# An Introduction to Reinforcement Learning

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## Agenda

- What is Reinforcement Learning
- Markov Decision Processes
- Dynamic Programming
- Monte Carlo Methods
- Temporal Difference Learning
  - Sarsa
  - Q-learning
- More advanced approximation methods

# What is reinforcement learning

## Reinforcement Learning

- `Reinforcement learning` is learning what to do—how to map situations to actions to maximize a numerical reward signal.
- The learner is not told which actions to take, but instead must discover which actions yield the most reward by trying them.

## Core Concepts

- **`Agent`** is the learner and decision maker.
  - It interacts with the environment continually to select actions
  - The environment responds to these actions and presents new situations to the agent.
- A **`policy`** defines the learning agent's way of behaving at a given time.
  - A mapping from states of the environment to actions to be taken when in those states.
- The **`reward`** signal indicates what is good immediately after each decision time.
- A **`value function`** specifies what is good in the long run.
  - The value of a state is the total amount of reward an agent can expect to accumulate over the future, starting from that state.

# Markov Decision Processes (MDPs)

## Core definitions

- MDPs are a classical formalization of `sequential decision making` or reinforcement learning problem

- Actions taken now influence not only `immediate contributions` (e.g. reward, cost, profit), but also future situations (states), and consequently, `future contributions`
- MDPs involve delayed contribution and the need to trade off immediate and delayed contributions

## The agent–environment interaction in a decision process

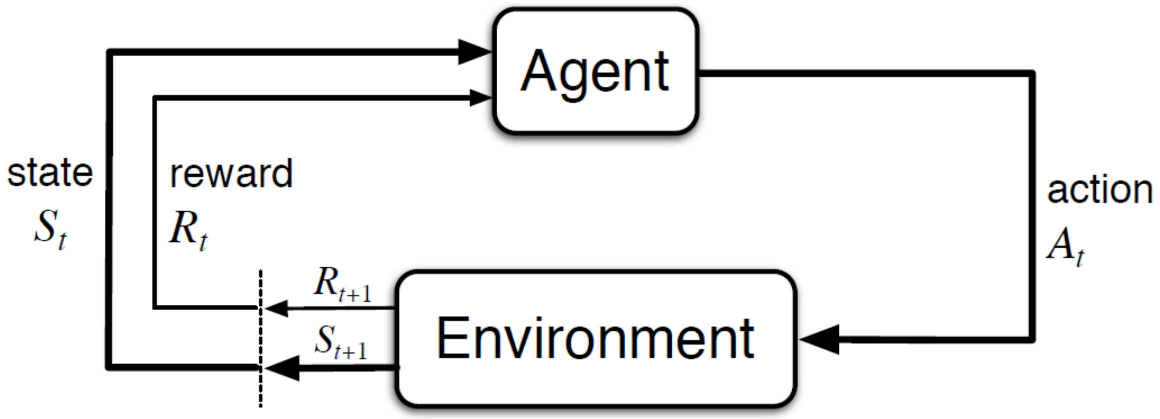


Figure 1: The agent–environment interaction in a decision process

Agent gives rise to a `sequence` that begins like this

$$S_0, A_0, R_1, S_1, A_1, R_2, S_2, A_2, R_3, ...S_t, A_t, R_{t+1}$$

## The agent–environment interaction in a decision process (continued)

- An MDP can be described by the tuple $(S, A, p, r(a, s), \pi)$, where:
  - $S$ is a finite set of states,
  - $A$ is a finite set of actions,
  - $p(s', r \mid s, a)$ is the probability of transitioning to state $s' \in S$ and receiving reward $r(a, s)$ when taking action $a \in A$ in state $s \in S$,
  - $r(s, a)$ is the expected immediate reward received after taking action $a$ in state $s$,
  - $\pi$ is the policy, a mapping from states to probabilities of selecting each possible action.
- The $p(s', \mid s, a)$ defines the *dynamics* of the MDP and $p$ specifies a probability distribution for each choice of $s$ and $a$:

$$\sum_{s' \in S} p(s' \mid s, a) = 1, \text{ for all } \ s \in S, a \in A(s)$$

## The Goal of Agent

- At each time step, the reward is a simple number, $R_t \in \mathbb{R}$ passing from the environment to the agent.
- The agent's goal is to maximize the total (cumulative) amount of reward it receives in the long run.

