having Q^* makes choosing optimal actions still easier. With Q^* , the agent does not even have to do a one-step-ahead search: for any state s , it can simply find any action that maximizes $Q^*(s, a)$. The action-value function effectively caches the results of all one-step-ahead searches. It provides the optimal expected long-term return as a value that is locally and immediately available for each state–action pair. Hence, at the cost of representing a function of state–action pairs, instead of just of states, the optimal action-value function allows optimal actions to be selected without having to know anything about possible successor states and their values, that is, without having to know anything about the environment’s dynamics.

Example 3.11: Bellman Optimality Equations for the Recycling Robot Using (3.15), we can explicitly give the Bellman optimality equation for the recycling robot example. To make things more compact, we abbreviate the states `high` and `low`, and the actions `search`, `wait`, and `recharge` respectively by `h`, `l`, `s`, `w`, and `re`. Since there are only two states, the Bellman optimality equation consists of two equations. The equation for $V^*(h)$ can be written as follows:

$$\begin{aligned} V^*(h) &= \max \left\{ \begin{array}{l} \mathcal{P}_{hh}^s[\mathcal{R}_{hh}^s + \gamma V^*(h)] + \mathcal{P}_{hl}^s[\mathcal{R}_{hl}^s + \gamma V^*(l)], \\ \mathcal{P}_{hh}^w[\mathcal{R}_{hh}^w + \gamma V^*(h)] + \mathcal{P}_{hl}^w[\mathcal{R}_{hl}^w + \gamma V^*(l)] \end{array} \right\} \\ &= \max \left\{ \begin{array}{l} \alpha[\mathcal{R}^s + \gamma V^*(h)] + (1 - \alpha)[\mathcal{R}^s + \gamma V^*(h)], \\ 1[\mathcal{R}^w + \gamma V^*(h)] + 0[\mathcal{R}^w + \gamma V^*(l)] \end{array} \right\} \\ &= \max \left\{ \begin{array}{l} \mathcal{R}^s + \gamma[\alpha V^*(h) + (1 - \alpha)V^*(l)], \\ \mathcal{R}^w + \gamma V^*(h) \end{array} \right\}. \end{aligned}$$

Following the same procedure for $V^*(l)$ yields the equation

$$V^*(l) = \max \left\{ \begin{array}{l} \beta \mathcal{R}^s - 3(1 - \beta) + \gamma[(1 - \beta)V^*(h) + \beta V^*(l)], \\ \mathcal{R}^w + \gamma V^*(l), \\ \gamma V^*(h) \end{array} \right\}.$$

For any choice of \mathcal{R}^s , \mathcal{R}^w , α , β , and γ , with $0 \leq \gamma < 1$, $0 \leq \alpha, \beta \leq 1$, there is exactly one pair of numbers, $V^*(h)$ and $V^*(l)$, that simultaneously satisfy these two nonlinear equations. ■

Example 3.12: Solving the Gridworld Suppose we solve the Bellman optimality equation for V^* for the simple grid task introduced in Example 3.8 and shown again in Figure 3.8a. Recall that state **A** is followed by a reward of +10 and transition to

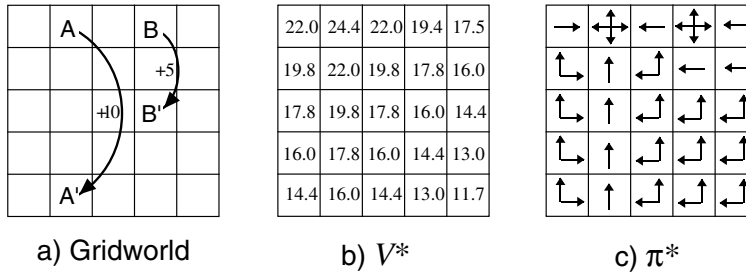


Figure 3.8 Optimal solutions to the gridworld example.

state A' , while state B is followed by a reward of $+5$ and transition to state B' . Figure 3.8b shows the optimal value function, and Figure 3.8c shows the corresponding optimal policies. Where there are multiple arrows in a cell, any of the corresponding actions is optimal. ■

Explicitly solving the Bellman optimality equation provides one route to finding an optimal policy, and thus to solving the reinforcement learning problem. However, this solution is rarely directly useful. It is akin to an exhaustive search, looking ahead at all possibilities, computing their probabilities of occurrence and their desirabilities in terms of expected rewards. This solution relies on at least three assumptions that are rarely true in practice: (1) we accurately know the dynamics of the environment; (2) we have enough computational resources to complete the computation of the solution; and (3) the Markov property. For the kinds of tasks in which we are interested, one is generally not able to implement this solution exactly because various combinations of these assumptions are violated. For example, although the first and third assumptions present no problems for the game of backgammon, the second is a major impediment. Since the game has about 10^{20} states, it would take millions of years on today's fastest computers to solve the Bellman equation for V^* , and the same is true for finding Q^* . In reinforcement learning one typically has to settle for approximate solutions.

