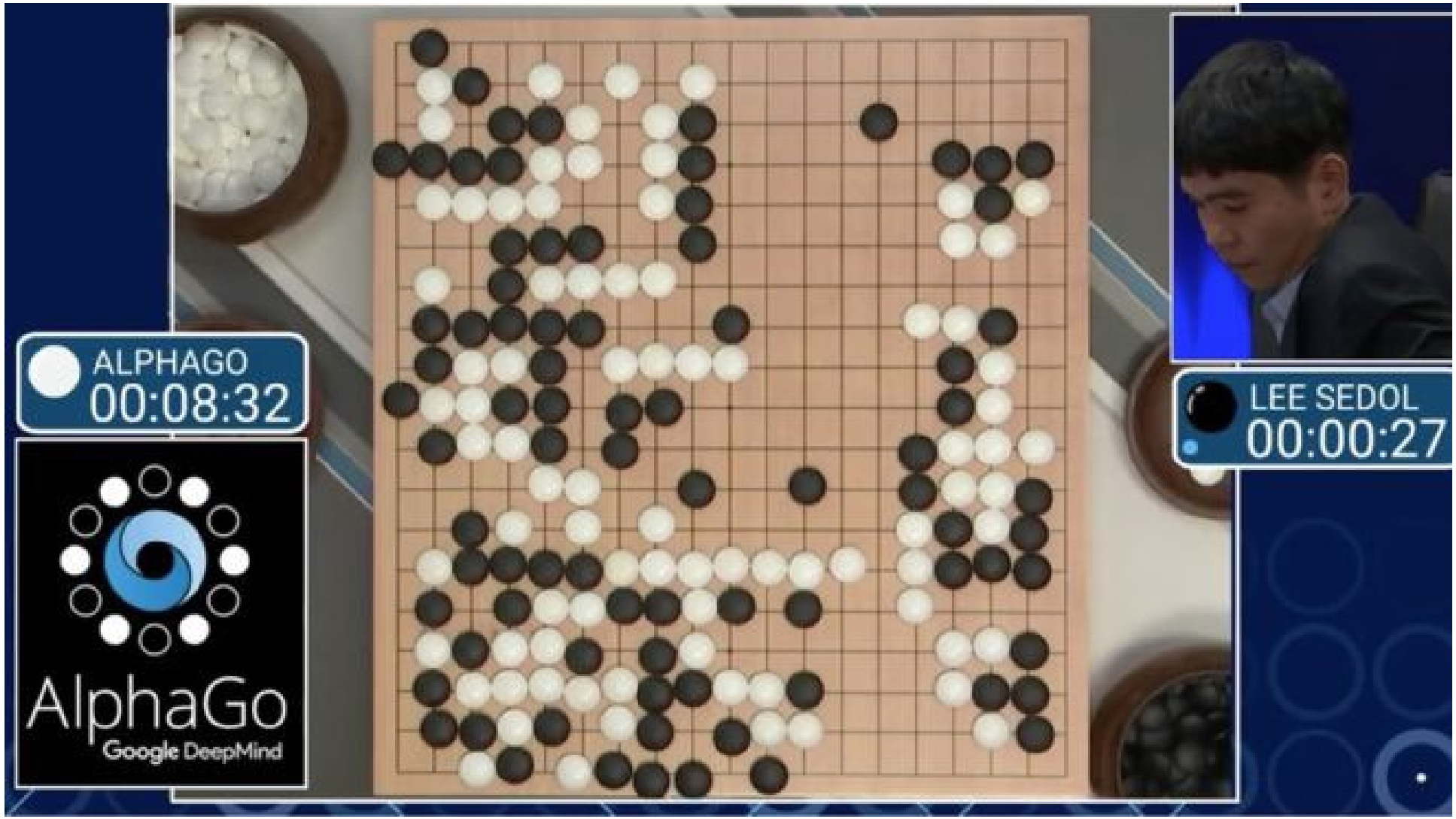
Reinforcement Learning

Adapted from slides by Shusen Wang at Stevens Institute of Technology

http://wangshusen.github.io/

AlphaGo



A little bit probability theory…

Random Variable

- Random variable: unknown; its values depends on outcomes of a random event.
- Uppercase letter X for random variable.

Random Variable	*Possible Values*	*Random Events*	*Probabilities*
$X =$	0		$\mathbb{P}(X = 0) = 0.5$
	1		$\mathbb{P}(X = 1) = 0.5$

Random Variable

- Random variable: unknown; its values depends on outcomes of a random event.
- Uppercase letter X for random variable.
- Lowercase letter x for an observed value.
- For example, I flipped a coin 4 times and observed:
  - $x_1 = 1,$
  - $x_2 = 1,$
  - $x_3 = 0,$
  - $x_4 = 1.$

Probability Density Function (PDF)

- PDF provides a relative likelihood that the value of the random variable would equal that sample.

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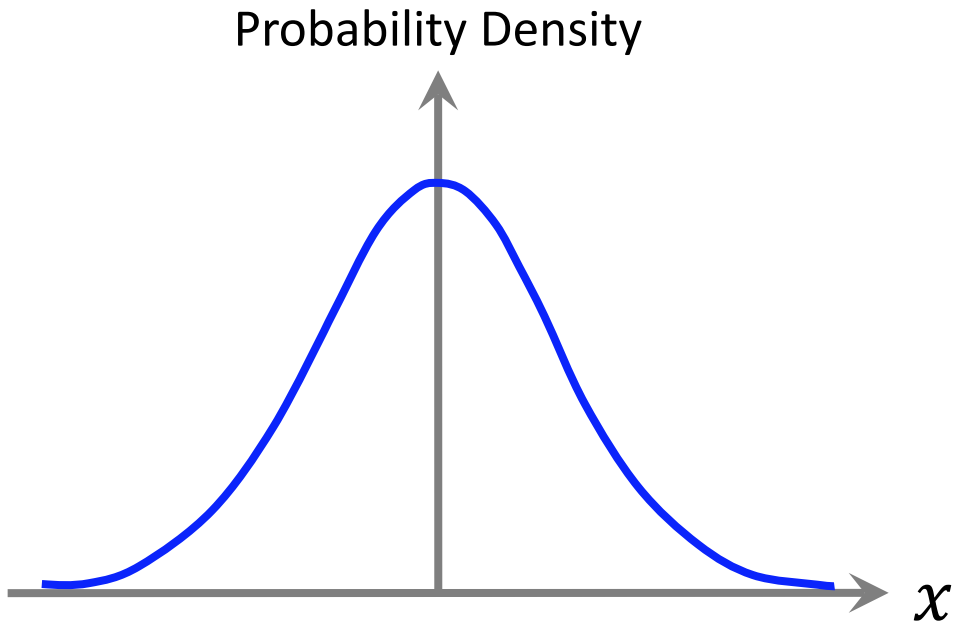
Example: Gaussian distribution

- It is a continuous distribution.
- PDF:

$$p(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x-\mu)^2}{2\,\sigma^2}\right).$$



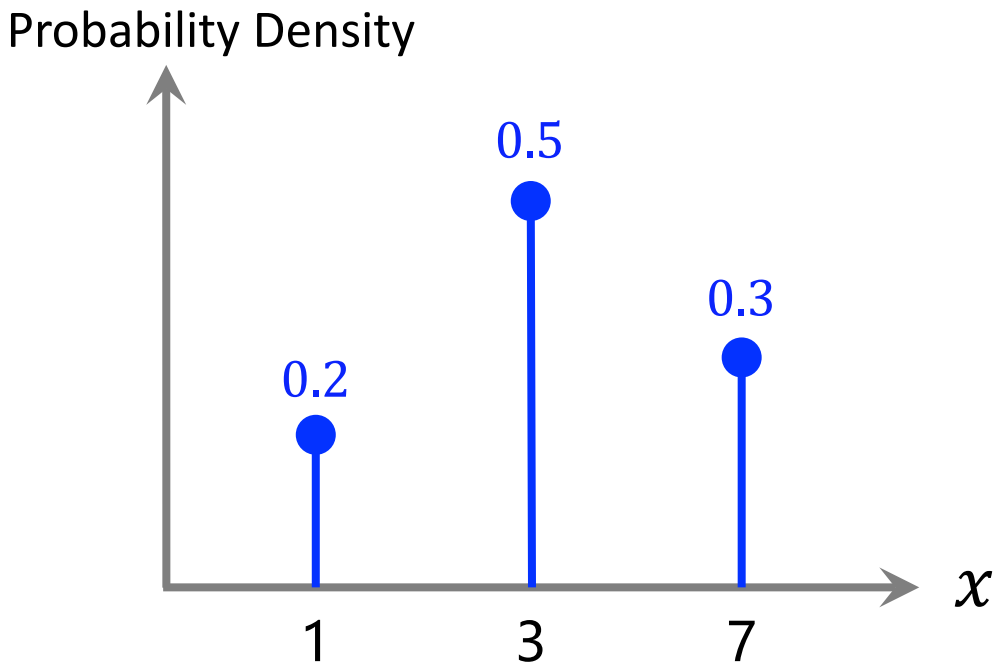
Probability Mass Function (PMF)

- PMF is a function that gives the probability that a discrete random variable is exactly equal to some value

Example

- Discrete random variable: $X \in \{1, 3, 7\}$.
- PDF:

$$p(1) = 0.2,$$
$$p(3) = 0.5,$$
$$p(7) = 0.3.$$



Properties of PDF/PMF

- Random variable X is in the domain $\mathcal{X}$.
- For continuous distribution,

$$\int_{\mathcal{X}} p(x)\, dx = 1.$$

- For discrete distribution,

$$\sum_{x \in \mathcal{X}} p(x) = 1.$$

Expectation

- Random variable X is in the domain $\mathcal{X}$.
- For continuous distribution, the expectation of $f(X)$ is:

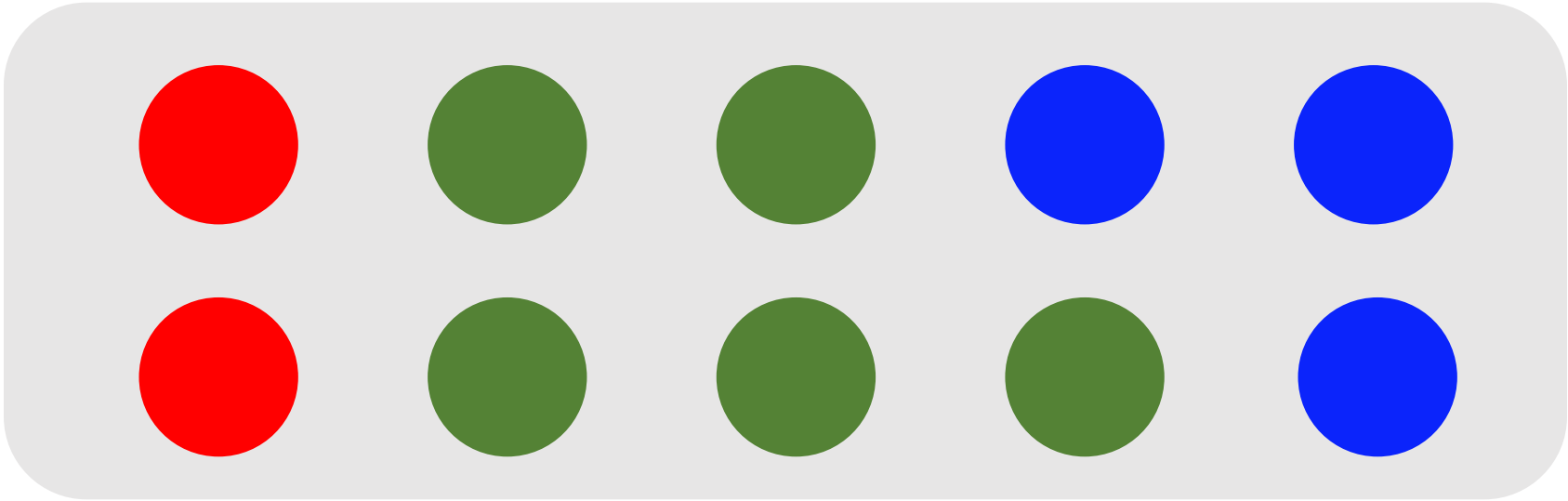
$$\mathbb{E}[f(X)] = \int_{\mathcal{X}} p(x) \cdot f(x)\, dx.$$

- For discrete distribution, the expectation of $f(X)$ is:

$$\mathbb{E}[f(X)] = \sum_{x \in \mathcal{X}} p(x) \cdot f(x)\,.$$

Random Sampling

- There are 10 balls in the bin: 2 are red, 5 are green, and 3 are blue.
- Randomly sample a ball.
- What will be the color?



Random Sampling

- Sample red ball w.p. 0.2, green ball w.p. 0.5, and blue ball w.p. 0.3.
- Randomly sample a ball.
- What will be the color?

