UNIT-VI

Temporal-Difference (TD) Learning: TD Prediction, Advantages of TD Prediction Methods, Optimality of TD (0), Sarsa: On-Policy TD Control, Q-Learning: Off-Policy TD Control, Games, Afterstates, and Other Special Cases.

1.TD Prediction

- Both TD and Monte Carlo methods use experience to solve the prediction problem.
- Given some experience following a policy _, both methods update their estimate v of v_ for the nonterminal states St occurring in that experience.
- Roughly speaking, Monte Carlo methods wait until the return following the visit is known, then use that return as a target for V (St).
- A simple every-visit Monte Carlo method suitable for nonstationary environments is

$$V(S_t) \leftarrow V(S_t) + \alpha\Big[G_t - V(S_t)\Big], \qquad (6.1)$$

- where Gt is the actual return following time t, and α is a constant stepsize parameter (c.f., Equation 2.4).
- Let us call this method constant-α MC.
- Whereas Monte Carlo methods must wait until the end of the episode to determine the increment to V (St) (only then is Gt known), TD methods need wait only until the next time step.
- At time t+1 they immediately form a target and make a useful update using the observed reward Rt+1 and the estimate V (St+1).
- The simplest TD method, known as TD(0), is

$$V(S_t) \leftarrow V(S_t) + \alpha\Big[R_{t+1} + \gamma V(S_{t+1}) - V(S_t)\Big]. \qquad (6.2)$$

In effect, the target for the Monte Carlo update is G_t, whereas the target for the TD update is $R_{t+1} + \gamma V(S_{t+1})$.

Because the TD method bases its update in part on an existing estimate, we say that it is a *bootstrapping* method, like DP. We know from Chapter 3 that

$$\begin{aligned} v_\pi(s) &= \mathbb{E}_\pi[G_t \mid S_t = s] && (6.3)\\ &= \mathbb{E}_\pi\Big[\sum_{k=0}^{\infty} \gamma^k R_{t+k+1} \,\Big|\, S_t = s\Big] \\ &= \mathbb{E}_\pi\Big[R_{t+1} + \gamma \sum_{k=0}^{\infty} \gamma^k R_{t+k+2} \,\Big|\, S_t = s\Big] \\ &= \mathbb{E}_\pi[R_{t+1} + \gamma v_\pi(S_{t+1}) \mid S_t = s]. && (6.4) \end{aligned}$$

- Roughly speaking, Monte Carlo methods use an estimate of (6.3) as a target, whereas DP methods use an estimate of (6.4) as a target.
- The Monte Carlo target is an estimate because the expected value in (6.3) is not known; a sample return is used in place of the real expected return.

- The DP target is an estimate not because of the expected values, which are assumed to be completely provided by a model of the environment, but because vπ(St+1) is not known and the current estimate, V (St+1), is used instead.
- The TD target is an estimate for both reasons: it samples the expected values in (6.4) and it uses the current estimate V instead of the true vπ. Thus, TD methods combine the sampling of Monte Carlo with the bootstrapping of DP.
- As we shall see, with care and imagination this can take us a long way toward obtaining the advantages of both Monte Carlo and DP methods.
- Figure 6.1 specifies TD(0) completely in procedural form, and Figure 6.2 shows its backup diagram. The value estimate for the state node at the top of the backup diagram is updated on the basis of the one sample transition from it to the immediately following state.
- We refer to TD and Monte Carlo updates as sample backups because they involve looking ahead to a sample successor state (or state–action pair), using the value of the successor and the reward along the way to compute a backed-up value, and then changing the value of the original state (or state–action pair) accordingly.
- Sample backups differ from the full backups of DP methods in that they are based on a single sample successor rather than on a complete distribution of all possible successors.

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Input: the policy $\pi$ to be evaluated
Initialize $V(s)$ arbitrarily (e.g., $V(s) = 0, \forall s \in \mathcal{S}^+$)
Repeat (for each episode):
    Initialize $S$
    Repeat (for each step of episode):
        $A \leftarrow$ action given by $\pi$ for $S$
        Take action $A$; observe reward, $R$, and next state, $S'$
        $V(S) \leftarrow V(S) + \alpha[R + \gamma V(S') - V(S)]$
        $S \leftarrow S'$
    until $S$ is terminal
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Figure 6.1: Tabular TD(0) for estimating v_π.

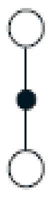


Figure 6.2: The backup diagram for TD(0).