Many different decision-making methods can be viewed as ways of approximately solving the Bellman optimality equation. For example, heuristic search methods can be viewed as expanding the right-hand side of (3.15) several times, up to some depth, forming a “tree” of possibilities, and then using a heuristic evaluation function to approximate V^* at the “leaf” nodes. (Heuristic search methods such as A^* are almost always based on the episodic case.) The methods of dynamic programming can be related even more closely to the Bellman optimality equation. Many reinforcement

learning methods can be clearly understood as approximately solving the Bellman optimality equation, using actual experienced transitions in place of knowledge of the expected transitions. We consider a variety of such methods in the following chapters.

Exercise 3.14 Draw or describe the optimal state-value function for the golf example.

Exercise 3.15 Draw or describe the contours of the optimal action-value function for putting, $Q^*(s, \text{putter})$, for the golf example.

Exercise 3.16 Give the Bellman equation for Q^* for the recycling robot.

Exercise 3.17 Figure 3.8 gives the optimal value of the best state of the gridworld as 24.4, to one decimal place. Use your knowledge of the optimal policy and (3.2) to express this value symbolically, and then to compute it to three decimal places.

3.9 Optimality and Approximation

We have defined optimal value functions and optimal policies. Clearly, an agent that learns an optimal policy has done very well, but in practice this rarely happens. For the kinds of tasks in which we are interested, optimal policies can be generated only with extreme computational cost. A well-defined notion of optimality organizes the approach to learning we describe in this book and provides a way to understand the theoretical properties of various learning algorithms, but it is an ideal that agents can only approximate to varying degrees. As we discussed above, even if we have a complete and accurate model of the environment's dynamics, it is usually not possible to simply compute an optimal policy by solving the Bellman optimality equation. For example, board games such as chess are a tiny fraction of human experience, yet large, custom-designed computers still cannot compute the optimal moves. A critical aspect of the problem facing the agent is always the computational power available to it, in particular, the amount of computation it can perform in a single time step.

The memory available is also an important constraint. A large amount of memory is often required to build up approximations of value functions, policies, and models. In tasks with small, finite state sets, it is possible to form these approximations using arrays or tables with one entry for each state (or state–action pair). This we call the *tabular* case, and the corresponding methods we call tabular methods. In many cases of practical interest, however, there are far more states than could possibly be entries

in a table. In these cases the functions must be approximated, using some sort of more compact parameterized function representation.

Our framing of the reinforcement learning problem forces us to settle for approximations. However, it also presents us with some unique opportunities for achieving useful approximations. For example, in approximating optimal behavior, there may be many states that the agent faces with such a low probability that selecting suboptimal actions for them has little impact on the amount of reward the agent receives. Tesauro's backgammon player, for example, plays with exceptional skill even though it might make very bad decisions on board configurations that never occur in games against experts. In fact, it is possible that TD-Gammon makes bad decisions for a large fraction of the game's state set. The on-line nature of reinforcement learning makes it possible to approximate optimal policies in ways that put more effort into learning to make good decisions for frequently encountered states, at the expense of less effort for infrequently encountered states. This is one key property that distinguishes reinforcement learning from other approaches to approximately solving MDPs.

3.10 Summary

Let us summarize the elements of the reinforcement learning problem that we have presented in this chapter. Reinforcement learning is about learning from interaction how to behave in order to achieve a goal. The reinforcement learning *agent* and its *environment* interact over a sequence of discrete time steps. The specification of their interface defines a particular task: the *actions* are the choices made by the agent; the *states* are the basis for making the choices; and the *rewards* are the basis for evaluating the choices. Everything inside the agent is completely known and controllable by the agent; everything outside is incompletely controllable but may or may not be completely known. A *policy* is a stochastic rule by which the agent selects actions as a function of states. The agent's objective is to maximize the amount of reward it receives over time.