Random Sampling

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```
from numpy.random import choice

samples = choice(['R', 'G', 'B'], size=100, p=[0.2, 0.5, 0.3])
print(samples)
```

```
['R' 'G' 'R' 'R' 'R' 'R' 'B' 'B' 'B' 'G' 'G' 'B' 'G' 'B' 'B' 'G' 'B' 'G'
 'B' 'B' 'G' 'B' 'G' 'B' 'B' 'G' 'B' 'B' 'G' 'B' 'G' 'G' 'G' 'G' 'G' 'B'
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```

Terminologies

Terminology: state and action

state s **(this frame)**

Action $a \in \{\text{left}, \text{right}, \text{up}\}$

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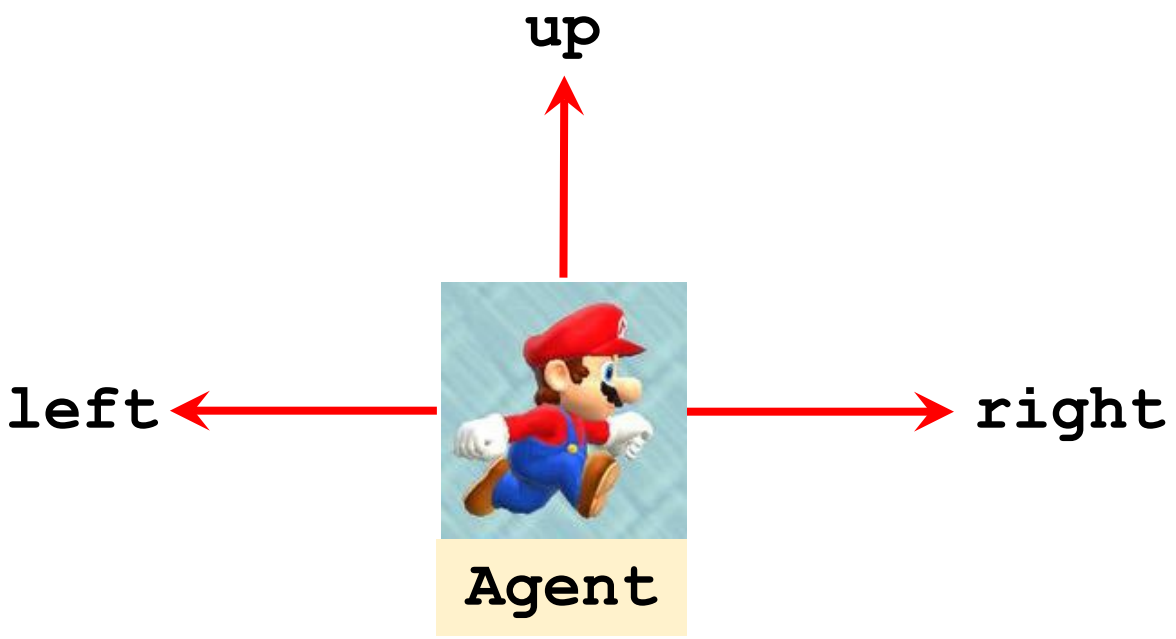
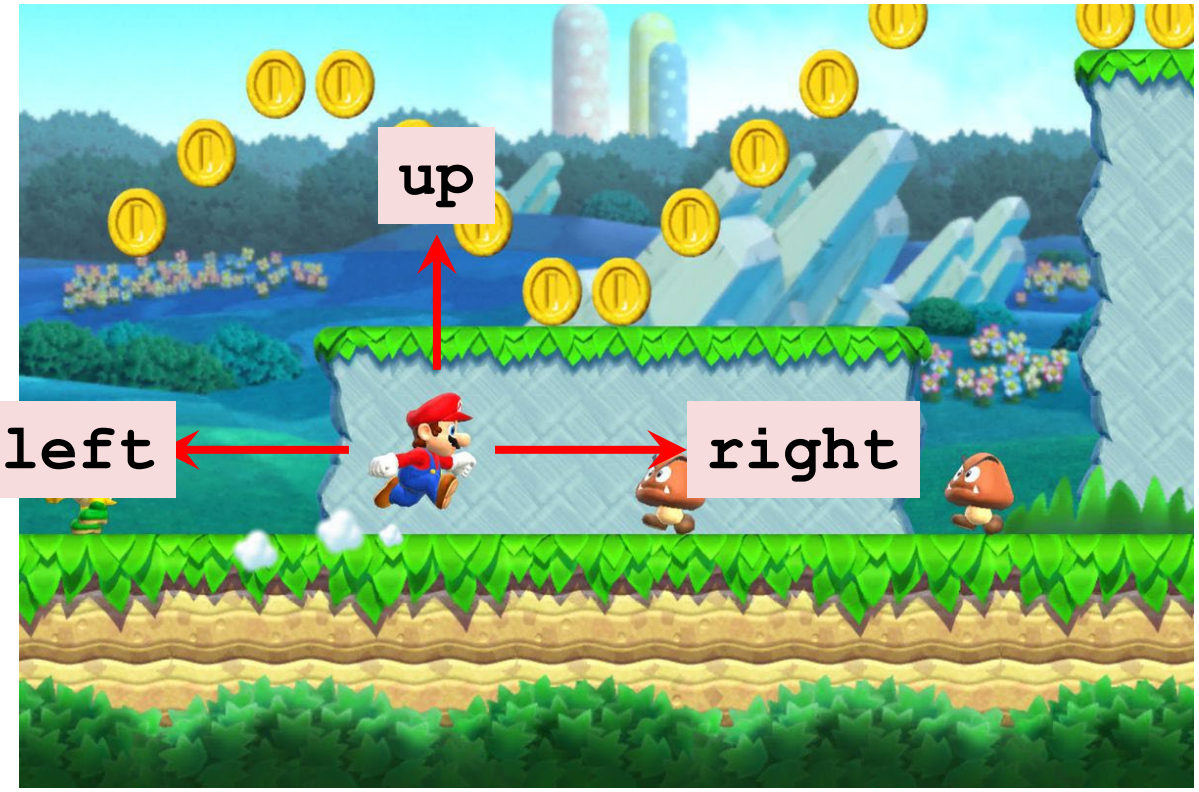


Terminology: policy



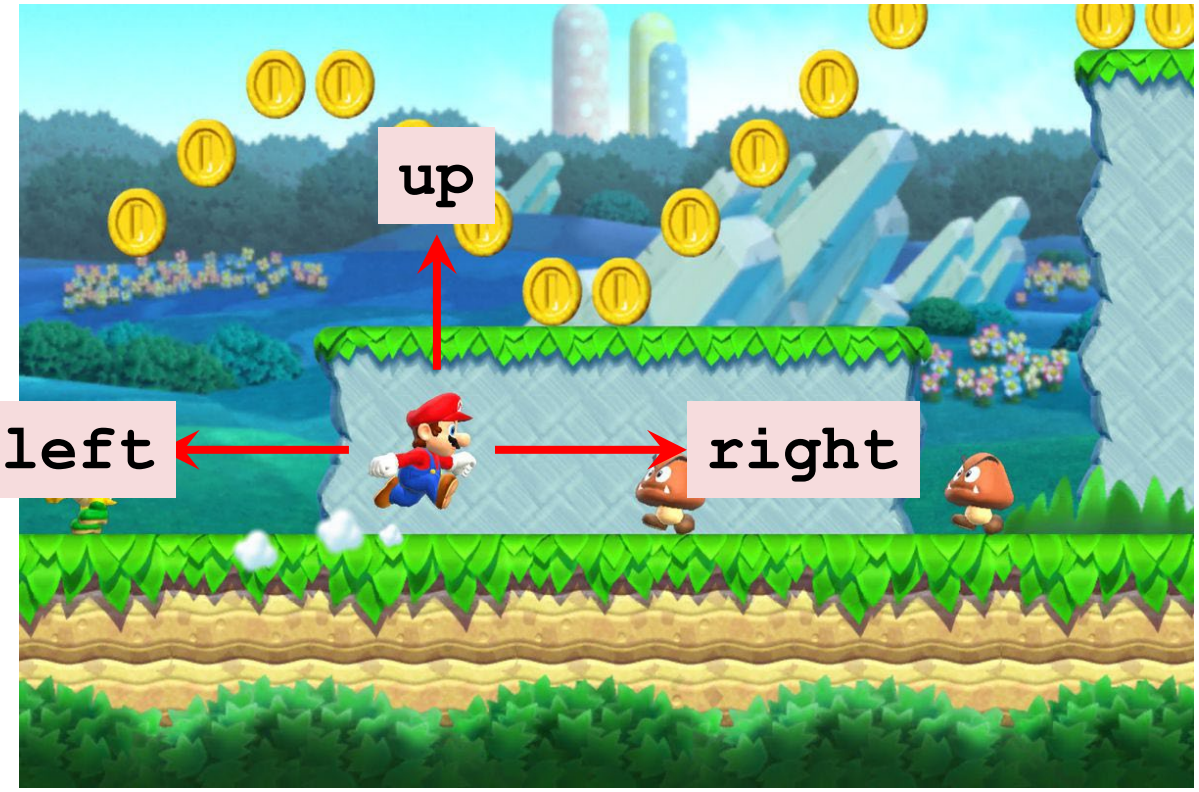
policy π

- Policy function $\pi: (s, a) \mapsto [0,1]$:

$$\pi(a \mid s) = \mathbb{P}(A = a \mid S = s).$$

- It is the probability of taking action $A = a$ given state s, e.g.,
  - $\pi(\text{left} \mid s) = 0.2$,
  - $\pi(\text{right} \mid s) = 0.1$,
  - $\pi(\text{up} \mid s) = 0.7$.
- Upon observing state $S = s$, the agent's action A can be random.

Terminology: policy



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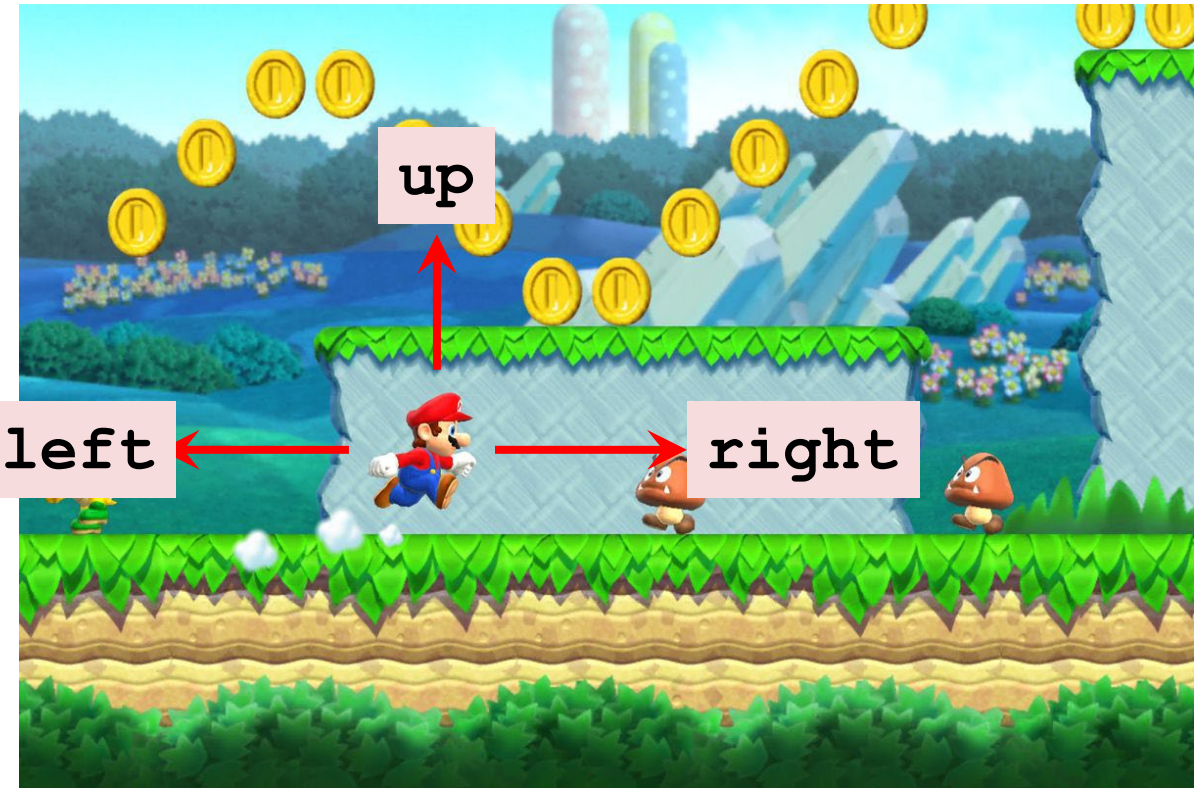

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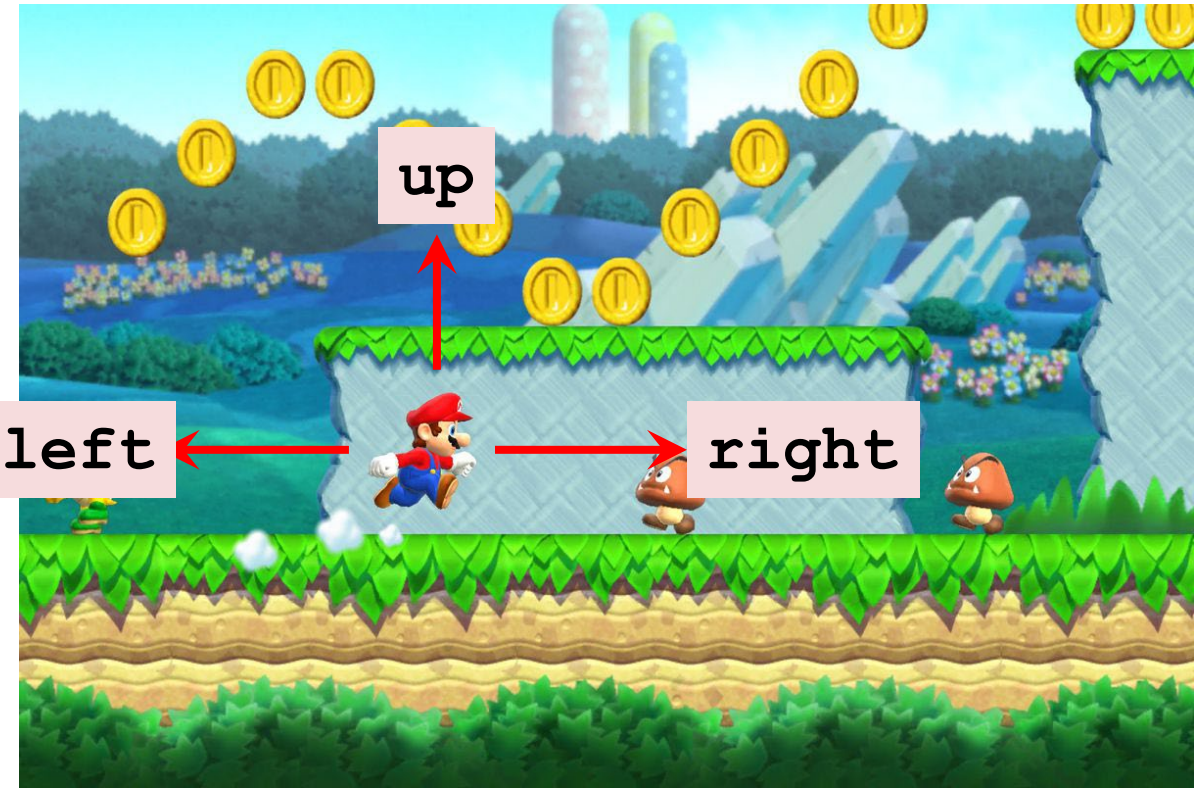

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Terminology: reward

reward R

- Collect a coin: $R = +1$

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- Collect a coin: $R = +1$
- Win the game: $R = +10000$

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- Collect a coin: $R = +1$
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- Touch a Goomba: $R = -10000$ (game over).