2. Advantages of TD Prediction Methods

- TD methods learn their estimates in part on the basis of other estimates.
- They learn a guess from a guess—they bootstrap. Is this a good thing to do? What advantages do TD methods have over Monte Carlo and DP methods? Developing and answering such questions will take the rest of this book and more.
- Obviously, TD methods have an advantage over DP methods in that they do not require a model of the environment, of its reward and next-state probability distributions.
- The next most obvious advantage of TD methods over Monte Carlo methods is that they are naturally implemented in an on-line, fully incremental fashion.
- With Monte Carlo methods one must wait until the end of an episode, because only then is the return known, whereas with TD methods one need wait only one time step. Surprisingly often this turns out to be a critical consideration.
- Some applications have very long episodes, so that delaying all learning until an episode's end is too slow.
- Other applications are continuing tasks and have no episodes at all.
- Some Monte Carlo methods must ignore or discount episodes on which experimental actions are taken, which can greatly slow learning.
- TD methods are much less susceptible to these problems because they learn from each transition regardless of what subsequent actions are taken.
- But are TD methods sound? Certainly, it is convenient to learn one guess from the next, without waiting for an actual outcome, but can we still guarantee convergence to the correct answer? Happily, the answer is yes.
- For any fixed policy π, the TD algorithm described above has been proved to converge to vπ, in the mean for a constant step-size parameter if it is sufficiently small, and with probability 1 if the step-size parameter decreases according to the usual stochastic approximation conditions (2.7).
- If both TD and Monte Carlo methods converge asymptotically to the correct predictions, then a natural next question is "Which gets there first?" In other words, which method learns faster? Which makes the more efficient use of limited data? At the current time this is an open question in the sense that no one has been able to prove mathematically that one method converges faster than the other.
- In fact, it is not even clear what is the most appropriate formal way to phrase this question! In practice, however, TD methods have usually been found to converge faster than constant-α MC methods on stochastic tasks, as illustrated in the following example.

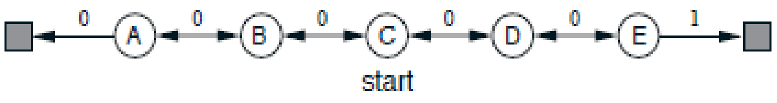


Figure 6.5: A small Markov process for generating random walks.

Example 6.2: Random Walk In this example we empirically compare the prediction abilities of TD(0) and constant-α MC applied to the small Markov process shown in Figure 6.5. All episodes start in the center state, C, and proceed either left or right by one state on each step, with equal probability. This behavior is presumably due to the combined effect of a fixed policy and an environment's state-transition probabilities, but we do not care which; we are concerned only with predicting returns however they are generated. Episodes terminate either on the extreme left or the extreme right. When an episode terminates on the right a reward of +1 occurs; all other rewards are zero. For example, a typical walk might consist of the following state-and-reward sequence: $\mathsf{C}, 0, \mathsf{B}, 0, \mathsf{C}, 0, \mathsf{D}, 0, \mathsf{E}, 1$. Because this task is undiscounted and episodic, the true value of each state is the probability of terminating on the right if starting from that state. Thus, the true value of the center state is $v_\pi(\mathsf{C}) = 0.5$. The true values of all the states, A through E, are $\frac{1}{6}, \frac{2}{6}, \frac{3}{6}, \frac{4}{6}$, and $\frac{5}{6}$. Figure 6.6 shows the values learned by TD(0) approaching the true values as more episodes are experienced. Averaging over many episode sequences, Figure 6.7 shows the average error in the predictions found by TD(0) and constant-α MC, for a variety of values of α, as a function of number of episodes. In all cases the approximate value function was initialized to the intermediate value $V(s) = 0.5$, for all s. The TD method is consistently better than the MC method on this task over this number of episodes.

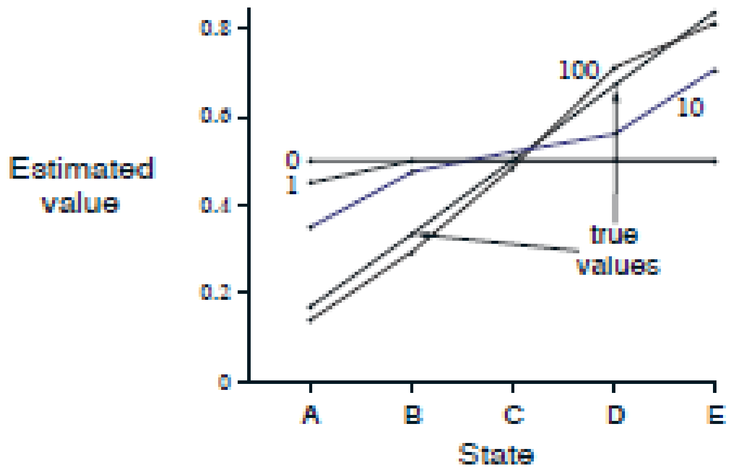


Figure 6.6: Values learned by TD(0) after various numbers of episodes. The final estimate is about as close as the estimates ever get to the true values. With a constant step-size parameter ($\alpha = 0.1$ in this example), the values fluctuate indefinitely in response to the outcomes of the most recent episodes.