- The aim is to maximize the `expected return`, $G_t$, which is defined as:

$$G_t \doteq R_{t+1} + R_{t+2} + R_{t+3} + \ldots + R_T$$

`Discounting` technique is used to prioritize immediate rewards over future rewards.

- The idea is to multiply future rewards by a discount factor $\gamma \in (0, 1]$
- This makes future rewards worth less than immediate rewards.
- The return $G_t$ with discounting is defined as:

$$G_t \doteq R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \cdots = \sum_{k=0}^{\infty} \gamma^k R_{t+k+1}$$

## Policies and Value Functions

- A **`policy`** is a mapping from states to probabilities of selecting each possible action. If the agent is following policy $\pi$ at time $t$, then $\pi(a \mid s)$ is the probability that $A_t = a$ if $S_t = s$
- **`Value functions–functions of states`** 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 value of a state $s$ under a policy $\pi$, denoted $v_\pi$ is expressed as

$$v_\pi(s) \doteq \mathbb{E}_\pi[G_t \mid S_t = s] = \mathbb{E}_\pi\left[\sum_{k=0}^{\infty} \gamma^k R_{t+k+1} \mid S_t = s\right], \text{ for all } \; s \in S,$$

where $\mathbb{E}[\cdot]$ denotes the expected value of a random variable given that the agent follows policy $\pi$, and $t$ is any time step.

## Bellman Equation

To solve stochastic sequential decision problems

1. We have to model the fact that new information becomes available after we make the decision $a_t$.
2. The result can be uncertainty in both the contribution earned, and in the determination of the next state we visit, $S_{t+1}$.

We estimate the `expected future contributions (cumulative rewards)` and add the `immediate contribution` received from the action taken in the current state `following a given policy`. This relationship is expressed by the Bellman equation, defined as:

$$V_\pi(S_t) = \max_{a_t \in A_t}\left(\underbrace{r_{t+1}(S_t, a_t)}_{\text{immediate contribution}} + \underbrace{\gamma E[V_{t+1}(S_{t+1}) \mid S_t, a_t]}_{\text{future contributions}}\right)$$

This equation can be solved backward or forward recursively. You get the value functions and at the same time an optimal policy at time $t$

$$a_t^*(S_t) = \arg \max_{a_t \in A_t} (r_{t+1}(S_t, a_t) + \gamma[V_{t+1}(S_{t+1}) \mid S_t, a_t]),$$

## Dynamic Programming

### Model-based methods (Dynamic Programming)

- They are used to derive optimal policies and value functions in Markov Decision Processes (MDPs) and reinforcement learning.

#### Bellman Equation

- The Bellman equations express the relationship between the value of a state and the values of its successor states. For the state-value function $v_\pi$, the Bellman equation is:

$$\begin{aligned} v_\pi(s) &\doteq \mathbb{E}_\pi \left[ \ G_t \mid S_t = s \ \right] \\ &= \mathbb{E}_\pi \left[ \ R_{t+1} + \gamma G_{t+1} \mid S_t = s \ \right] \\ &= \mathbb{E}_\pi \left[ \ R_{t+1} + \gamma v_\pi(S_{t+1}) \mid S_t = s \ \right] \\ &= \sum_a \pi(a \mid s) \sum_{s',r} p(s', r \mid s, a) \left[ \ r + \gamma v_\pi(s') \ \right] . \end{aligned}$$

### Model-based methods (Dynamic Programming)

- An optimal policy is a policy that achieves the maximum expected return from any initial state.
- The optimal state-value function $v_*$ is the maximum value function over all policies:

$$v_*(s) = \max_\pi v_\pi(s), \text{ for all } \ s \in S$$

- The optimal action-value function $q_*$ is the maximum action-value function over all policies:

$$q_*(s,a) = \max_\pi q_\pi(s,a), \text{ for all } \ s \in S, a \in A(s)$$

We use Dynamic Programming (DP) to leverage value functions in the search for good policies.