Terminology: reward

reward R

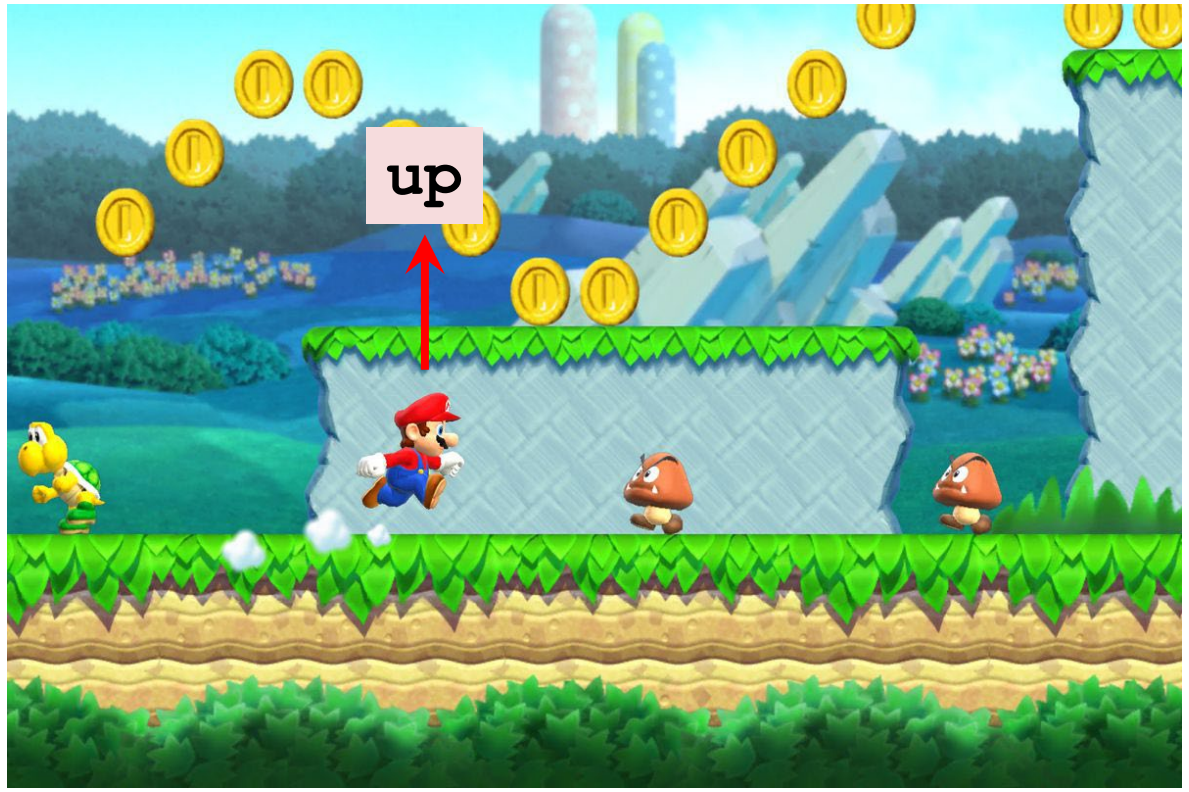
- Collect a coin: $R = +1$
- Win the game: $R = +10000$
- Touch a Goomba: $R = -10000$ (game over).
- Nothing happens: $R = 0$

Terminology: state transition

state transition

old state —action→ new state

Terminology: state transition



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- E.g., “up” action leads to a new state.

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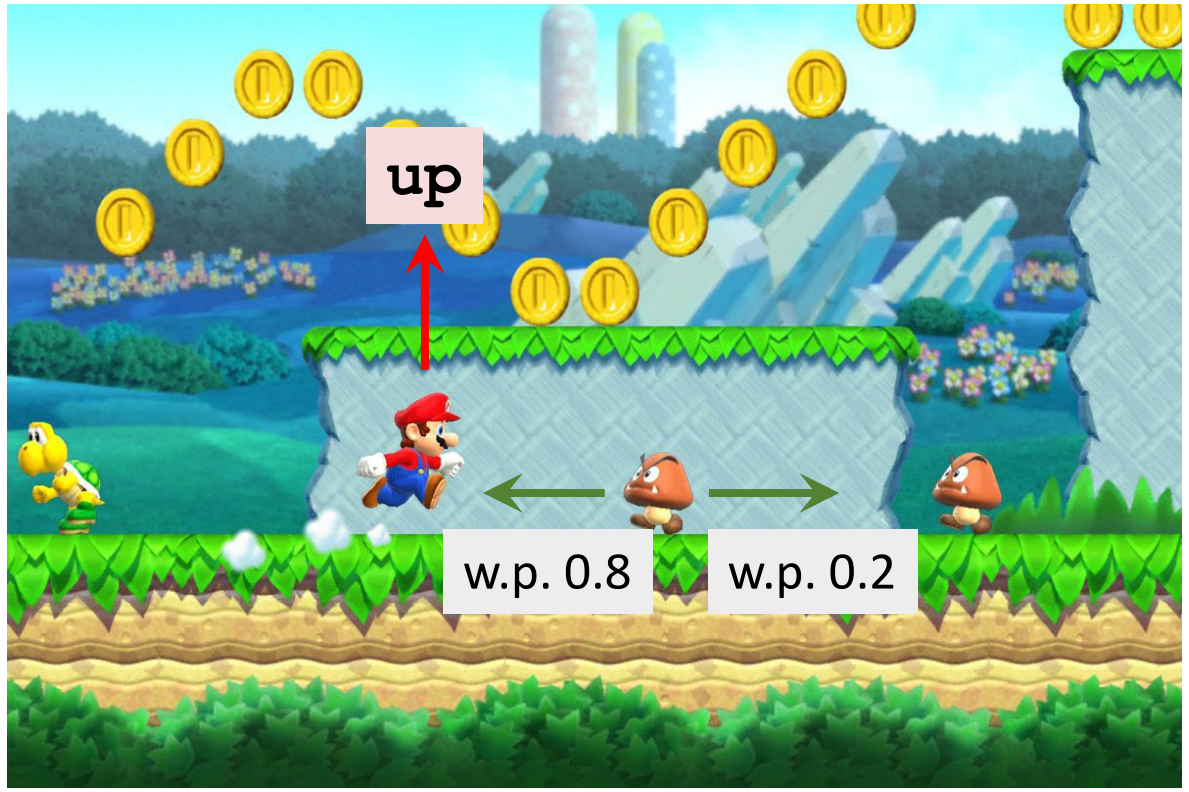

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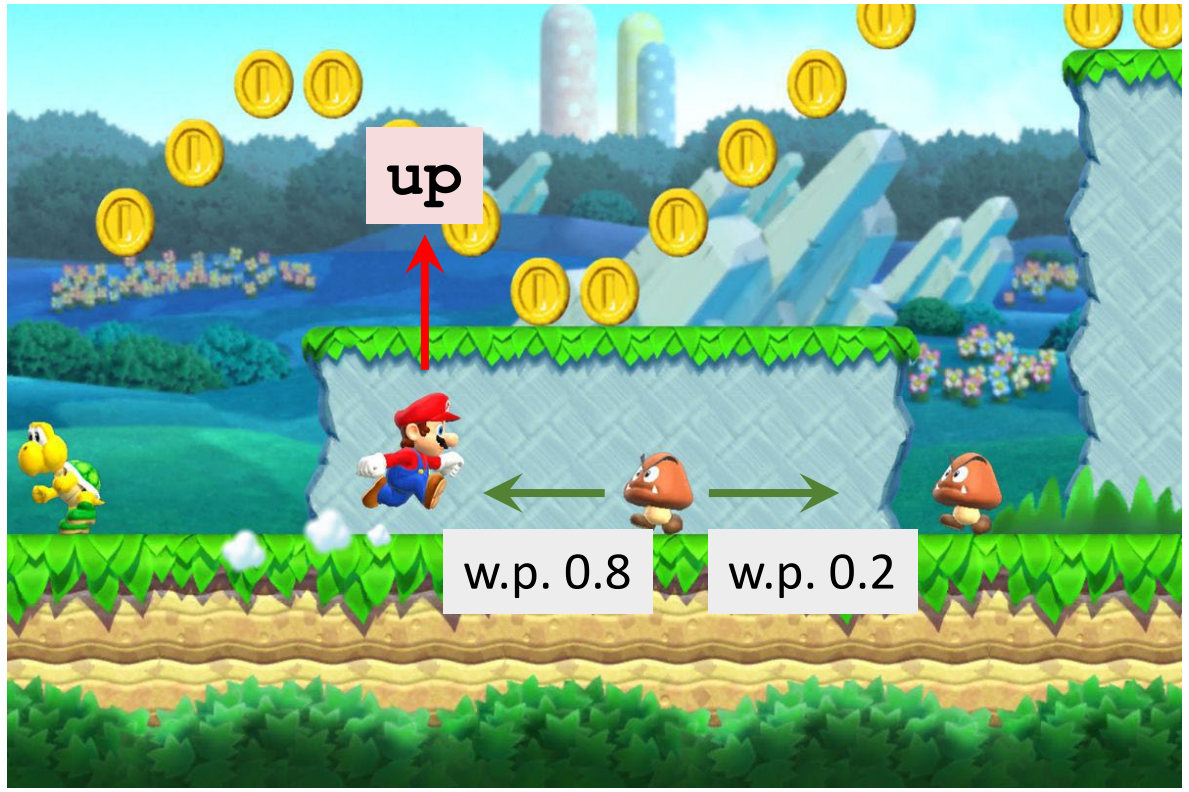

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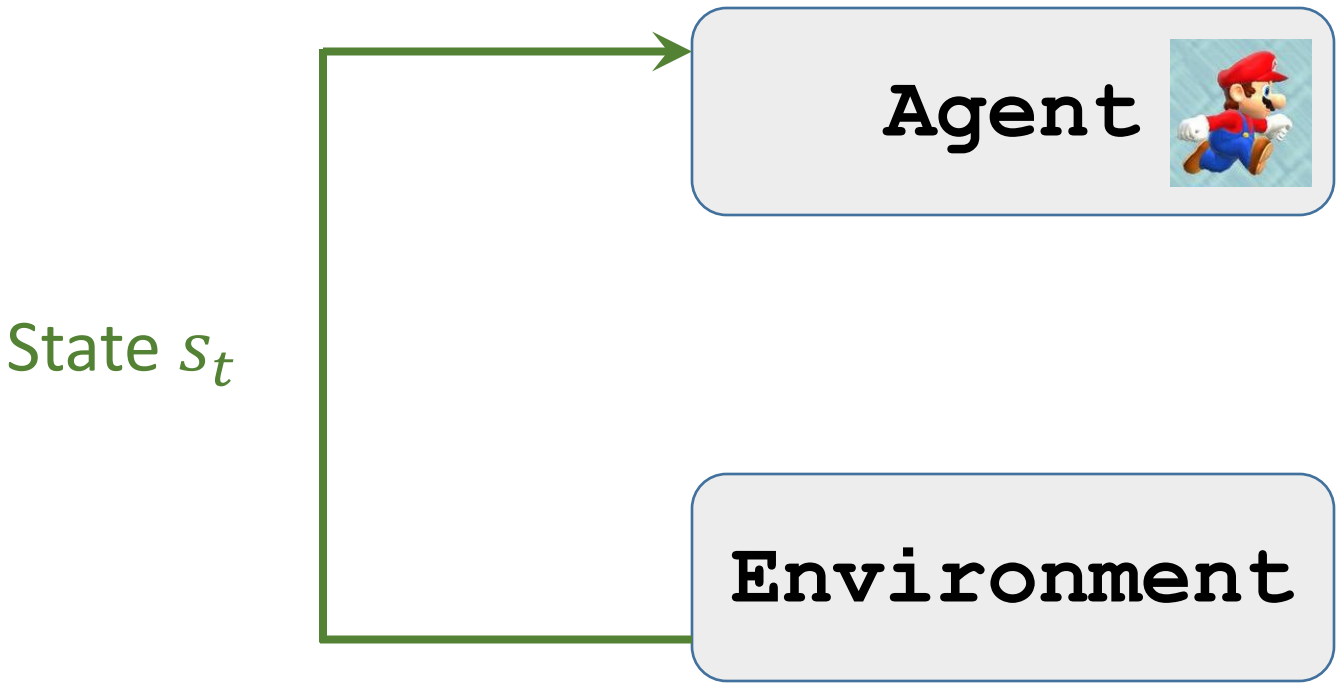
- $p(s'|s,a) = \mathbb{P}(S' = s'|S = s, A = a)$.