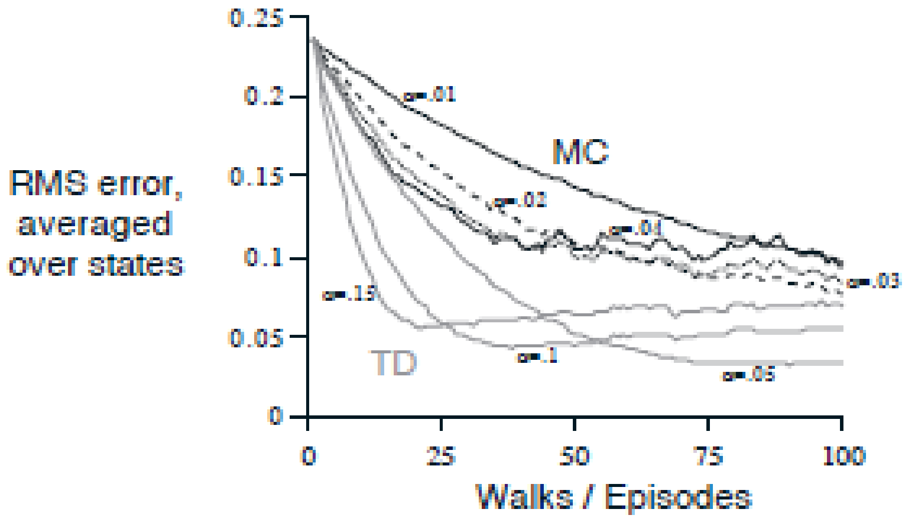


Figure 6.7: Learning curves for TD(0) and constant-α MC methods, for various values of α, on the prediction problem for the random walk. The performance measure shown is the root mean-squared (RMS) error between the value function learned and the true value function, averaged over the five states. These data are averages over 100 different sequences of episodes.

3. Optimality of TD (0)

- Suppose there is available only a finite amount of experience, say 10 episodes or 100 time steps.
- In this case, a common approach with incremental learning methods is to present the experience repeatedly until the method converges upon an answer.
- Given an approximate value function, V, the increments specified by (6.1) or (6.2) are computed for every time step t at which a nonterminal state is visited, but the value function is changed only once, by the sum of all the increments.
- Then all the available experience is processed again with the new value function to produce a new overall increment, and so on, until the value function converges.
- We call this batch updating because updates are made only after processing each complete batch of training data.
- Under batch updating, TD(0) converges deterministically to a single answer independent of the step-size parameter, α, as long as α is chosen to be sufficiently small.
- The constant-α MC method also converges deterministically under the same conditions, but to a different answer.
- Understanding these two answers will help us understand the difference between the two methods.
- Under normal updating the methods do not move all the way to their respective batch answers, but in some sense, they take steps in these directions.
- Before trying to understand the two answers in general, for all possible tasks, we first look at a few examples.

Example 6.3 Random walk under batch updating. Batch-updating versions of TD(0) and constant-α MC were applied as follows to the random walk prediction example (Example 6.2). After each new episode, all episodes seen so far were treated as a batch. They were repeatedly presented to the algorithm, either TD(0) or constant-α MC, with α sufficiently small that the value function converged. The resulting value function was then compared with vπ, and the average root mean-squared error across the five states (and across 100 independent repetitions of the whole experiment) was plotted to obtain the learning curves shown in Figure 6.8. Note that the batch TD method was consistently better than the batch Monte Carlo method.

Under batch training, constant-α MC converges to values, V (s), that are sample averages of the actual returns experienced after visiting each state s. These are optimal estimates in the sense that they minimize the mean-squared error from the actual returns in the training set. In this sense it is surprising that the batch TD method was able to perform better according to the root mean-squared error measure shown in Figure 6.8. How is it that batch TD was able to perform better than this optimal method? The answer is that the Monte Carlo method is optimal only in a limited way, and that TD is optimal in a way that is more relevant to predicting returns. But first let's develop our intuitions about different kinds of optimality through another example.

