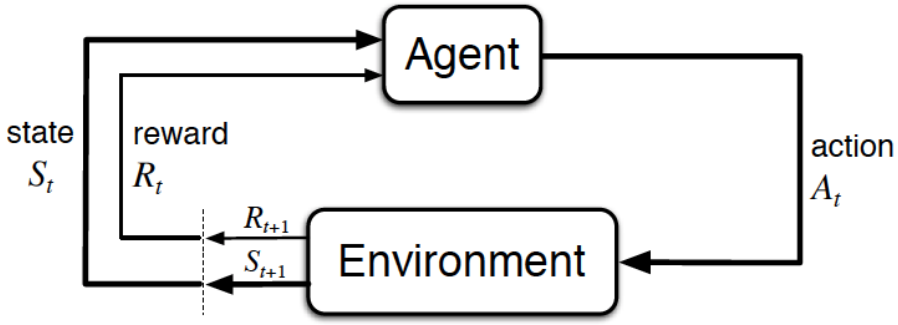
Summary



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.
- **Continuing tasks** are tasks that continue forever, without end.
- **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** $G_t := R_{t+1} + R_{t+2} + R_{t+3} + \ldots$
- 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** $G_t := R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \ldots$.
- The **discount rate** γ is something that you set, to refine the goal that you have the agent.
  - It must satisfy $0 \le \gamma \le 1$.
  - 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** S is the set of all (*nonterminal*) states.
- In episodic tasks, we use S^+ to refer to the set of all states, including terminal states.
- The **action space** A is the set of possible actions. (Alternatively, A(*s*) refers to the set of possible actions available in state $s \in S$.)
- (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

  $p(s', r|s, a) \doteq \mathbb{P}(S_{t+1} = s', R_{t+1} = r|S_t = s, A_t = a)$ for each possible $s', r, s,$ and a.

- A **(finite) Markov Decision Process (MDP)** is defined by:
  - a (finite) set of states S (or S^+, in the case of an episodic task)
  - a (finite) set of actions A
  - a set of rewards R
  - the one-step dynamics of the environment
  - the discount rate $\gamma \in [0,1]$