Terminology: agent environment interaction



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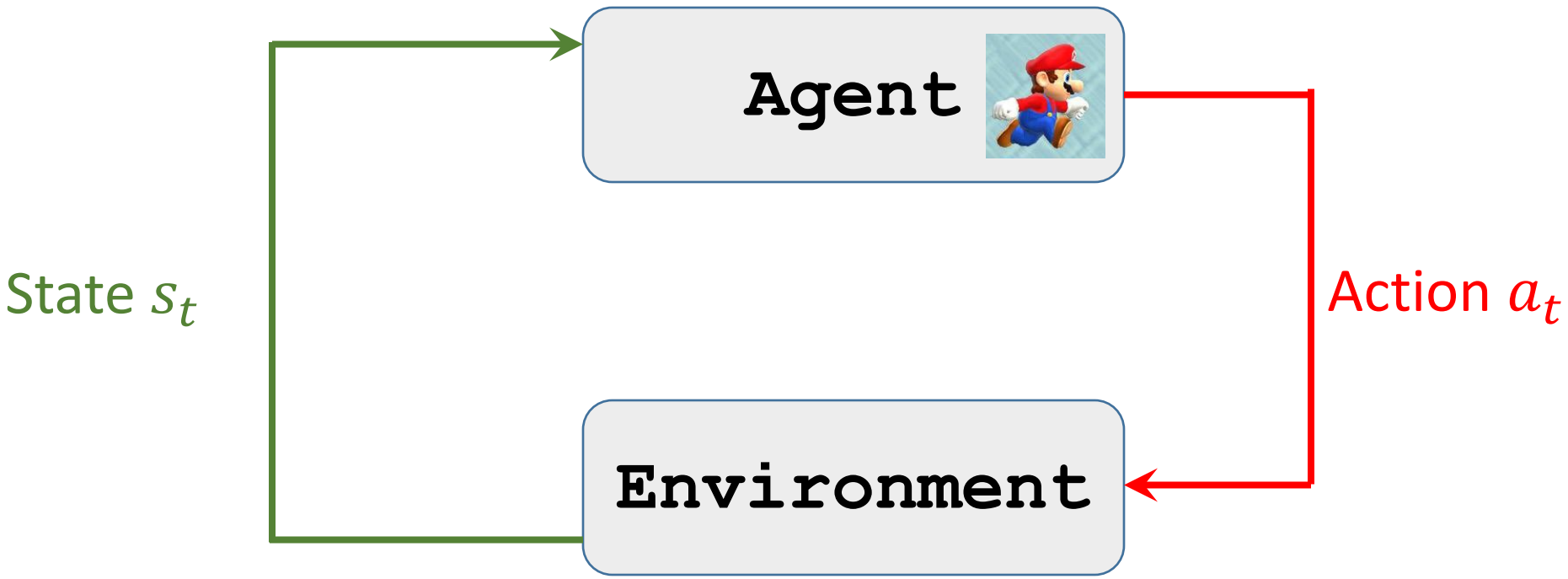

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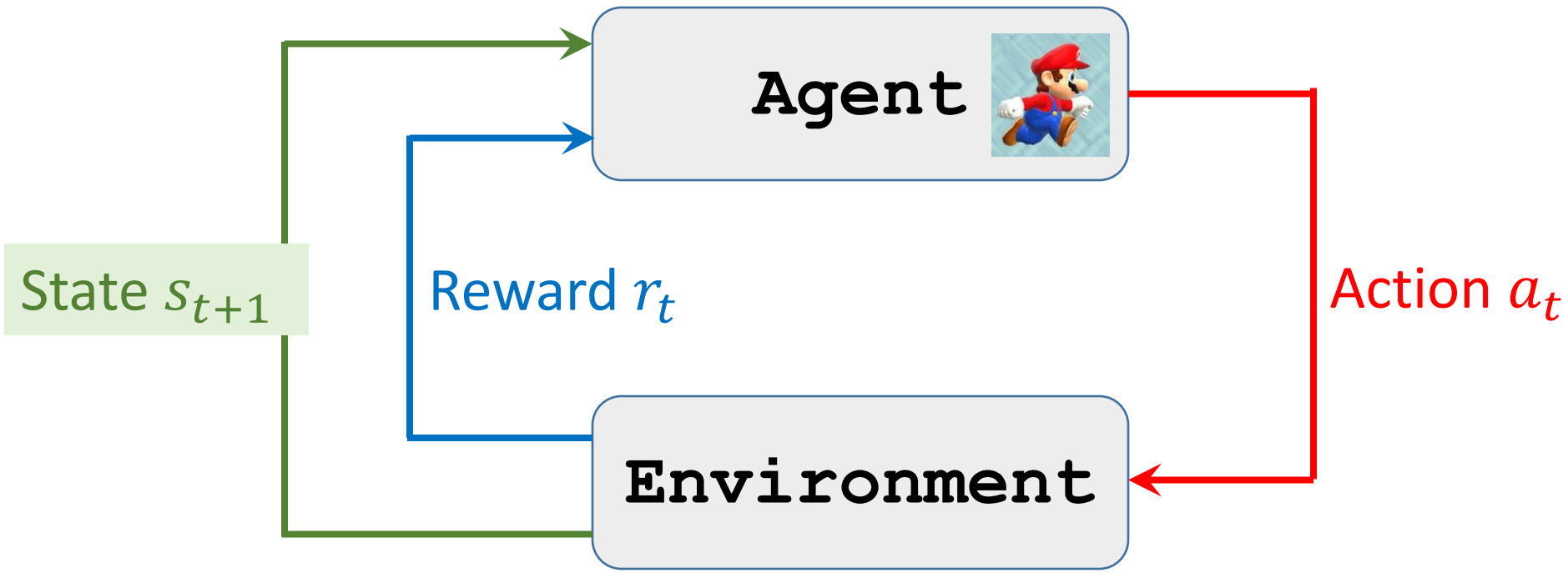
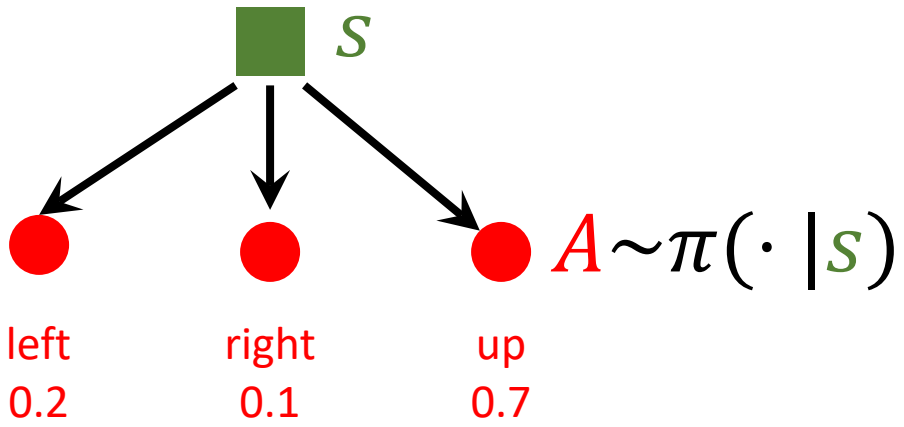


Randomness in Reinforcement Learning



Actions have randomness.

- Given state s, the action can be random, e.g., .
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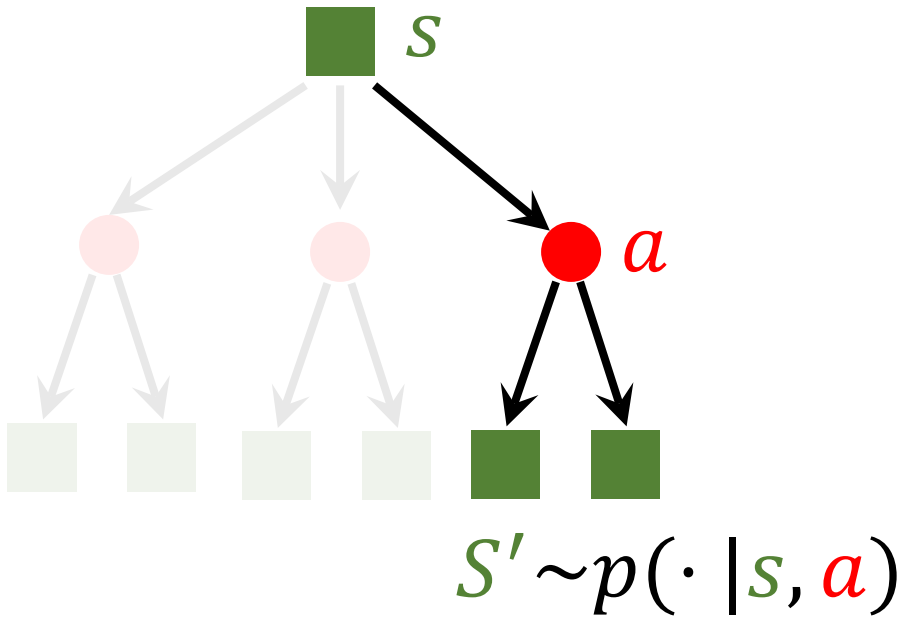

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State transitions have randomness.

- Given state $S = s$ and action $A = a$, the environment randomly generates a new state S'.

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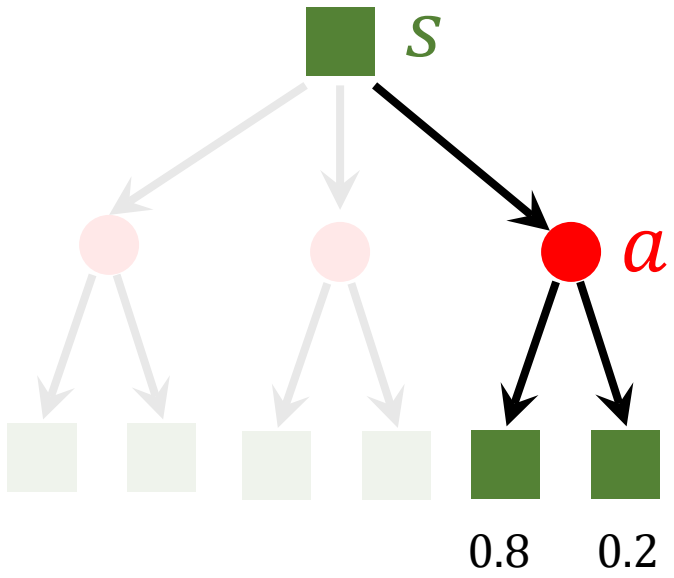

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Play the game using AI

- Observe a frame (state s_1)
- ➔ Make action a_1 (left, right, or up)
- ➔ Observe a new frame (state s_2) and reward r_1
- ➔ Make action a_2
- ➔ …

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- ➔ Make action a_2
- ➔ …

- (state, action, reward) trajectory:

$$s_1, a_1, r_1, s_2, a_2, r_2, \quad \cdots \quad , s_T, a_T, r_T.$$

Rewards and Returns

Return

Definition: Return (aka cumulative future reward).

- $U_t = R_t + R_{t+1} + R_{t+2} + R_{t+3} + \cdots$

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- $U_t = R_t + R_{t+1} + R_{t+2} + R_{t+3} + \cdots$

Question: Are R_t and R_{t+1} equally important?

- Which of the followings do you prefer?
  - I give you $100 right now.
  - I will give you $100 one year later.

Return

Definition: Return (aka cumulative future reward).

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Question: Are R_t and R_{t+1} equally important?

- Which of the followings do you prefer?
  - I give you $100 right now.
  - I will give you $100 one year later.

- Future reward is less valuable than present reward.
- R_{t+1} should be given less weight than R_t.

Return

Definition: Return (aka cumulative future reward).

- $U_t = R_t + R_{t+1} + R_{t+2} + R_{t+3} + \cdots$

Definition: Discounted return (aka cumulative discounted future reward).

- γ: discount rate (tuning hyper-parameter).
- $U_t = R_t + \gamma\, R_{t+1} + \gamma^2\, R_{t+2} + \gamma^3\, R_{t+3} + \cdots$

Randomness in Returns

Definition: Discounted return (at time step t).

- $U_t = R_t + \gamma\, R_{t+1} + \gamma^2\, R_{t+2} + \gamma^3\, R_{t+3} + \cdots$

At time step t, the return U_t is random.

- Two sources of randomness:
  1. Action can be random: $\mathbb{P}[A = a \mid S = s] = \pi(a|s)$.
  2. New state can be random: $\mathbb{P}[S' = s'|S = s, A = a] = p(s'|s, a)$.

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  2. New state can be random: $\mathbb{P}[S' = s'|S = s, A = a] = p(s'|s, a)$.
- For any $i \geq t$, the reward R_i depends on S_i and A_i.
- Thus, given s_t, the return U_t depends on the random variables:
  - $A_t, A_{t+1}, A_{t+2}, \cdots$ and $S_{t+1}, S_{t+2}, \cdots$.

Value Functions

Action-Value Function $Q(s, a)$

Definition: Discounted return (aka cumulative discounted future reward).

- $U_t = R_t + \gamma\, R_{t+1} + \gamma^2\, R_{t+2} + \gamma^3\, R_{t+3} + \cdots$

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- $U_t = R_t + \gamma\, R_{t+1} + \gamma^2\, R_{t+2} + \gamma^3\, R_{t+3} + \cdots$

Definition: Action-value function for policy π.

- $Q_\pi(s_t, a_t) = \mathbb{E}\,[U_t | S_t = s_t, A_t = a_t]$.

- Return U_t depends on states $S_t, S_{t+1}, S_{t+2}, \cdots$ and actions $A_t, A_{t+1}, A_{t+2}, \cdots$.

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- Return U_t depends on states $S_t, S_{t+1}, S_{t+2}, \cdots$ and actions $A_t, A_{t+1}, A_{t+2}, \cdots$.
- Actions are random: $\mathbb{P}[A = a \mid S = s] = \pi(a|s)$. (Policy function.)
- States are random: $\mathbb{P}[S' = s' | S = s, A = a] = p(s'|s, a)$. (State transition.)

Action-Value Function $Q(s, a)$

Definition: Discounted return (aka cumulative discounted future reward).