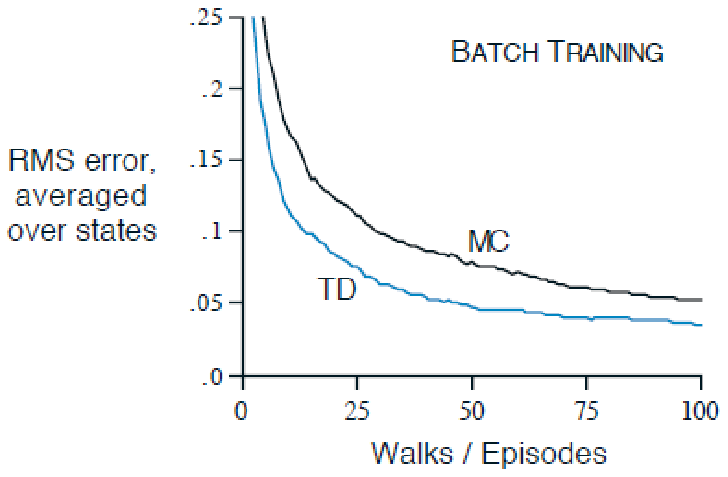
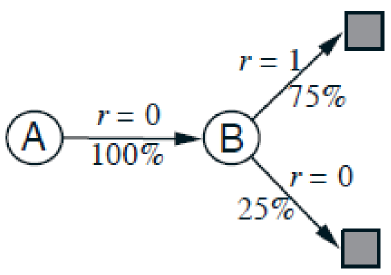
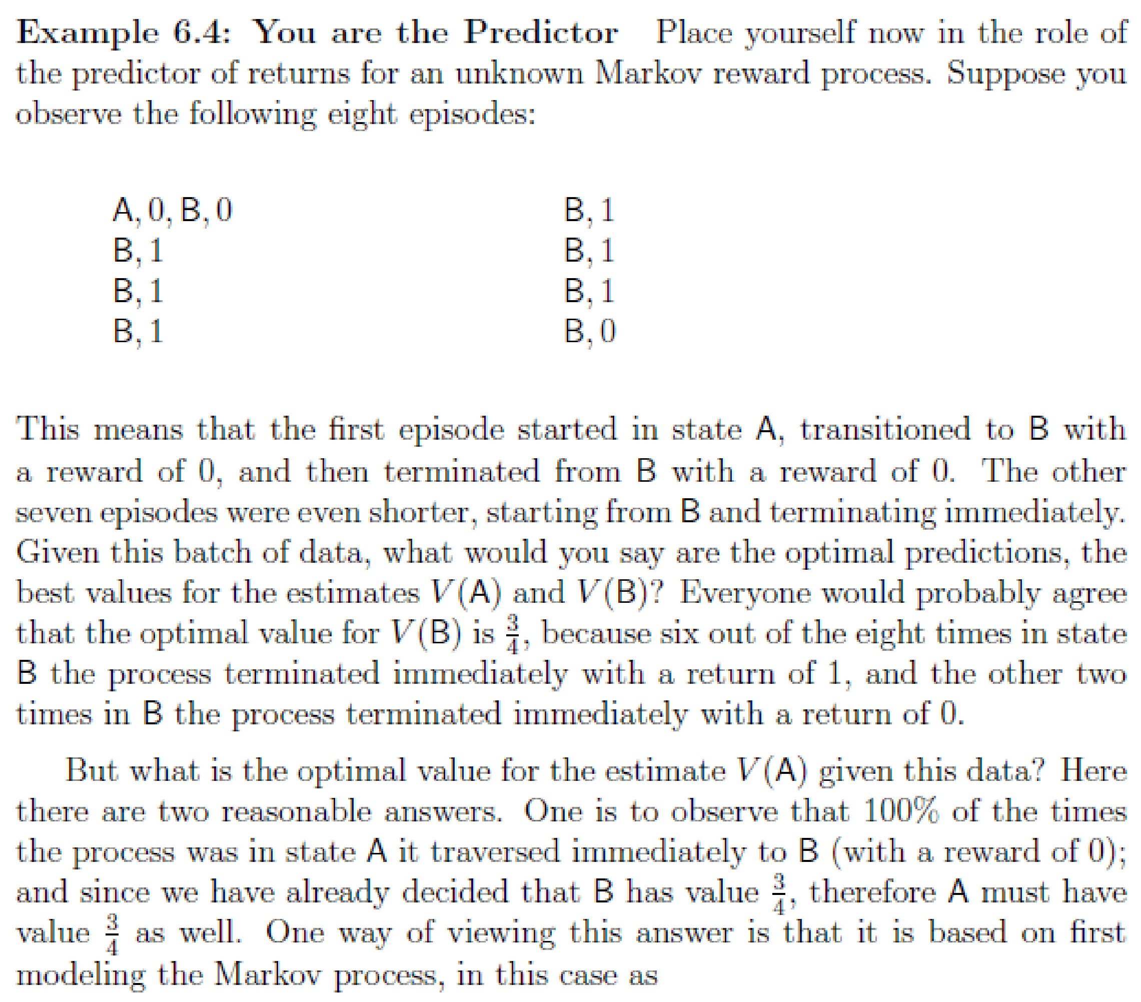


Figure 6.8: Performance of TD(0) and constant-α MC under batch training on the random walk task.



and then computing the correct estimates given the model, which indeed in this case gives $V(\mathsf{A}) = \frac{3}{4}$. This is also the answer that batch TD(0) gives.