- The Bellman optimality equation for $v_*$ is:

$$\begin{aligned} v_*(s) &= \max_a \mathbb{E} \left[ \ R_{t+1} + \gamma v_*(S_{t+1}) \mid S_t = s, A_t = a \ \right] \\ &= \max_a \sum_{s',r} p(s', r \mid s, a) \left[ \ r + \gamma v_*(s')\right], \end{aligned}$$

- The Bellman optimality equation for $q_*$ is:

$$q_*(s,a) = \sum_{s',r} p(s', r \mid s, a) \left[ \ r + \gamma \max_{a'} q_*(s', a') \ \right]$$

### Policy Evaluation (Prediction)

*Policy evaluation* is the computation of the state-value function $v_\pi$ for an arbitrary policy $\pi$. We also refer to it as the *prediction problem.

$$
\begin{aligned}
v_\pi(s) &\doteq \mathbb{E}_\pi \left[ G_t \mid S_t = s \right] \\
&= \mathbb{E}_\pi \left[ R_{t+1} + \gamma G_{t+1} \mid S_t = s \right] \\
&= \mathbb{E}_\pi \left[ R_{t+1} + \gamma v_\pi(S_{t+1}) \mid S_t = s \right] \\
&= \sum_a \pi(a \mid s) \sum_{s',r} p(s', r \mid s, a) \left[ r + \gamma v_\pi(s') \right] .
\end{aligned}
$$

where $\pi(a \mid s)$ is the probability of taking action $a$ in state $s$ under policy $\pi$, and the expectations are subscripted by $\pi$ to indicate that they are conditional on $\pi$ being followed.

Consider a sequence of approximate value functions $v_0, v_1, v_2, \ldots,$. Each successive approximation is obtained by using the Bellman equation for $v_\pi$ as an update rule:

$$
\begin{aligned}
v_{k+1}(s) &\doteq \mathbb{E}_\pi \left[ R_{t+1} + \gamma v_k(S_{t+1}) \mid S_t = s \right] \\
&= \sum_a \pi(a \mid s) \sum_{s',r} p(s', r \mid s, a) \left[ r + \gamma v_k(s') \right] .
\end{aligned}
$$

## Policy Evaluation (Prediction)

The sequence $v_k$ can be shown in general to converge to $v_\pi$ as $k \to \infty$ under the same conditions that guarantee the existence of $v_\pi$. This algorithm is called *iterative policy evaluation.*

i Iterative Policy Evaluation, for estimating $V \approx v_\pi$

```
Input:
$\pi$, the policy to be evaluated
Algorithm parameter: a small threshold $\theta > 0$ determining accuracy of estimation
Initialize $V(s)$ arbitrarily, for $s \in S$, and $V(\text{terminal}) = 0$

Loop:
$\Delta \leftarrow 0$
Loop for each $s \in S$:
  $v \leftarrow V(s)$
  $V(s) \leftarrow \sum_a \pi(a \mid s) \sum_{s',r} p(s', r \mid s, a)[r + \gamma V(s')]$
  $\Delta \leftarrow \max(\Delta, |v - V(s)|)$
until $\Delta < \theta$
```

## Policy Improvement

- We know how good it is to follow the current policy from $s$—that is $v_\pi(s)$—but would it be better or worse to change to the new policy?

One way to answer this question is to consider selecting $a$ in $s$ and thereafter following the existing policy $\pi$.

This leads to the definition of the *q-value* of a state-action pair:

$$
\begin{aligned}
q_\pi(s, a) &\doteq \mathbb{E} \left[ R_{t+1} + \gamma v_\pi(S_{t+1}) \mid S_t = s, A_t = a \right] \\
&= \sum_{s',r} p(s', r \mid s, a) \left[ r + \gamma v_\pi(s') \right] .
\end{aligned}
$$

The policy improvement theorem states that if we improve the policy by acting greedily with respect to $q_\pi$, the new policy $\pi'$ will be at least as good as $\pi$.

Formally, if

$$\begin{aligned}\pi'(s) &= \arg\max_a q_\pi(s,a) \\ &= \arg\max_a \mathbb{E}\left[\, R_{t+1} + \gamma v_\pi(S_{t+1}) \mid S_t = s, A_t = a \,\right] \\ &= \arg\max_a \sum_{s',r} p(s', r \mid s, a)\left[\, r + \gamma v_\pi(s') \,\right]\end{aligned}$$

then

$$v_{\pi'}(s) \geq v_\pi(s).$$

for all $s \in S$.