- $U_t = R_t + \gamma\, R_{t+1} + \gamma^2\, R_{t+2} + \gamma^3\, R_{t+3} + \cdots$

Definition: Action-value function for policy π.

- $Q_\pi(s_t, a_t) = \mathbb{E}\left[U_t | S_t = s_t, A_t = a_t\right]$.

Definition: Optimal action-value function.

- $Q^\star(s_t, a_t) = \max_\pi Q_\pi(s_t, a_t)$.

State-Value Function $V(s)$

Definition: Discounted return (aka cumulative discounted future reward).

- $U_t = R_t + \gamma\, R_{t+1} + \gamma^2\, R_{t+2} + \gamma^3\, R_{t+3} + \cdots$

Definition: Action-value function for policy π.

- $Q_\pi(s_t, a_t) = \mathbb{E}\,[U_t | S_t = s_t, A_t = a_t]$.

Definition: State-value function.

- $V_\pi(s_t) = \mathbb{E}_A\,[Q_\pi(s_t, A)]$

State-Value Function $V(s)$

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Definition: State-value function.

- $V_\pi(s_t) = \mathbb{E}_A\,[Q_\pi(s_t, A)] = \sum_a \pi(a|s_t) \cdot Q_\pi(s_t, a)$. (Actions are discrete.)

Taken w.r.t. the action $A \sim \pi(\cdot\,|s_t)$.

State-Value Function $V(s)$

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Definition: State-value function.

- $V_\pi(s_t) = \mathbb{E}_A\,[Q_\pi(s_t, A)] = \sum_a \pi(a|s_t) \cdot Q_\pi(s_t, a)$. (Actions are discrete.)
- $V_\pi(s_t) = \mathbb{E}_A\,[Q_\pi(s_t, A)] = \int \pi(a|s_t) \cdot Q_\pi(s_t, a)\, da$. (Actions are continuous.)

Understanding the Value Functions

- Action-value function: $Q_\pi(s_t, a_t) = \mathbb{E}\left[U_t | S_t = s_t, A_t = a_t\right]$.
- Given policy π, $Q_\pi(s, a)$ evaluates how good it is for an agent to pick action a while being in state s.
- $Q^\star(s_t, a_t)$ evaluates how good it is for an agent to pick action a while being in state s no matter what the policy is.

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- State-value function: $V_\pi(s) = \mathbb{E}_A\left[Q_\pi(s, A)\right]$
- For fixed policy π, $V_\pi(s)$ evaluates how good the situation is in state s.
- $\mathbb{E}_S[V_\pi(S)]$ evaluates how good the policy π is.

Play games using reinforcement learning

How does AI control the agent?

Suppose we have a good policy $\pi(a|s)$.

- Upon observing the state s_t,
- random sampling: $a_t \sim \pi(\cdot\,|s_t)$.

How does AI control the agent?

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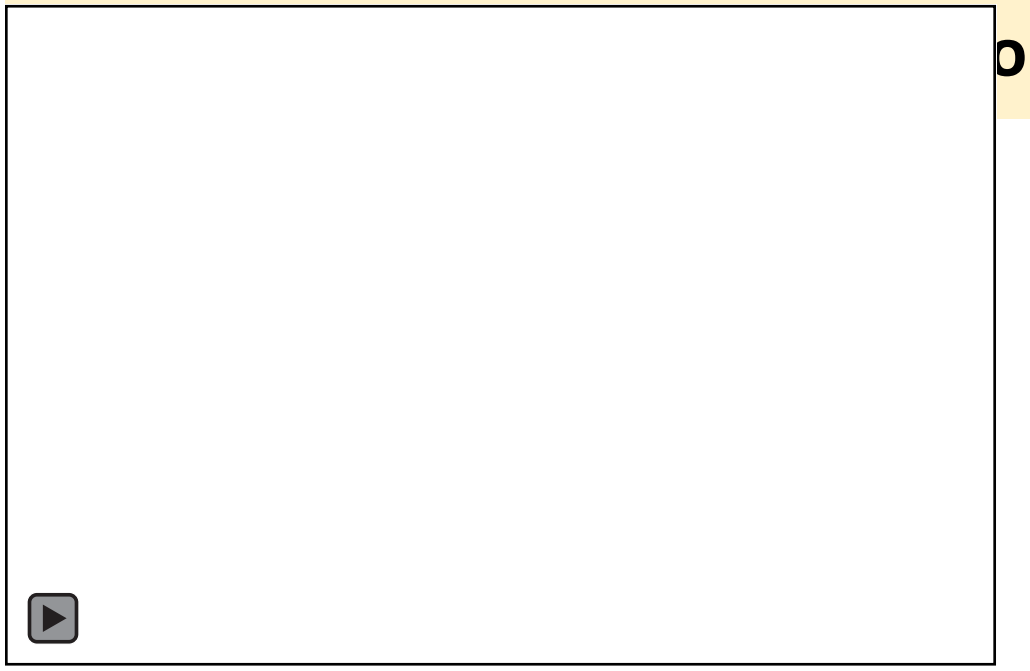
- random sampling: $a_t \sim \pi(\cdot\,|s_t)$.

Suppose we know the optimal action-value function $Q^\star(s, a)$.

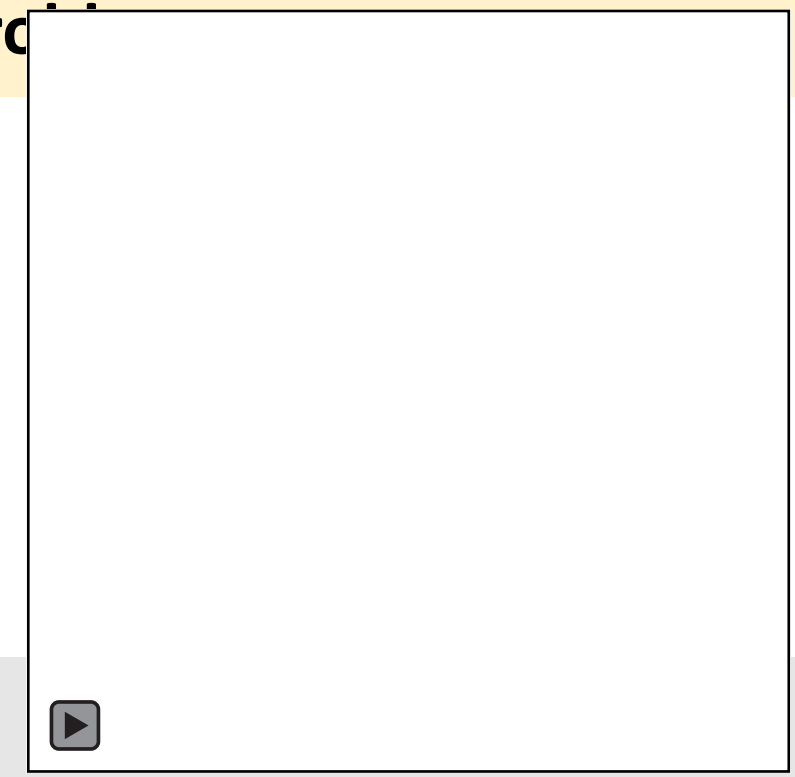
- Upon observe the state s_t,
- choose the action that maximizes the value: $a_t = \text{argmax}_a\, Q^\star(s_t, a)$.

OpenAI Gym

- Gym is a toolkit for developing and comparing reinforcement learning algorithms.
- https://gym.openai.com/



Cart Pole



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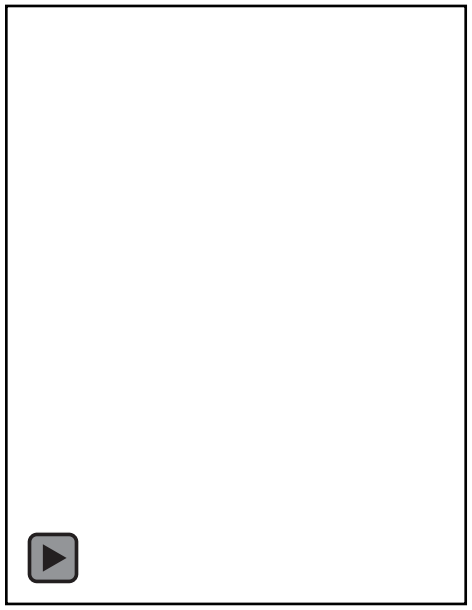
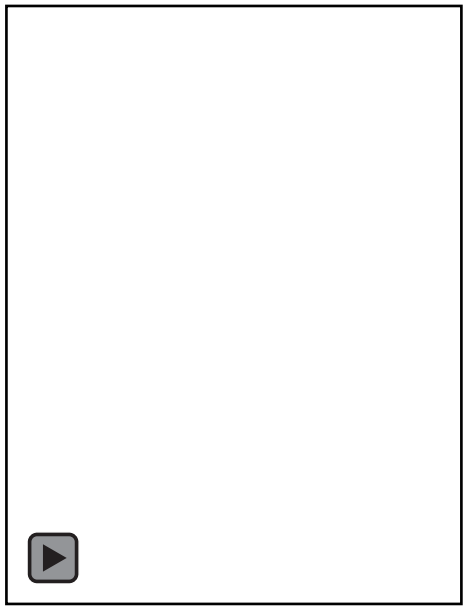
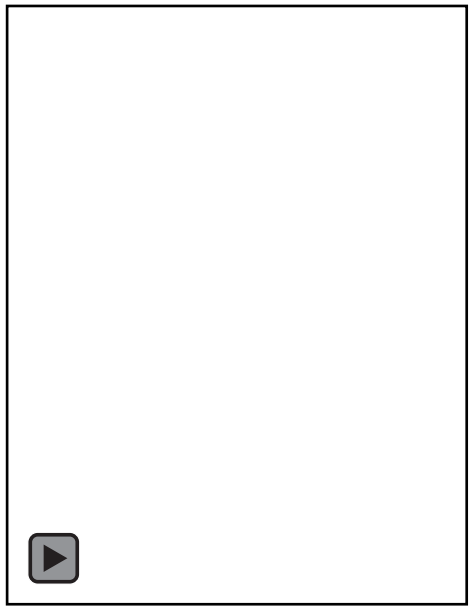
Atari Games



Pong



Space Invader



Breakout

OpenAI Gym

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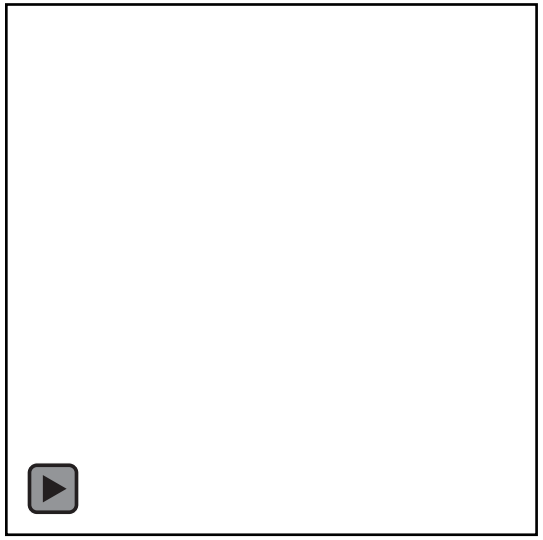
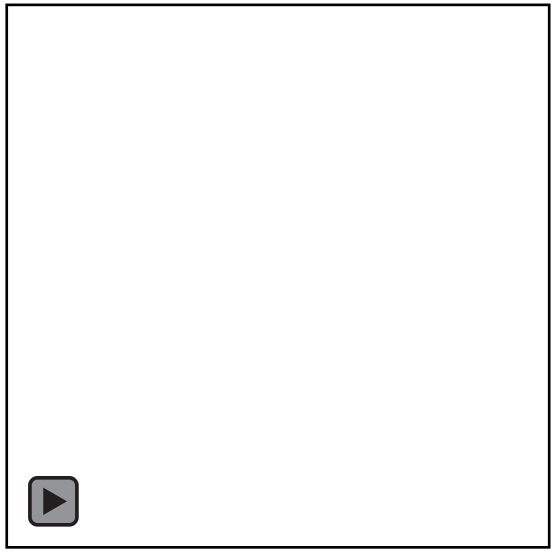
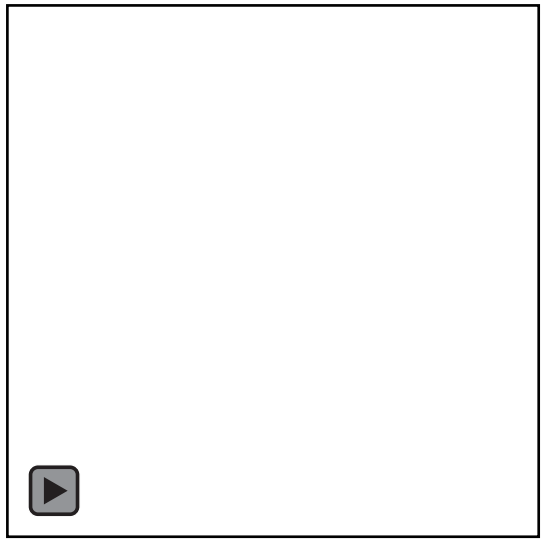
MuJoCo (Continuous control tasks.)