The *return* is the function of future rewards that the agent seeks to maximize. It has several different definitions depending upon the nature of the task and whether one wishes to *discount* delayed reward. The undiscounted formulation is appropriate for *episodic tasks*, in which the agent–environment interaction breaks naturally into *episodes*; the discounted formulation is appropriate for *continuing tasks*, in which the interaction does not naturally break into episodes but continues without limit.

An environment satisfies the *Markov property* if its state signal compactly summarizes the past without degrading the ability to predict the future. This is rarely exactly true, but often nearly so; the state signal should be chosen or constructed so that the Markov property holds as nearly as possible. In this book we assume that this has already been done and focus on the decision-making problem: how to decide what to do as a function of whatever state signal is available. If the Markov property does hold, then the environment defines a *Markov decision process* (MDP). A *finite MDP* is an MDP with finite state and action sets. Most of the current theory of reinforcement learning is restricted to finite MDPs, but the methods and ideas apply more generally.

A policy's *value functions* assign to each state, or state–action pair, the expected return from that state, or state–action pair, given that the agent uses the policy. The *optimal value functions* assign to each state, or state–action pair, the largest expected return achievable by any policy. A policy whose value functions are optimal is an *optimal policy*. Whereas the optimal value functions for states and state–action pairs are unique for a given MDP, there can be many optimal policies. Any policy that is *greedy* with respect to the optimal value functions must be an optimal policy. The *Bellman optimality equations* are special consistency conditions that the optimal value functions must satisfy and that can, in principle, be solved for the optimal value functions, from which an optimal policy can be determined with relative ease.

A reinforcement learning problem can be posed in a variety of different ways depending on assumptions about the level of knowledge initially available to the agent. In problems of *complete knowledge*, the agent has a complete and accurate model of the environment's dynamics. If the environment is an MDP, then such a model consists of the one-step *transition probabilities* and *expected rewards* for all states and their allowable actions. In problems of *incomplete knowledge*, a complete and perfect model of the environment is not available.

Even if the agent has a complete and accurate environment model, the agent is typically unable to perform enough computation per time step to fully use it. The memory available is also an important constraint. Memory may be required to build up accurate approximations of value functions, policies, and models. In most cases of practical interest there are far more states than could possibly be entries in a table, and approximations must be made.

A well-defined notion of optimality organizes the approach to learning we describe in this book and provides a way to understand the theoretical properties of various learning algorithms, but it is an ideal that reinforcement learning agents can only approximate to varying degrees. In reinforcement learning we are very much concerned with cases in which optimal solutions cannot be found but must be approximated in some way.

3.11 Bibliographical and Historical Remarks

The reinforcement learning problem is deeply indebted to the idea of Markov decision processes (MDPs) from the field of optimal control. These historical influences and other major influences from psychology are described in the brief history given in Chapter 1. Reinforcement learning adds to MDPs a focus on approximation and incomplete information for realistically large problems. MDPs and the reinforcement learning problem are only weakly linked to traditional learning and decision-making problems in artificial intelligence. However, artificial intelligence is now vigorously exploring MDP formulations for planning and decision-making from a variety of perspectives. MDPs are more general than previous formulations used in artificial intelligence in that they permit more general kinds of goals and uncertainty.

Our presentation of the reinforcement learning problem was influenced by Watkins (1989).

3.1 The bioreactor example is based on the work of Ungar (1990) and Miller and Williams (1992). The recycling robot example was inspired by the can-collecting robot built by Jonathan Connell (1989).

3.3–4 The terminology of *episodic* and *continuing* tasks is different from that usually used in the MDP literature. In that literature it is common to distinguish three types of tasks: (1) finite-horizon tasks, in which interaction terminates after a particular *fixed* number of time steps; (2) indefinite-horizon tasks, in which interaction can last arbitrarily long but must eventually terminate; and (3) infinite-horizon tasks, in which interaction does not terminate. Our episodic and continuing tasks are similar to indefinite-horizon and infinite-horizon tasks, respectively, but we prefer to emphasize the difference in the nature of the interaction. This difference seems more fundamental than the difference in the objective functions emphasized by the usual terms. Often episodic tasks use an indefinite-horizon objective function and continuing tasks an infinite-horizon objective function, but we see this as a common coincidence rather than a fundamental difference.

