# Reinforcement Learning

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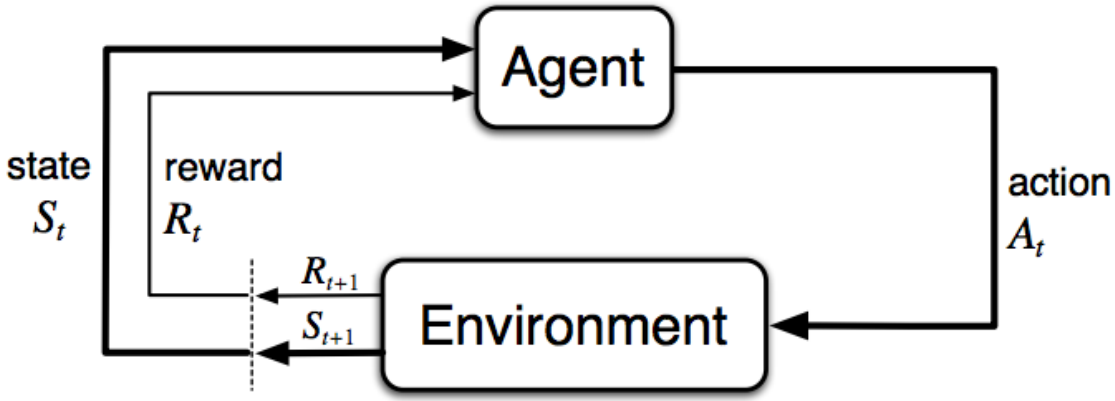
# Overview

# Reinforcement Learning

- **Framing of the problem of learning from interaction to achieve a goal.**
- **Agent**: learner and decision maker
- **Environment**: what the learner interacts with (everything outside the agent)
- Agent selects actions and the environment responds to those actions and presents new situations

# Reinforcement Learning




- At each time step $t$, the agent receives the environment **state** $S_t \in \mathcal{S}$, and the agent then selects an **action** $A_t \in \mathcal{A}(S_t)$
  - $\mathcal{S}$ is the set of possible states (whatever information is available to the agent).
  - $\mathcal{A}(S_t)$ is set of actions available in state $S_t$
- One time step later, the agent receives a **reward**, $R_{t+1} \in \mathcal{R} \subset \mathbb{R}$, and ends up in a new state $S_{t+1}$

# Reinforcement Learning

- At each time step, the agent implements a mapping $\pi_t$ from states to probabilities of selecting each possible action, where $\pi_t$ is called a **policy**
  - $\pi_t(a|s)$ = probability that $A_t = a$ if $S_t = s$

## Reinforcement Learning Objective

The agent's goal is to maximize the total amount of reward it receives over the long run by changing its policy as a result of its experience

# Reinforcement Learning

- Let the sequence of rewards after time step $t$ is $R_{t+1}, R_{t+2}, R_{t+3}, \ldots$, then we want to maximize the return $G_t$
- The agent chooses $A_t$ to maximize the discounted return:

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

  where $\gamma$ is the discount rate and $0 \geq \gamma \leq 1$
- The closer $\gamma$ is to 1, the more the agent accounts for future rewards

# Markov Property

- Probability of transitioning to new state s:

$$p(s', r|s, a) = Pr\{S_{t+1} = s', R_{t+1} = r|S_0, A_0, R_1, ..., S_{t-1}, A_{t-1}, R_t, S_t, A_t\}$$

- Probability with Markov assumption

$$p(s', r|s, a) = Pr\{S_{t+1} = s', R_{t+1} = r|S_t = s, A_t = a\}$$

- Markov assumption allows us to predict the next state and expected rewards from knowledge of only the current state
  - Assume that the current state tells us everything we need to know for future (e.g. current state of checker board)

# Multiple Columns

**Heading**

1. Statement
2. Explanation
3. Example

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# Table

| Treatments | Response 1 | Response 2 |
|---|---|---|
| Treatment 1 | 0.0003262 | 0.562 |
| Treatment 2 | 0.0015681 | 0.910 |
| Treatment 3 | 0.0009271 | 0.296 |

Table: Table caption

# References

Richard S. Sutton and Andrew G. Barto. Reinforcement Learning: An Introduction. MIT Press 2015.