## Policy Iteration

Once a policy, $\pi$, has been improved using $v_\pi$ to yield a better policy, $\pi'$, we can then compute $v_{\pi'}$ and improve it again to yield an even better $\pi''$.

$$\pi_0 \overset{E}{\to} v_{\pi_0} \overset{I}{\to} \pi_1 \overset{E}{\to} v_{\pi_1} \overset{I}{\to} \pi_2, \ldots \overset{I}{\to} \pi_* \overset{E}{\to} v_*$$

where $\overset{E}{\to}$ denotes a policy *evaluation* and $\overset{I}{\to}$ denotes a policy *improvement*. This way of finding an optimal policy is called policy iteration.

## Policy Iteration

A complete *policy iteration* algorithm

Policy Iteration (using iterative policy evaluation) for estimating $\pi \approx \pi_*$

```
1. Initialization
$V(s) \in \mathbb{R}$ and $\pi(s) \in A(s)$ arbitrarily for all $s \in S$
$V(\text{terminal}) \doteq 0$

2. Policy Evaluation
Loop:
  $\Delta \leftarrow 0$
  Loop for each $s \in S$:
    $v \leftarrow V(s)$
    $V(s) \leftarrow \sum_{s',r} p(s', r \mid s, \pi(s))[r + \gamma V(s')]$
    $\Delta \leftarrow \max(\Delta, |v - V(s)|)$
Until $\Delta < \theta$ (a small positive number determining the accuracy of estimation)

3. Policy Improvement
*policy-stable* $\leftarrow$ true
For each $s \in S$:
  *old-action* $\leftarrow \pi(s)$
  $\pi(s) \leftarrow \arg\max_a \sum_{s',r} p(s', r \mid s, a)[r + \gamma V(s')]$
  If *old-action* $\neq \pi(s)$, then *policy-stable* $\leftarrow$ false

If *policy-stable*, then stop and return $V \approx v_*$ and $\pi \approx \pi_*$;
Else go to step 2
```

## Value Iteration

- One drawback to policy iteration is that each of its iterations involves policy evaluation, which may itself be a protracted iterative computation requiring multiple sweeps through the state set.
- Value iteration is a special case of policy iteration where the policy evaluation step is truncated to just one sweep.
- This algorithm combines the policy improvement and truncated policy evaluation steps into a single update operation:

$$\begin{aligned} v_{k+1}(s) &= \mathbb{E}\left[\, R_{t+1} + \gamma v_k(S_{t+1}) \mid S_t = s, A_t = a \,\right] \\ &= \max_a \sum_{s',r} p(s', r \mid s, a) \left[\, r + \gamma v_k(s') \,\right] \end{aligned}$$

for all $s \in S$.

## Value Iteration

- Value iteration is obtained simply by turning the Bellman optimality equation into an update rule.
- Also note how the value iteration update is identical to the policy evaluation update except that it requires the maximum to be taken over all actions.

Value Iteration, for estimating $\pi \approx \pi_*$

**Algorithm parameter:**
A small threshold $\theta > 0$ determining the accuracy of estimation

**Initialization:**
Initialize $V(s)$ arbitrarily for all $s \in S^+$, except that $V(\text{terminal}) = 0$

**Loop:**

```
  $\Delta \leftarrow 0$
  Loop for each $s \in S$:
    $v \leftarrow V(s)$
    $V(s) \leftarrow \max_a \sum_{s',r} p(s', r \mid s, a)[r + \gamma V(s')]$
    $\Delta \leftarrow \max(\Delta, |v - V(s)|)$
until $\Delta < \theta$
```