The other reasonable answer is simply to observe that we have seen A once and the return that followed it was 0; we therefore estimate $V(\mathsf{A})$ as 0. This is the answer that batch Monte Carlo methods give. Notice that it is also the answer that gives minimum squared error on the training data. In fact, it gives zero error on the data. But still we expect the first answer to be better. If the process is Markov, we expect that the first answer will produce lower error on *future* data, even though the Monte Carlo answer is better on the existing data. ■



Example 6.4: You are the Predictor Place yourself now in the role of the predictor of returns for an unknown Markov reward process. Suppose you observe the following eight episodes:

A, 0, B, 0
B, 1
B, 1
B, 1
B, 1
B, 1
B, 1
B, 0

This means that the first episode started in state A, transitioned to B with a reward of 0, and then terminated from B with a reward of 0. The other seven episodes were even shorter, starting from B and terminating immediately. Given this batch of data, what would you say are the optimal predictions, the best values for the estimates $V(\mathsf{A})$ and $V(\mathsf{B})$? Everyone would probably agree that the optimal value for $V(\mathsf{B})$ is $\frac{3}{4}$, because six out of the eight times in state B the process terminated immediately with a return of 1, and the other two times in B the process terminated immediately with a return of 0.

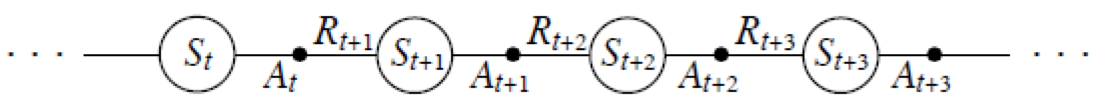
But what is the optimal value for the estimate $V(\mathsf{A})$ given this data? Here there are two reasonable answers. One is to observe that 100% of the times the process was in state A it traversed immediately to B (with a reward of 0); and since we have already decided that B has value $\frac{3}{4}$, therefore A must have value $\frac{3}{4}$ as well. One way of viewing this answer is that it is based on first modeling the Markov process, in this case as

- The above example illustrates a general difference between the estimates found by batch TD(0) and batch Monte Carlo methods.
- Batch Monte Carlo methods always find the estimates that minimize mean-squared error on the training set, whereas batch TD(0) always finds the estimates that would be exactly correct for the maximum-likelihood model of the Markov process.
- In general, the maximum-likelihood estimate of a parameter is the parameter value whose probability of generating the data is greatest.
- In this case, the maximum-likelihood estimate is the model of the Markov process formed in the obvious way from the observed episodes: the estimated transition probability from i to j is the fraction of observed transitions from i that went to j, and the associated expected reward is the average of the rewards observed on those transitions.
- Given this model, we can compute the estimate of the value function that would be exactly correct if the model were exactly correct.
- This is called the certainty-equivalence estimate because it is equivalent to assuming that the estimate of the underlying process was known with certainty rather than being approximated.

- In general, batch TD(0) converges to the certainty equivalence estimate.
- This helps explain why TD methods converge more quickly than Monte Carlo methods. In batch form, TD(0) is faster than Monte Carlo methods because it computes the true certainty-equivalence estimate.
- This explains the advantage of TD(0) shown in the batch results on the random walk task (Figure 6.8).
- The relationship to the certainty-equivalence estimate may also explain in part the speed advantage of nonbatch TD(0) (e.g., Figure 6.7).
- Although the nonbatch methods do not achieve either the certainty-equivalence or the minimum squared-error estimates, they can be understood as moving roughly in these directions. Nonbatch TD(0) may be faster than constant-α MC because it is moving toward a better estimate, even though it is not getting all the way there.
- At the current time nothing more definite can be said about the relative efficiency of on-line TD and Monte Carlo methods.
- Finally, it is worth noting that although the certainty-equivalence estimate is in some sense an optimal solution, it is almost never feasible to compute it directly.
- If N is the number of states, then just forming the maximum likelihood estimate of the process may require N2 memory, and computing the corresponding value function requires on the order of N3 computational steps if done conventionally.
- In these terms it is indeed striking that TD methods can approximate the same solution using memory no more than N and repeated computations over the training set.
- On tasks with large state spaces, TD methods may be the only feasible way of approximating the certainty equivalence solution.

4. Sarsa: On-Policy TD Control,

- We turn now to the use of TD prediction methods for the control problem. As usual, we follow the pattern of generalized policy iteration (GPI), only this time using TD methods for the evaluation or prediction part.
- As with Monte Carlo methods, we face the need to trade off exploration and exploitation, and again approaches fall into two main classes: on-policy and off-policy.
- In this section we present an on-policy TD control method.
- The first step is to learn an action-value function rather than a state-value function.
- In particular, for an on-policy method we must estimate qπ(s, a) for the current behaviour policy π and for all states s and actions a.
- This can be done using essentially the same TD method described above for learning vπ. Recall that an episode consists of an alternating sequence of states and state–action pairs:



- In the previous section we considered transitions from state to state and learned the values of states.
- Now we consider transitions from state–action pair to state–action pair, and learn the value of state–action pairs.
- Formally these cases are identical: they are both Markov chains with a reward process. The theorems assuring the convergence of state values under TD(0) also apply to the corresponding algorithm for action values:

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha\Big[R_{t+1} + \gamma Q(S_{t+1}, A_{t+1}) - Q(S_t, A_t)\Big]. \qquad (6.5)$$