The pole-balancing example is from Michie and Chambers (1968) and Barto, Sutton, and Anderson (1983).

3.5 For further discussion of the concept of state, see Minsky (1967).

3.6 The theory of MDPs is treated by, e.g., Bertsekas (1995), Ross (1983), White (1969), and Whittle (1982, 1983). This theory is also studied under the heading of stochastic optimal control, where *adaptive* optimal control methods are most closely related to reinforcement learning (e.g., Kumar, 1985; Kumar and Varaiya, 1986).

The theory of MDPs evolved from efforts to understand the problem of making sequences of decisions under uncertainty, where each decision can depend on the previous decisions and their outcomes. It is sometimes called the theory of multistage decision processes, or sequential decision processes, and has roots in the statistical literature on sequential sampling beginning with the papers by Thompson (1933, 1934) and Robbins (1952) that we cited in Chapter 2 in connection with bandit problems (which are prototypical MDPs if formulated as multiple-situation problems).

The earliest instance of which we are aware in which reinforcement learning was discussed using the MDP formalism is Andreae's (1969b) description of a unified view of learning machines. Witten and Corbin (1973) experimented with a reinforcement learning system later analyzed by Witten (1977) using the MDP formalism. Although he did not explicitly mention MDPs, Werbos (1977) suggested approximate solution methods for stochastic optimal control problems that are related to modern reinforcement learning methods (see also Werbos, 1982, 1987, 1988, 1989, 1992). Although Werbos's ideas were not widely recognized at the time, they were prescient in emphasizing the importance of approximately solving optimal control problems in a variety of domains, including artificial intelligence. The most influential integration of reinforcement learning and MDPs is due to Watkins (1989). His treatment of reinforcement learning using the MDP formalism has been widely adopted.

Our characterization of the reward dynamics of an MDP in terms of $\mathcal{R}_{ss'}^a$ is slightly unusual. It is more common in the MDP literature to describe the reward dynamics in terms of the expected next reward given just the current state and action, that is, by $\mathcal{R}_s^a = E\{r_{t+1}|s_t = s, a_t = a\}$. This quantity is related to our $\mathcal{R}_{ss'}^a$ as follows:

$$\mathcal{R}_s^a = \sum_{s'} \mathcal{P}_{ss'}^a \mathcal{R}_{ss'}^a.$$

In conventional MDP theory, $\mathcal{R}_{ss'}^a$ always appears in a sum like this one, and therefore it is easier to use \mathcal{R}_s^a . In reinforcement learning, however, we more often have to refer to individual actual or sample outcomes. In teaching reinforcement learning, we have found the $\mathcal{R}_{ss'}^a$ notation to be more straightforward conceptually and easier to understand.

3.7–8 Assigning value on the basis of what is good or bad in the long run has ancient roots. In control theory, mapping states to numerical values representing the long-term consequences of control decisions is a key part of optimal control theory, which was developed in the 1950s by extending nineteenth century state-function theories of classical mechanics (see, e.g., Schultz and Melsa, 1967). In describing how a computer could be programmed to play chess, Shannon (1950) suggested using an evaluation function that took into account the long-term advantages and disadvantages of chess positions.

Watkins's (1989) Q-learning algorithm for estimating Q^* (Chapter 6) made action-value functions an important part of reinforcement learning, and consequently these functions are often called *Q-functions*. But the idea of an action-value function is much older than this. Shannon (1950) suggested that a function $h(P, M)$ could be used by a chess-playing program to decide whether a move M in position P is worth exploring. Michie's (1961, 1963) MENACE system and Michie and Chambers's (1968) BOXES system can be understood as estimating action-value functions. In classical physics, Hamilton's principal function is an action-value function; Newtonian dynamics are greedy with respect to this function (e.g., Goldstein, 1957). Action-value functions also played a central role in Denardo's (1967) theoretical treatment of DP in terms of contraction mappings.

What we call the Bellman optimality equation for V^* was first introduced by Richard Bellman (1957a), who called it the “basic functional equation.” The counterpart of the Bellman optimality equation for continuous time and state problems is known as the Hamilton–Jacobi–Bellman equation (or often just the Hamilton–Jacobi equation), indicating its roots in classical physics (e.g., Schultz and Melsa, 1967).

The golf example was suggested by Chris Watkins.