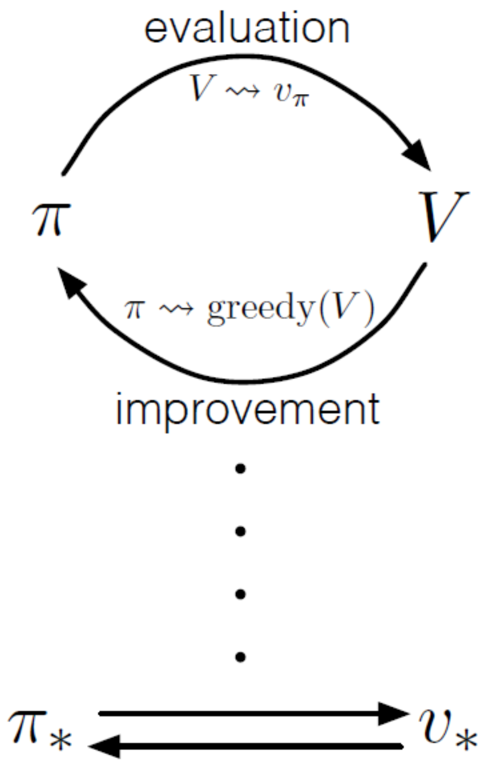
**Output:**
A deterministic policy, $\pi \approx \pi_*$, such that
$\pi(s) = \arg\max_a \sum_{s',r} p(s', r \mid s, a)[r + \gamma V(s')]$

# Let's code

## Generalized Policy Iteration

- GPI is a general idea that describes how two processes — *evaluating a policy and improving it* — work together and influence each other.

- Most reinforcement learning algorithms use a value function to judge how good a policy is, and then update the policy based on that judgment.
- If both value estimation and policy improvement stabilize (i.e., stop changing), then the policy must be the best possible one for that value function—meaning the policy is optimal.


evaluation
$V \rightsquigarrow v_\pi$
$\pi$
$V$
$\pi \rightsquigarrow \text{greedy}(V)$
improvement
$\pi_*$
$v_*$

## Model-free methods

- **Monte Carlo Methods**
- **Sarsa**
- **Q-learning**

## Monte Carlo Methods

### Monte Carlo (MC) Methods

- The term “Monte Carlo” is often used more broadly for any estimation method whose operation involves a significant random component.
- MC methods solve reinforcement learning problems by averaging results (returns) from sampled experiences sequences of states, actions, and rewards.
- They do not require knowledge of the environment’s dynamics, making them powerful for learning from real or simulated experiences.

### Monte Carlo Prediction

- Suppose we wish to estimate $v_\pi(s)$, the values of a state $s$ under policy $\pi$, given a set of episodes obtained by following $\pi$ and passing through $s$.

**First-Visit Monte Carlo Prediction (for estimating $V \approx v_\pi$)**

```
Input:
A policy $\pi$ to be evaluated

Initialize:
  $V(s) \in \mathbb{R}$ arbitrarily, for all $s \in S$
  Returns $(s) \leftarrow$ an empty list, for all $s \in S$

Loop forever (for each episode):
  Generate an episode following $\pi$: $S_0, A_0, R_1, S_1, A_1, R_2, \ldots, S_{T-1}, A_{T-1}, R_T$
  $G \leftarrow 0$
  Loop for each step of the episode, $t = T - 1, T - 2, \ldots, 0$:
    $G \leftarrow \gamma G + R_{t+1}$
    Unless $S_t$ appears in $S_0, S_1, \ldots, S_{t-1}$:
      Append $G$ to Returns $(S_t)$
      $V(S_t) \leftarrow$ average (Returns $(S_t)$)
```

## Monte Carlo Control

Alternating complete steps of policy evaluation and policy improvement are performed, beginning with an arbitrary policy $\pi_0$ and ending with the optimal policy and optimal action-value function:

$$\pi_0 \xrightarrow{E} q_{\pi_0} \xrightarrow{I} \pi_1 \xrightarrow{E} q_{\pi_1} \xrightarrow{I} \pi_2, \ldots, \xrightarrow{I} \pi_* \xrightarrow{E} q_*$$

Monte Carlo ES (Exploring Starts), for estimating $\pi \approx \pi_*$

```
**Initialize:**
$\pi(s) \in A(s)$ arbitrarily, for all $s \in S$
$Q(s, a) \in \mathbb{R}$ arbitrarily, for all $s \in S, a \in A(s)$
Returns $(s, a) \leftarrow$ empty list, for all $s \in S, a \in A(s)$

**Loop forever** (for each episode):
  Choose $S_0 \in S, A_0 \in A(S_0)$ randomly, such that all pairs have probability $> 0$
  Generate an episode from $S_0, A_0$, following $\pi$:
    $S_0, A_0, R_1, ..., S_{T-1}, A_{T-1}, R_T$
  $G \leftarrow 0$
  Loop for each step of episode, $t = T-1, T-2, ..., 0$:
    $G \leftarrow \gamma G + R_{t+1}$
    Unless the pair $(S_t, A_t)$ appears in
      $S_0, A_0, S_1, A_1, ..., S_{t-1}, A_{t-1}$:
      Append $G$ to Returns $(S_t, A_t)$
      $Q(S_t, A_t) \leftarrow$ average (Returns $(S_t, A_t)$)
      $\pi(S_t) \leftarrow \arg\max_a Q(S_t, a)$
```