Ant

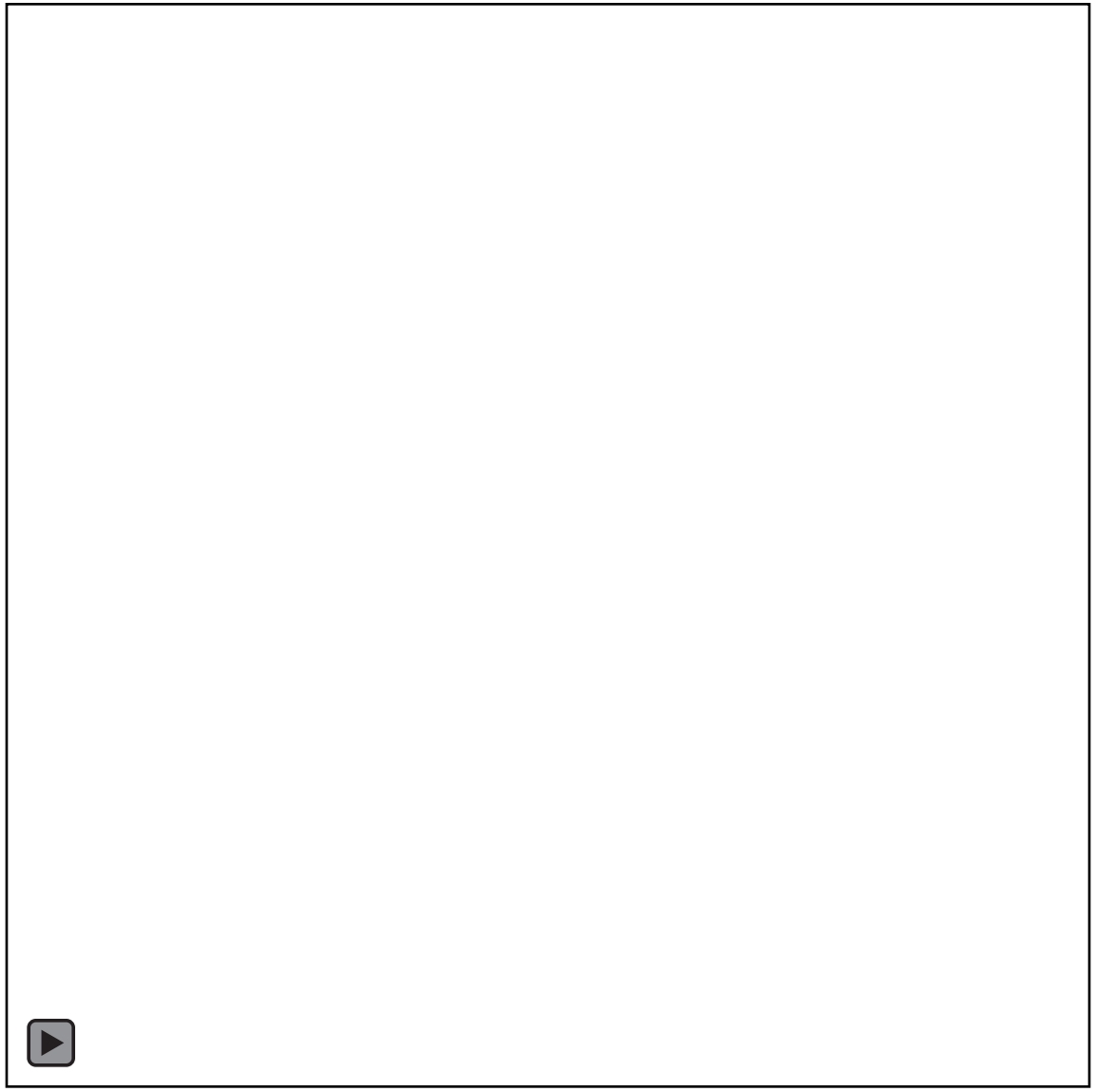


Humanoid



Half Cheetah

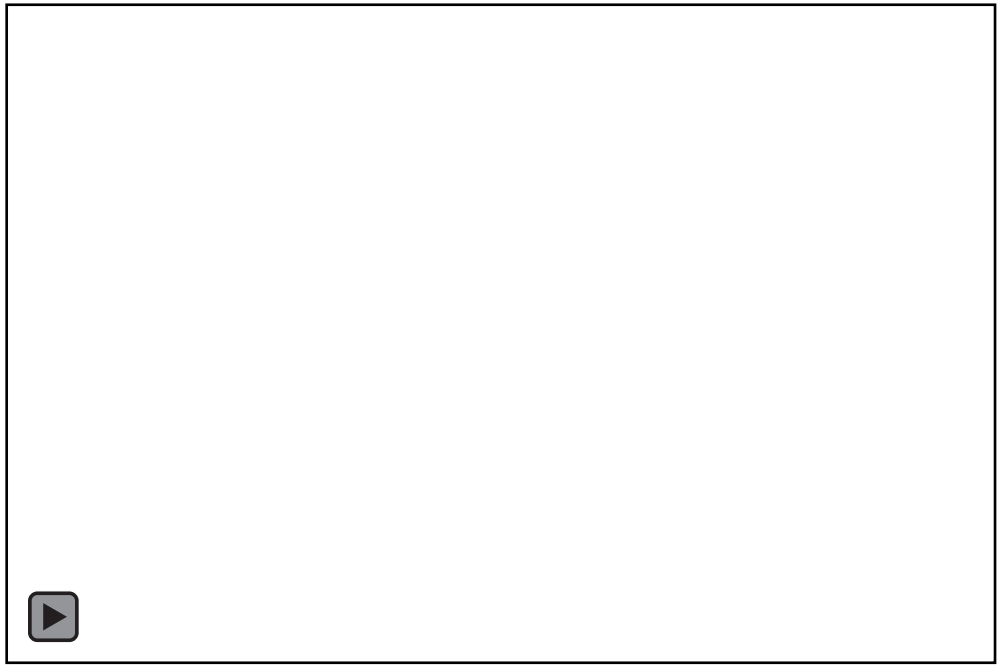
OpenAI Gym



Play CartPole Game

```
import gym
env = gym.make('CartPole-v0')
```

- Get the environment of CartPole from Gym.
- "env" provides states and reward.



Play CartPole Game

```
state = env.reset()

for t in range(100):
    env.render()
    print(state)

    action = env.action_space.sample()
    state, reward, done, info = env.step(action)

    if done:
        print('Finished')
        break

env.close()
```

A window pops up rendering CartPole.

A random action.

"done=1" means finished (win or lose the game)

Summary

Summary

Terminologies

- Agent 
- Environment
- State s.
- Action a.
- Reward r.
- Policy $\pi(a|s)$
- State transition $p(s'|s,a)$.

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Return and Value

- Return:

$$U_t = R_t + \gamma\, R_{t+1} + \gamma^2\, R_{t+2} + \cdots$$

- Action-value function:

$$Q_\pi(s_t, a_t) = \mathbb{E}\,[U_t | s_t, a_t].$$

- Optimal action-value function:

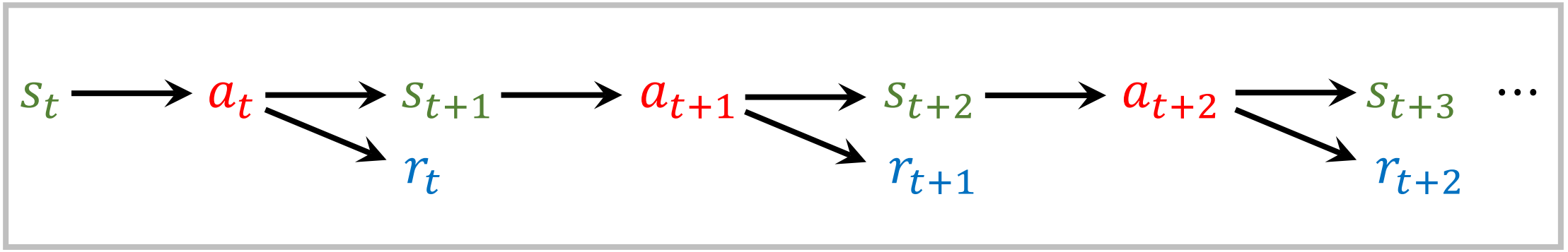
$$Q^\star(s_t, a_t) = \max_\pi Q_\pi(s_t, a_t).$$

- State-value function:

$$V_\pi(s_t) = \mathbb{E}_A[Q_\pi(s_t, A)].$$

Play game using reinforcement learning

- Observe state s_t, make action a_t, environment gives s_{t+1} and reward r_t.



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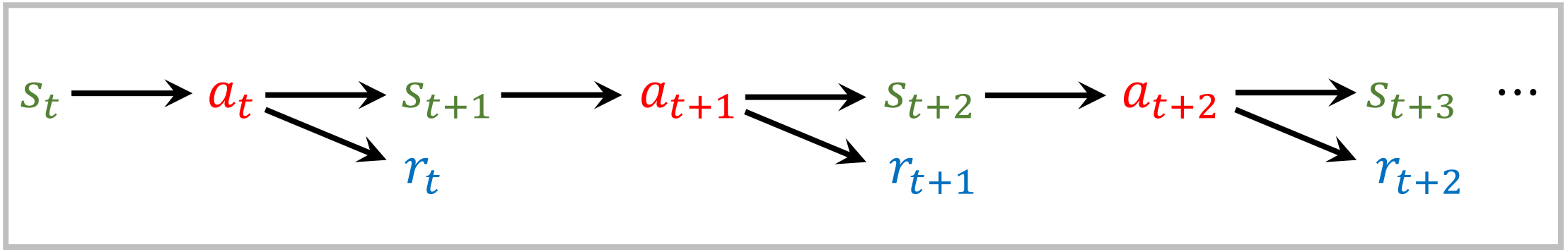

- The agent can be controlled by either $\pi(a|s)$ or $Q^\star(s,a)$.

We are going to study…

2. Value-based learning.
   - Deep Q network (DQN) for approximating $Q^\star(s, a)$.
   - Learn the network parameters using temporal different (TD).

3. Policy-based learning.
   - Policy network for approximating $\pi(a|s)$.
   - Learn the network parameters using policy gradient.

4. Actor-critic method. (Policy network + value network.)

5. Example: AlphaGo

Value-Based Reinforcement Learning

Shusen Wang

Action-Value Functions

Discounted Return

Definition: Discounted return (aka cumulative discounted future reward).

- $U_t = R_t + \gamma\, R_{t+1} + \gamma^2\, R_{t+2} + \gamma^3\, R_{t+3} + \cdots$

- The return depends on actions $A_t, A_{t+1}, A_{t+2}, \cdots$ and states $S_t, S_{t+1}, S_{t+2}, \cdots$
- Actions are random: $\mathbb{P}[A = a \mid S = s] = \pi(a|s)$. (Policy function.)
- States are random: $\mathbb{P}[S' = s'|S = s, A = a] = p(s'|s, a)$. (State transition.)

Action-Value Functions $Q(s, a)$

Definition: Discounted return (aka cumulative discounted future reward).

- $U_t = R_t + \gamma\, R_{t+1} + \gamma^2\, R_{t+2} + \gamma^3\, R_{t+3} + \cdots$

Definition: Action-value function for policy π.

- $Q_\pi(s_t, a_t) = \mathbb{E}\,[U_t | S_t = s_t, A_t = a_t]$.

  - Taken w.r.t. actions $A_{t+1}, A_{t+2}, A_{t+3}, \cdots$ and states $S_{t+1}, S_{t+2}, S_{t+3}, \cdots$
  - Integrate out everything except for the observations: $A_t = a_t$ and $S_t = s_t$.

Action-Value Functions $Q(s, a)$

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- $Q_\pi(s_t, a_t) = \mathbb{E}\left[U_t | S_t = s_t, A_t = a_t\right]$.

Definition: Optimal action-value function.

- $Q^\star(s_t, a_t) = \max_\pi Q_\pi(s_t, a_t)$.
- Whatever policy function π is used, the result of taking a_t at state s_t cannot be better than $Q^\star(s_t, a_t)$.

Deep Q-Network (DQN)

Approximate the Q Function

Goal: Win the game (≈ maximize the total reward.)

Question: If we know $Q^\star(s, a)$, what is the best action?

Approximate the Q Function

Goal: Win the game ($\approx$ maximize the total reward.)

Question: If we know $Q^\star(s, a)$, what is the best action?

- Obviously, the best action is $a^\star = \underset{a}{\operatorname{argmax}}\, Q^\star(s, a)$.

$Q^\star$ is an indicator of how good it is for an agent to pick action a while being in state s.

Approximate the Q Function

Goal: Win the game (≈ maximize the total reward.)

Question: If we know $Q^\star(s, a)$, what is the best action?

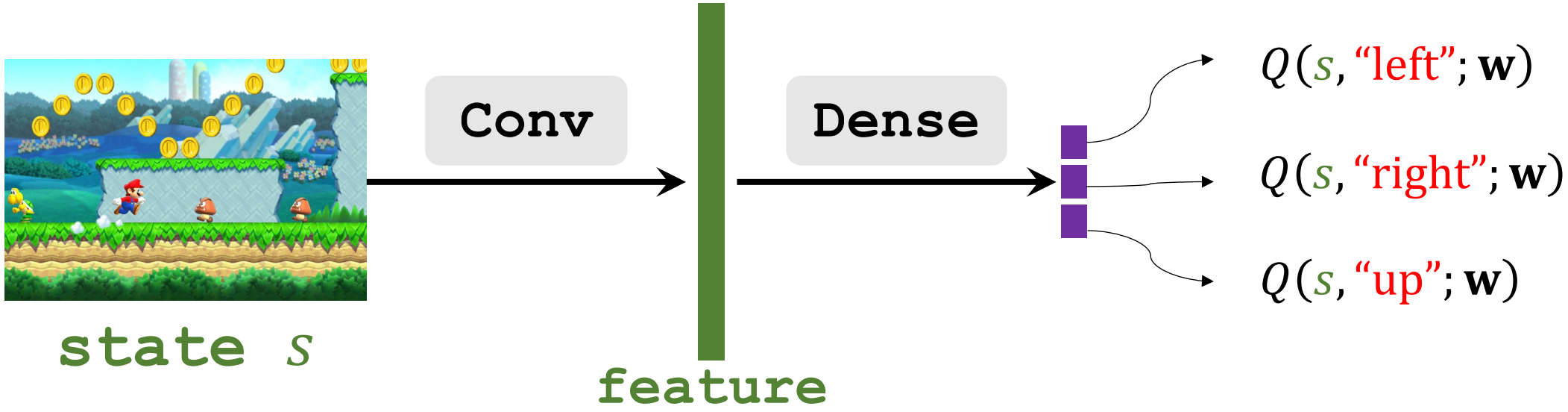
- Obviously, the best action is $a^\star = \underset{a}{\operatorname{argmax}}\, Q^\star(s, a)$.

