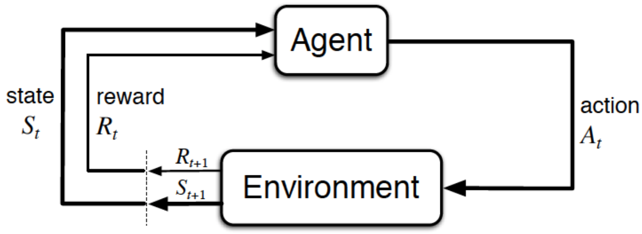
Summary

Summary



The agent-environment interaction in reinforcement learning. (Source: Sutton and Barto, 2017)

The Setting, Revisited

- The reinforcement learning (RL) framework is characterized by an **agent** learning to interact with its **environment**.
- At each time step, the agent receives the environment's **state** (*the environment presents a situation to the agent)*, and the agent must choose an appropriate **action** in response. One time step later, the agent receives a **reward** (*the environment indicates whether the agent has responded appropriately to the state*) and a new **state**.
- All agents have the goal to maximize expected **cumulative reward**, or the expected sum of rewards attained over all time steps.

Episodic vs. Continuing Tasks

- A **task** is an instance of the reinforcement learning (RL) problem.

Summary

- **Episodic tasks** are tasks with a well-defined starting and ending point.
  - In this case, we refer to a complete sequence of interaction, from start to finish, as an **episode**.
  - Episodic tasks come to an end whenever the agent reaches a **terminal state**.

The Reward Hypothesis

- **Reward Hypothesis**: All goals can be framed as the maximization of (expected) cumulative reward.

Goals and Rewards

- (Please see **Part 1** and **Part 2** to review an example of how to specify the reward signal in a real-world problem.)

Cumulative Reward

- The **return at time step** t is $G_t := R_{t+1} + R_{t+2} + R_{t+3} + \ldots$
- The agent selects actions with the goal of maximizing expected (discounted) return. (*Note: discounting is covered in the next concept.*)

Discounted Return

- The **discounted return at time step** t is $G_t := R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \ldots$

Knowledge

Summary

you have the agent.

- It must satisfy $0 \leq \gamma \leq 1$.
- If $\gamma = 0$, the agent only cares about the most immediate reward.
- If $\gamma = 1$, the return is not discounted.
- For larger values of γ, the agent cares more about the distant future. Smaller values of γ result in more extreme discounting, where - in the most extreme case - agent only cares about the most immediate reward.

MDPs and One-Step Dynamics

- The **state space** $\mathcal{S}$ is the set of all (*nonterminal*) states.
- In episodic tasks, we use $\mathcal{S}^+$ to refer to the set of all states, including terminal states.
- The **action space** $\mathcal{A}$ is the set of possible actions. (Alternatively, $\mathcal{A}(s)$ refers to the set of possible actions available in state $s \in \mathcal{S}$.)
- (Please see **Part 2** to review how to specify the reward signal in the recycling robot example.)
- The **one-step dynamics** of the environment determine how the environment decides the state and reward at every time step. The dynamics can be defined by specifying $p(s', r|s, a) \doteq \mathbb{P}(S_{t+1} = s', R_{t+1} = r|$ for each possible $s', r, s, \text{and } a$.

Knowledge

Summary

- a (finite) set of states $\mathcal{S}$ (or $\mathcal{S}^+$, in the case of an episodic task)
- a (finite) set of actions $\mathcal{A}$
- a set of rewards $\mathcal{R}$
- the one-step dynamics of the environment

NEXT

Knowledge