## Let's code

### Monte Carlo Control without Exploring Starts

- In on-policy control methods the policy is generally **soft**, meaning that $\pi(a \mid s) > 0$ for all $s \in S$ and all $a \in A(s)$, but gradually shifted closer and closer to a deterministic policy.
- The on-policy method we present in this section uses $\epsilon$-greedy policies, meaning that most of the time they choose an action that has maximal estimated action value, but with probability $\epsilon$ they instead select an action at random. That is, all nongreedy actions are given the minimal probability of selection, $\frac{\epsilon}{|A(s)|}$, and the remaining bulk of the probability $1 - \epsilon + \frac{\epsilon}{|A(s)|}$ is given to the greedy action.
- $\epsilon$-greedy policies are examples of $\epsilon - soft$ policies, definied as policies for which $\pi(a \mid s) \geq \frac{\epsilon}{|A(s)|}$ for all states and actions, for some $\epsilon > 0$. Among $\epsilon$-soft policies, $\epsilon$-greedy policies are in some sense those that are closest to greedy.

### Monte Carlo Control without Exploring Starts

On-policy First-Visit MC Control (for $\varepsilon$-soft policies), estimates $\pi \approx \pi_*$

```
Algorithm parameter:
Small $\varepsilon > 0$

Initialize:
$\pi \leftarrow$ an arbitrary $\varepsilon$-soft policy
$Q(s, a) \in \mathbb{R}$ arbitrarily, for all $s \in S, a \in A(s)$
Returns $(s, a) \leftarrow$ empty list, for all $s \in S, a \in A(s)$

Repeat forever (for each episode):
  Generate an episode following $\pi$: $S_0, A_0, R_1, \ldots, S_{T-1}, A_{T-1}, R_T$
  $G \leftarrow 0$
  Loop for each step of episode, $t = T - 1, T - 2, \ldots, 0$:
    $G \leftarrow \gamma G + R_{t+1}$
    Unless the pair $(S_t, A_t)$ appears in $S_0, A_0, \ldots, S_{t-1}, A_{t-1}$:
      Append $G$ to Returns $(S_t, A_t)$
      $Q(S_t, A_t) \leftarrow$ average (Returns $(S_t, A_t)$)
      $A^* \leftarrow \arg\max_a Q(S_t, a)$ (ties broken arbitrarily)
      For all $a \in A(S_t)$:
        $\pi(a \mid S_t) \leftarrow \begin{cases} 1-\varepsilon+\varepsilon/|A(S_t)| & \text{if } a=A^* \\ \varepsilon/|A(S_t)| & \text{if } a\neq A^* \end{cases}$
```

where $|A(s)|$ is the number of actions available in state $s$.

The $\epsilon$-greedy policy ensures that all actions are tried, but actions with higher value estimates are tried more frequently. This balances exploration (trying new actions) and exploitation (choosing the best-known action).

## Temporal-Difference Learning

### Temporal-Difference Learning

- TD learning is a combination of Monte Carlo ideas and dynamic programming (DP) ideas.
- Like Monte Carlo methods, TD methods can learn directly from raw experience without a model of the environment's dynamics.
- Like DP, TD methods update estimates based in part on other learned estimates, without waiting for a final outcome (they bootstrap).

### TD Prediction

Whereas Monte Carlo methods must wait until the end of the episode to determine the increment to $V(St)$ (only then is $G_t$ known), TD methods need to 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 $R_{t+1}$ and the estimate $V_{S_{t+1}}$. The simplest TD method makes the update:

$$V(S_t) \leftarrow V(S_t) + \alpha \left[ R_{t+1} + \gamma V(S_{t+1}) - V(S_t) \right]$$

immediately on transition to $S_{t+1}$ and receiving $R_{t+1}$. In effect, the target for the Monte Carlo update is $G_t$, whereas the target for the TD update is $R_{t+1} + \gamma V(S_{t+1})$. This TD method is called TD(0), or *one-step* TD.