- This update is done after every transition from a nonterminal state St . If St+1 is terminal, then Q(St+1, At+1) is defined as zero.
- This rule uses every element of the quintuple of events, (St , At , Rt+1, St+1, At+1), that make up a transition from one state–action pair to the next.
- This quintuple gives rise to the name Sarsa for the algorithm.
- It is straightforward to design an on-policy control algorithm based on the Sarsa prediction method.
- As in all on-policy methods, we continually estimate qπ for the behavior policy π, and at the same time change π toward greediness with respect to qπ.
- The general form of the Sarsa control algorithm is given in Figure 6.9.

```
Initialize $Q(s,a), \forall s \in \mathcal{S}, a \in \mathcal{A}(s)$, arbitrarily, and $Q(\textit{terminal-state}, \cdot) = 0$
Repeat (for each episode):
   Initialize $S$
   Choose $A$ from $S$ using policy derived from $Q$ (e.g., $\epsilon$-greedy)
   Repeat (for each step of episode):
      Take action $A$, observe $R$, $S'$
      Choose $A'$ from $S'$ using policy derived from $Q$ (e.g., $\epsilon$-greedy)
      $Q(S,A) \leftarrow Q(S,A) + \alpha[R + \gamma Q(S',A') - Q(S,A)]$
      $S \leftarrow S'$; $A \leftarrow A'$;
   until $S$ is terminal
```

Figure 6.9: Sarsa: An on-policy TD control algorithm.

- The convergence properties of the Sarsa algorithm depend on the nature of the policy's dependence on q.
- For example, one could use ε-greedy or ε soft policies.
- According to Satinder Singh (personal communication), Sarsa converges with probability 1 to an optimal policy and action-value function as long as all state–action pairs are visited an infinite number of times and the policy converges in the

limit to the greedy policy (which can be arranged, for example, with ε-greedy policies by setting $\varepsilon = 1/t$), but this result has not yet been published in the literature.

Example 6.5: Windy Gridworld Figure 6.10 shows a standard gridworld, with start and goal states, but with one difference: there is a crosswind upward through the middle of the grid. The actions are the standard four—up, down, right, and left—but in the middle region the resultant next states are shifted upward by a "wind," the strength of which varies from column to column. The strength of the wind is given below each column, in number of cells shifted upward. For example, if you are one cell to the right of the goal, then the action left takes you to the cell just above the goal. Let us treat this as an undiscounted episodic task, with constant rewards of −1 until the goal state is reached. Figure 6.11 shows the result of applying ε-greedy Sarsa to this task, with $\varepsilon = 0.1$, $\alpha = 0.5$, and the initial values $Q(s, a) = 0$ for all s, a. The increasing slope of the graph shows that the goal is reached more and more quickly over time. By 8000 time steps, the greedy policy (shown inset) was long since optimal; continued ε-greedy exploration kept the average episode length at about 17 steps, two more than the minimum of 15. Note that Monte Carlo methods cannot easily be used on this task because termination is not guaranteed for all policies. If a policy was ever found that caused the agent to stay in the same state, then the next episode would never end. Step-by-step learning methods such as Sarsa do not have this problem because they quickly learn during the episode that such policies are poor, and switch to something else.

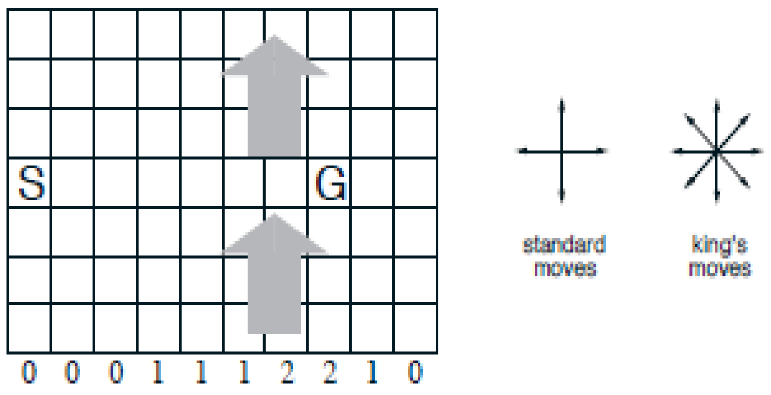


Figure 6.10: Gridworld in which movement is altered by a location-dependent, upward "wind."