Challenge: We do not know $Q^\star(s, a)$.

- Solution: Deep Q Network (DQN)
- Use neural network $Q(s, a; \mathbf{w})$ to approximate $Q^\star(s, a)$.

Deep Q Network (DQN)

- Input shape: size of the screenshot.
- Output shape: dimension of action space.



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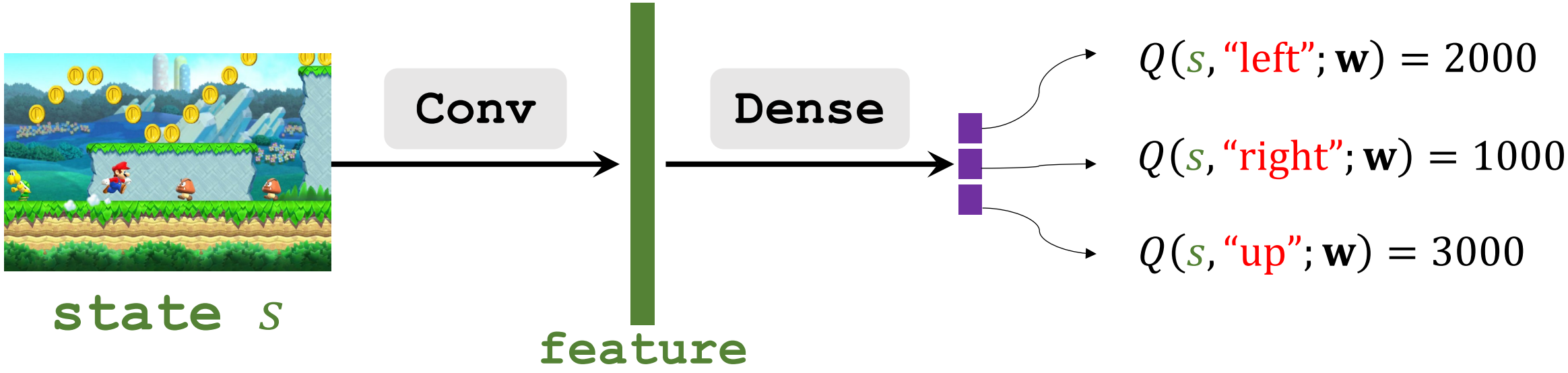
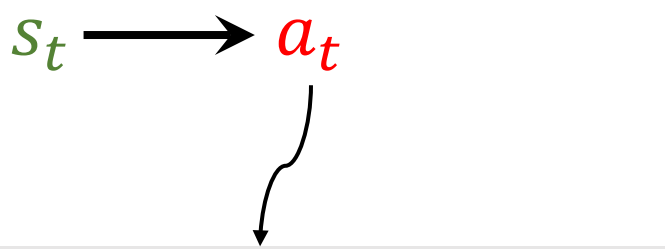


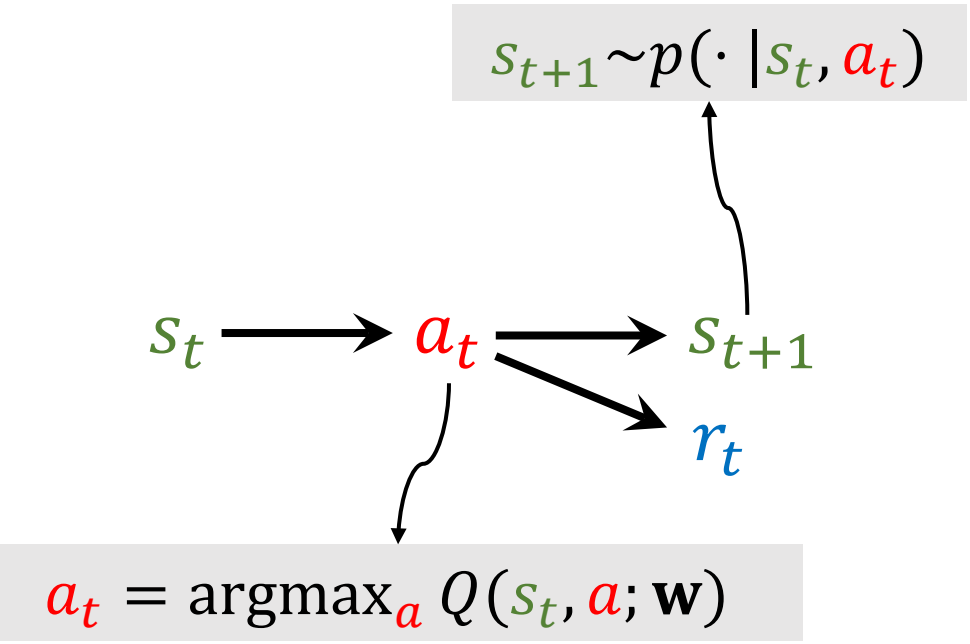
Question: Based on the predictions, what should be the action?

Apply DQN to Play Game



$$a_t = \text{argmax}_a \, Q(s_t, a; \mathbf{w})$$

Apply DQN to Play Game



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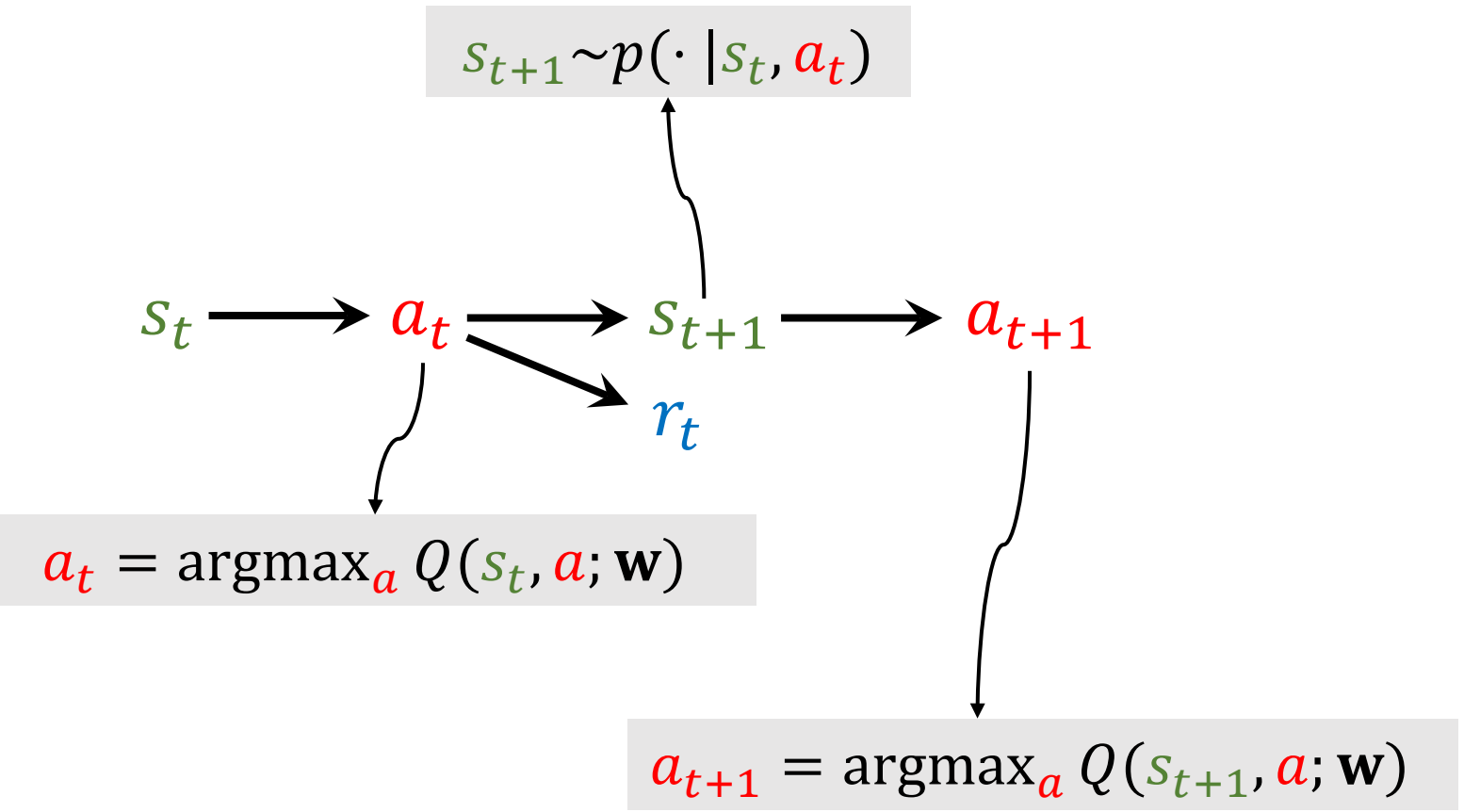

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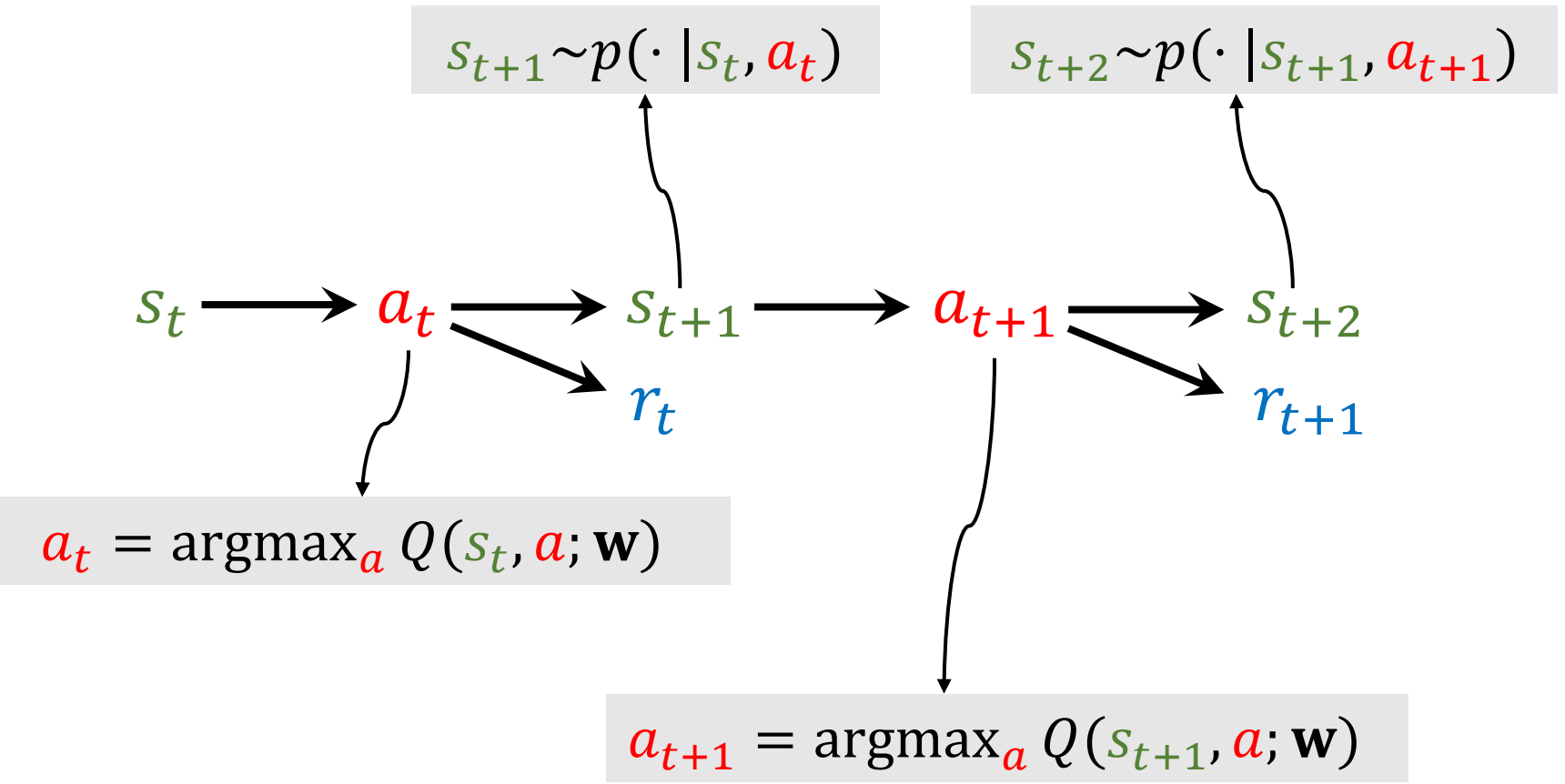