## TD Prediction

Tabular TD(0) for Estimating $v_\pi$

```
Input:
The policy $\pi$ to be evaluated

Algorithm parameter:
Step size $\alpha \in (0, 1]$

Initialize:
$V(s)$ arbitrarily for all $s \in S^+$, except that $V(\text{terminal}) = 0$

Loop for each episode:
  Initialize $S$
  Loop for each step of episode:
    $A \leftarrow$ action given by $\pi$ for $S$
    Take action $A$, observe $R$, $S'$
    $V(S) \leftarrow V(S) + \alpha[R + \gamma V(S') - V(S)]$
    $S \leftarrow S'$
  Until $S$ is terminal
```

## Sarsa: On-policy TD Control

we consider transitions from state–action pair to state–action pair, and learn the values of state–action pairs.

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha \left[ R_{t+1} + \gamma Q(S_{t+1}, A_{t+1}) - Q(S_t, A_t) \right]$$

SARSA (On-Policy TD Control), for estimating $Q \approx q_*$

```
**Algorithm parameters:**
Step size $\alpha \in (0, 1]$, small $\varepsilon > 0$

**Initialize:**
$Q(s, a)$ arbitrarily, for all $s \in S^+$, $a \in A(s)$
$Q(\text{terminal}, \cdot) = 0$

**Loop for each episode:**
  Initialize $S$
  Choose $A$ from $S$ using a policy derived from $Q$ (e.g., $\varepsilon$-greedy)

  **Loop for each step of episode:**
    Take action $A$, observe $R$, $S'$
    Choose $A'$ from $S'$ using a policy derived from $Q$ (e.g., $\varepsilon$-greedy)
    $Q(S, A) \leftarrow Q(S, A) + \alpha[R + \gamma Q(S', A') - Q(S, A)]$
    $S \leftarrow S'; \quad A \leftarrow A'$

Until $S$ is terminal
```

## Let's code

### Q-learning: Off-policy TD Control

*Q-learning* is defined by

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha \left[ R_{t+1} + \gamma \max_a Q(S_{t+1}, a) - Q(S_t, A_t) \right]$$

The Q-learning algorithm is shown below in procedural form.

i Q-learning (Off-Policy TD Control), for estimating $\pi \approx \pi_*$

```
Algorithm parameters:
Step size $\alpha \in (0, 1]$, small $\varepsilon > 0$

Initialize:
$Q(s, a)$ arbitrarily for all $s \in S^+$, $a \in S(s)$,
except that $Q(\text{terminal}, \cdot) = 0$

Loop for each episode:
  Initialize $S$
  Loop for each step of episode:
    Choose $A$ from $S$ using a policy derived from $Q$ (e.g., $\varepsilon$-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
```

## Let’s code

### Recommended materials

**Readings:**

- Reinforcement Learning: An Introduction by Richard S. Sutton and Andrew G. Barto
- Reinforcement Learning and Stochastic Optimization by Warren B. Powell

**Tutoriols:**

https://www.youtube.com/watch?v=0MNVhXEX9to&list=PLMrJAkhIeNNQe1JXNvaFvURxGY4gE9k74&index=1

https://www.youtube.com/watch?v=i7q8bISGwMQ&t=910s

https://www.youtube.com/watch?v=sJIFUTITfBc

https://www.youtube.com/watch?v=0iqz4tcKN58

https://www.youtube.com/watch?v=wDVteayWWvU

## Any questions or thoughts?

## Categories of RL methods

### Model-based vs Model-free Methods

`Model-based`

- The agent knows/learns the model of the environment

- They then compute the policy using the ADP methods or the model-free methods on simulated data

**Pros:**

- Sample efficient
- Safer exploration

**Cons:**

- Prone to the model errors
- Learning a model is challenging

**`Model-free`**

- The agent does not know the model of the environment
- They learn the values or policies from trial-and-error interactions with the environment

**Pros:**

- Do not need a model
- Flexible

**Cons:**

- Sample inefficient: requires a lot of interactions with the environment
- Slow convergence