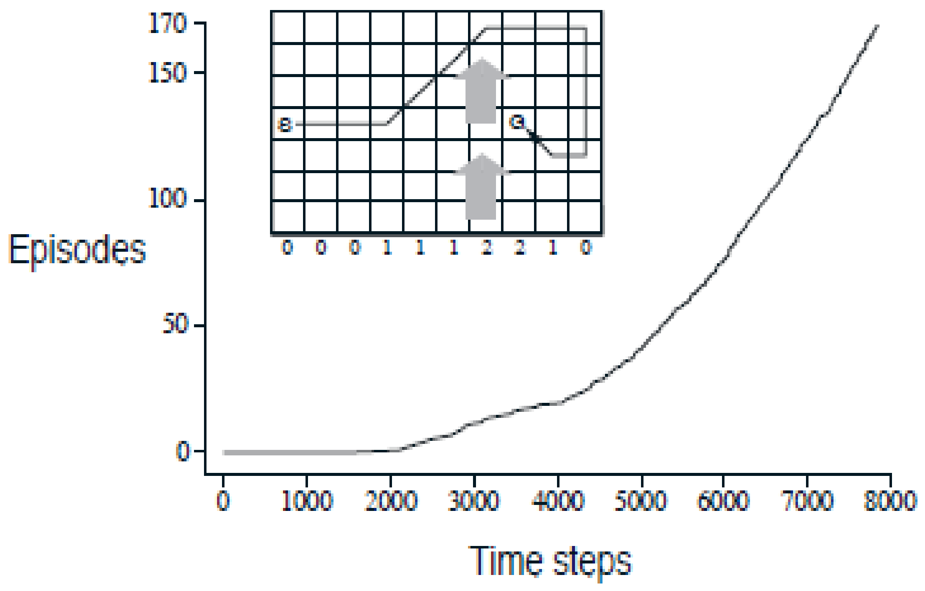


Figure 6.11: Results of Sarsa applied to the windy gridworld.

5. Q-Learning: Off-Policy TD Control

- One of the most important breakthroughs in reinforcement learning was the development of an off-policy TD control algorithm known as Q-learning (Watkins, 1989).
- Its simplest form, one-step Q-learning, is defined by

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha\Big[R_{t+1} + \gamma \max_a Q(S_{t+1}, a) - Q(S_t, A_t)\Big]. \quad (6.6)$$

- In this case, the learned action-value function, Q, directly approximates q∗, the optimal action-value function, independent of the policy being followed.
- This dramatically simplifies the analysis of the algorithm and enabled early convergence proofs.
- The policy still has an effect in that it determines which state–action pairs are visited and updated. However, all that is required for correct convergence is that all pairs continue to be updated.
- Under this assumption and a variant of the usual stochastic approximation conditions on the sequence of step-size parameters, Q has been shown to converge with probability 1 to q∗.
- The Q-learning algorithm is shown in procedural form in Figure 6.12.

```
Initialize $Q(s,a), \forall s \in \mathcal{S}, a \in \mathcal{A}(s)$, arbitrarily, and $Q(\textit{terminal-state}, \cdot) = 0$
Repeat (for each episode):
    Initialize $S$
    Repeat (for each step of episode):
        Choose $A$ from $S$ using policy derived from $Q$ (e.g., $\epsilon$-greedy)
        Take action $A$, observe $R$, $S'$
        $Q(S,A) \leftarrow Q(S,A) + \alpha[R + \gamma \max_a Q(S',a) - Q(S,A)]$
        $S \leftarrow S'$;
    until $S$ is terminal
```

Figure 6.12: Q-learning: An off-policy TD control algorithm.

- What is the backup diagram for Q-learning? The rule (6.6) updates a state–action pair, so the top node, the root of the backup, must be a small, filled action node.
- The backup is also from action nodes, maximizing over all those actions possible in the next state.

- Thus the bottom nodes of the backup diagram should be all these action nodes.
- Finally, remember that we indicate taking the maximum of these “next action” nodes with an arc across them (Figure 3.7). Can you guess now what the diagram is? If so, please do make a guess before turning to the answer in Figure 6.14.

Example 6.6: Cliff Walking This gridworld example compares Sarsa and Q-learning, highlighting the difference between on-policy (Sarsa) and offpolicy (Q-learning) methods. Consider the gridworld shown in the upper part of Figure 6.13. This is a standard undiscounted, episodic task, with start and goal states, and the usual actions causing movement up, down, right, and left. Reward is −1 on all transitions except those into the the region marked “The Cliff.” Stepping into this region incurs a reward of −100 and sends the agent instantly back to the start. The lower part of the figure shows the performance of the Sarsa and Q-learning methods with ε-greedy action selection, ε = 0.1. After an initial transient, Q-learning learns values for the optimal policy, that which travels right along the edge of the cliff. Unfortunately, this results in its occasionally falling off the cliff because of the ε-greedy action selection. Sarsa, on the other hand, takes the action selection into account and learns the longer but safer path through the upper part of the grid. Although Qlearning actually learns the values of the optimal policy, its on-line performance is worse than that of Sarsa, which learns the roundabout policy. Of course, if ε were gradually reduced, then both methods would asymptotically converge to the optimal policy.

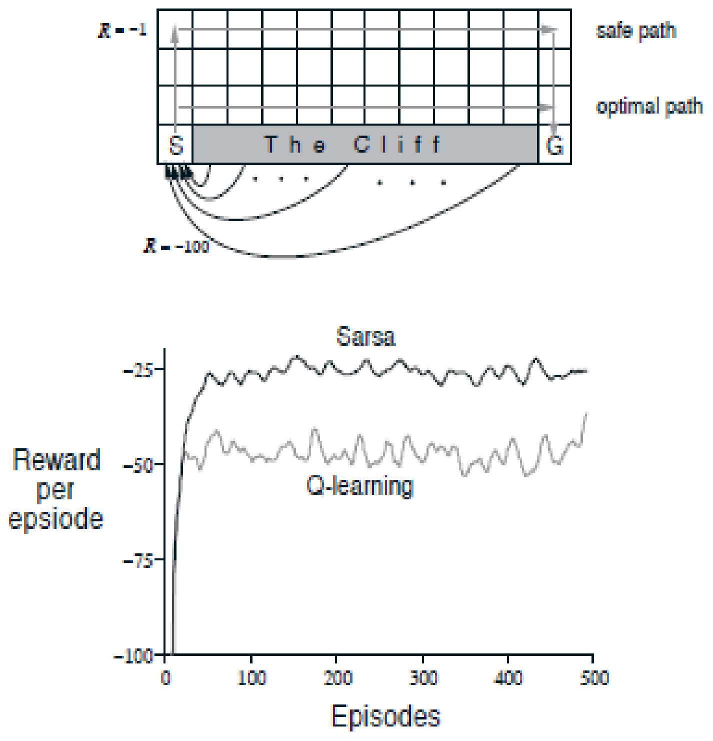


Figure 6.13: The cliff-walking task. The results are from a single run, but smoothed.

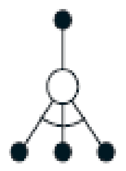
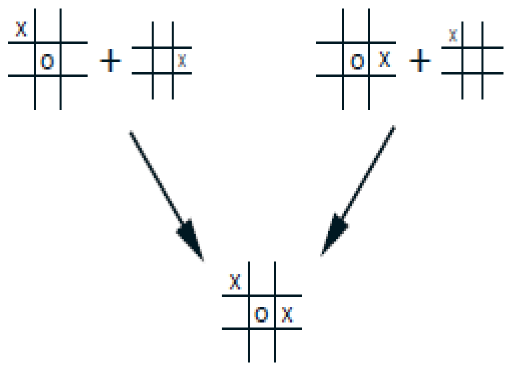


Figure 6.14: The backup diagram for Q-learning.

6. Games, Afterstates, and Other Special Cases.

- In this book we try to present a uniform approach to a wide class of tasks, but of course there are always exceptional tasks that are better treated in a specialized way.
- For example, our general approach involves learning an action-value function, but in Chapter 1 we presented a TD method for learning to play tic-tac-toe that learned something much more like a state-value function.
- If we look closely at that example, it becomes apparent that the function learned there is neither an action-value function nor a state-value function in the usual sense.
- A conventional state-value function evaluates states in which the agent has the option of selecting an action, but the state-value function used in tic-tac-toe evaluates board positions after the agent has made its move.
- Let us call these afterstates, and value functions over these, afterstate value functions. Afterstates are useful when we have knowledge of an initial part of the environment's dynamics but not necessarily of the full dynamics. For example, in games we typically know the immediate effects of our moves.
- We know for each possible chess move what the resulting position will be, but not how our opponent will reply.
- Afterstate value functions are a natural way to take advantage of this kind of knowledge and thereby produce a more efficient learning method.
- The reason it is more efficient to design algorithms in terms of afterstates is apparent from the tic-tac-toe example.
- A conventional action-value function would map from positions and moves to an estimate of the value.
- But many position–move pairs produce the same resulting position, as in this example:



In such cases the position–move pairs are different but produce the same "afterposition," and thus must have the same value.

- A conventional action-value function would have to separately assess both pairs, whereas an afterstate value function would immediately assess both equally.
- Any learning about the position–move pair on the left would immediately transfer to the pair on the right.
- Afterstates arise in many tasks, not just games.
- For example, in queuing tasks there are actions such as assigning customers to servers, rejecting customers, or discarding information.
- In such cases the actions are in fact defined in terms of their immediate effects, which are completely known.
- For example, in the access-control queuing example described in the previous section, a more efficient learning method could be obtained by breaking the environment's dynamics into the immediate effect of the action, which is deterministic and completely known, and the unknown random processes having to do with the arrival and departure of customers.
- The afterstates would be the number of free servers after the action but before the random processes had produced the next conventional state.
- Learning an afterstate value function over the afterstates would enable all actions that produced the same number of free servers to share experience.
- This should result in a significant reduction in learning time.
- It is impossible to describe all the possible kinds of specialized problems and corresponding specialized learning algorithms.
- However, the principles developed in this book should apply widely.
- For example, afterstate methods are still aptly described in terms of generalized policy iteration, with a policy and (afterstate) value function interacting in essentially the same way.
- In many cases one will still face the choice between on-policy and off-policy methods for managing the need for persistent exploration.