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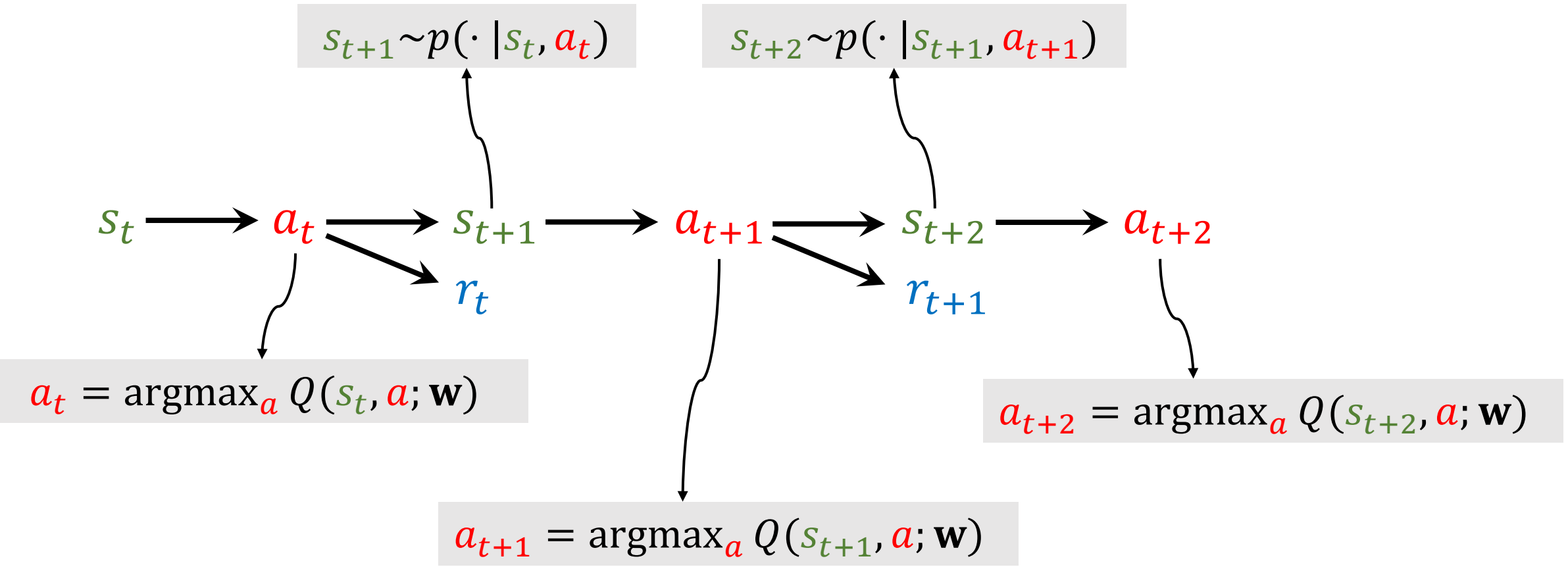

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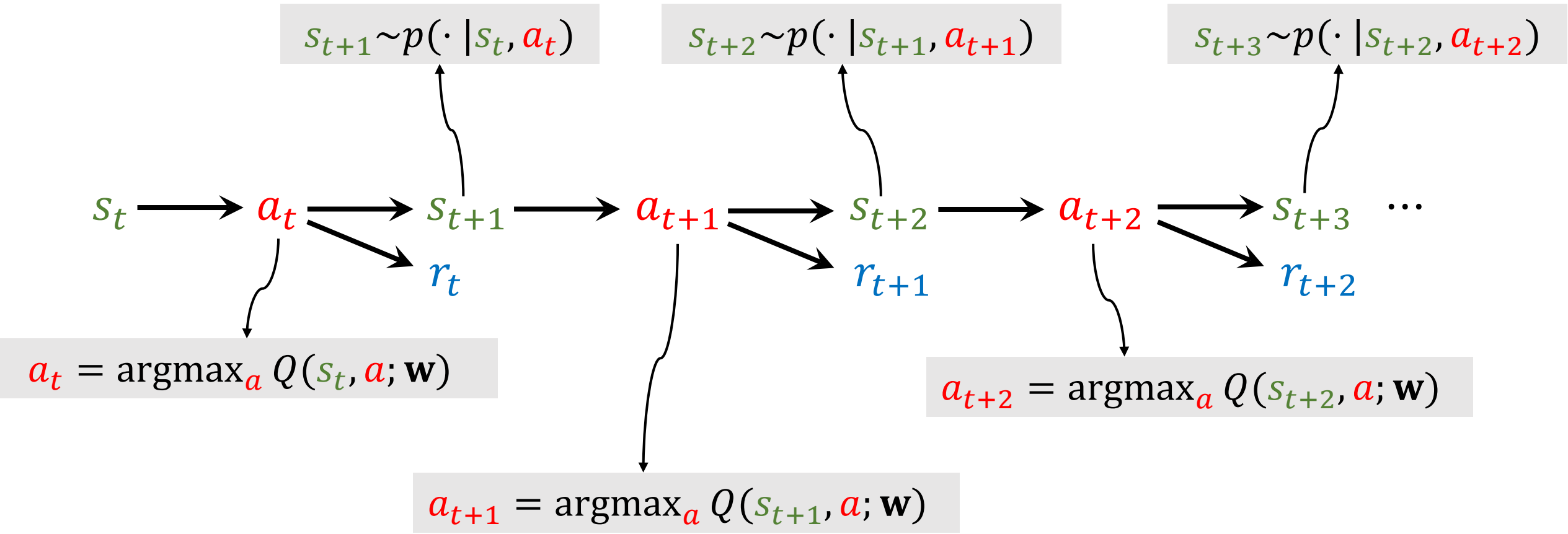


Temporal Difference (TD) Learning

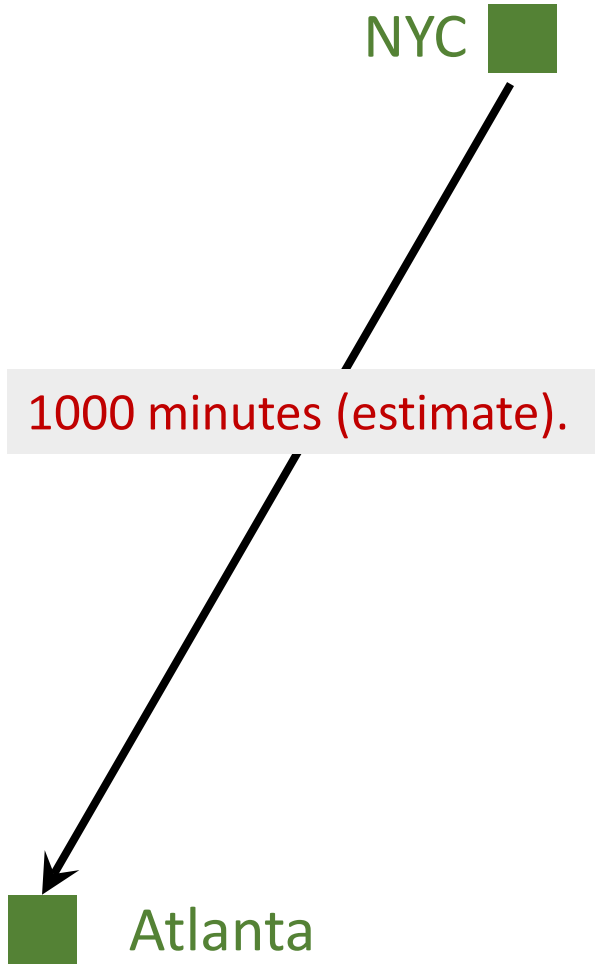
Reference

1. Sutton and others: A convergent O(n) algorithm for off-policy temporal-difference learning with linear function approximation. In *NIPS*, 2008.
2. Sutton and others: Fast gradient-descent methods for temporal-difference learning with linear function approximation. In *ICML*, 2009.

Example

- I want to drive from NYC to Atlanta.
- Model $Q(\mathbf{w})$ estimates the time cost, e.g., 1000 minutes.

Question: How do I update the model?



Example

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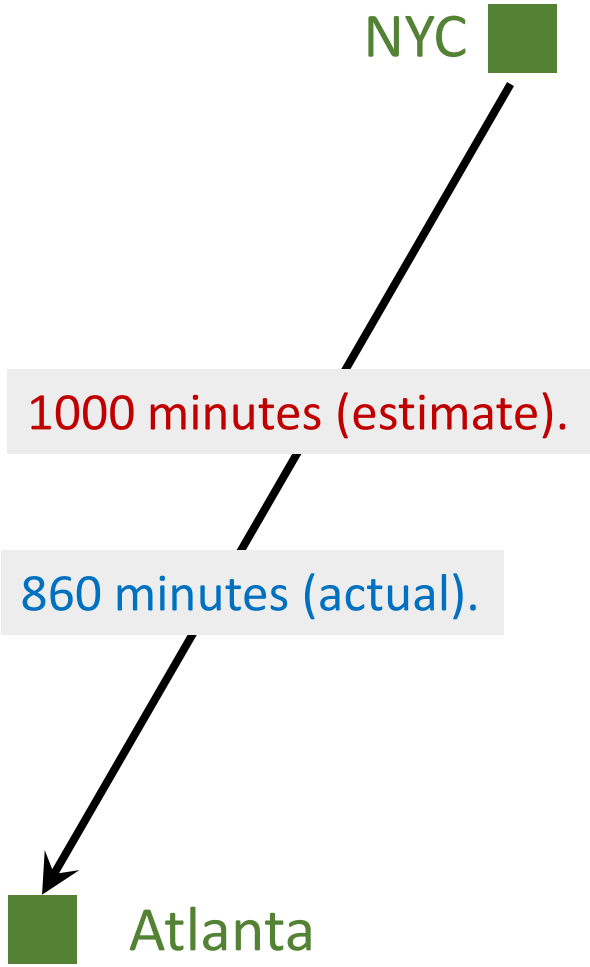
- Model $Q(\mathbf{w})$ estimates the time cost, e.g., 1000 minutes.

Question: How do I update the model?

- Make a prediction: $q = Q(\mathbf{w})$, e.g., $q = 1000$.
- Finish the trip and get the target y, e.g., $y = 860$.



Example

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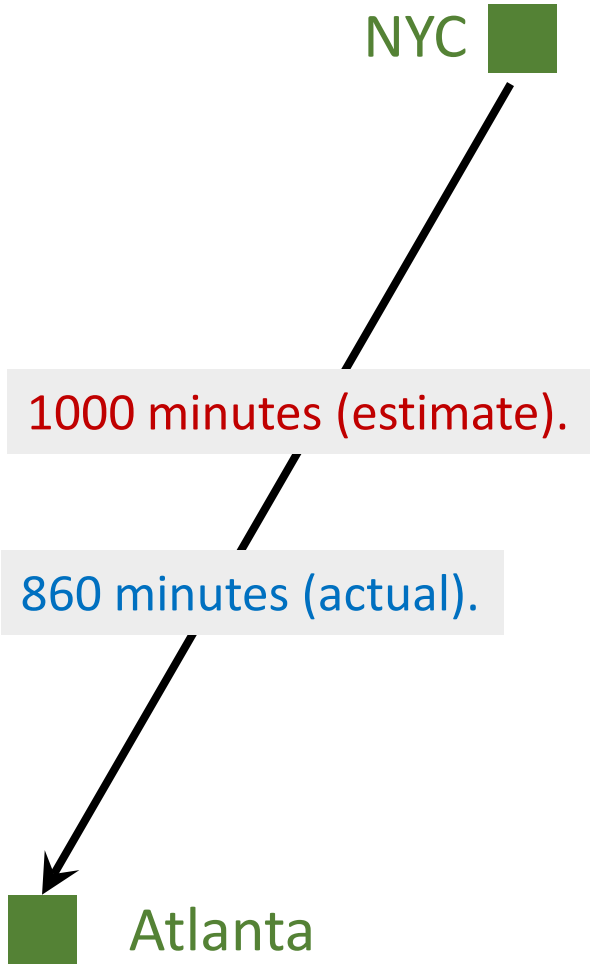
- Model $Q(\mathbf{w})$ estimates the time cost, e.g., 1000 minutes.

Question: How do I update the model?

- Make a prediction: $q = Q(\mathbf{w})$, e.g., $q = 1000$.
- Finish the trip and get the target y, e.g., $y = 860$.
- Loss: $L = \frac{1}{2}(q - y)^2$.
- Gradient: $\frac{\partial L}{\partial \mathbf{w}} = \frac{\partial q}{\partial \mathbf{w}} \cdot \frac{\partial L}{\partial q} = (q - y) \cdot \frac{\partial Q(\mathbf{w})}{\partial \mathbf{w}}$.
- Gradient descent: $\mathbf{w}_{t+1} = \mathbf{w}_t - \alpha \cdot \frac{\partial L}{\partial \mathbf{w}} \Big|_{\mathbf{w}=\mathbf{w}_t}$.

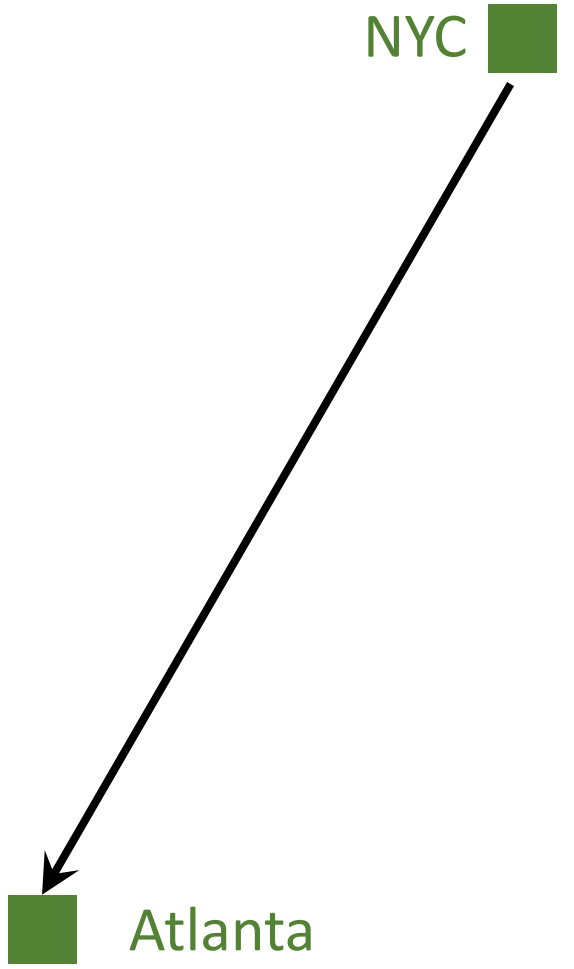


Example

- I want to drive from NYC to Atlanta.
- Model $Q(\mathbf{w})$ estimates the time cost, e.g., 1000 minutes.

Question: How do I update the model?

- Can I update the model before finishing the trip?

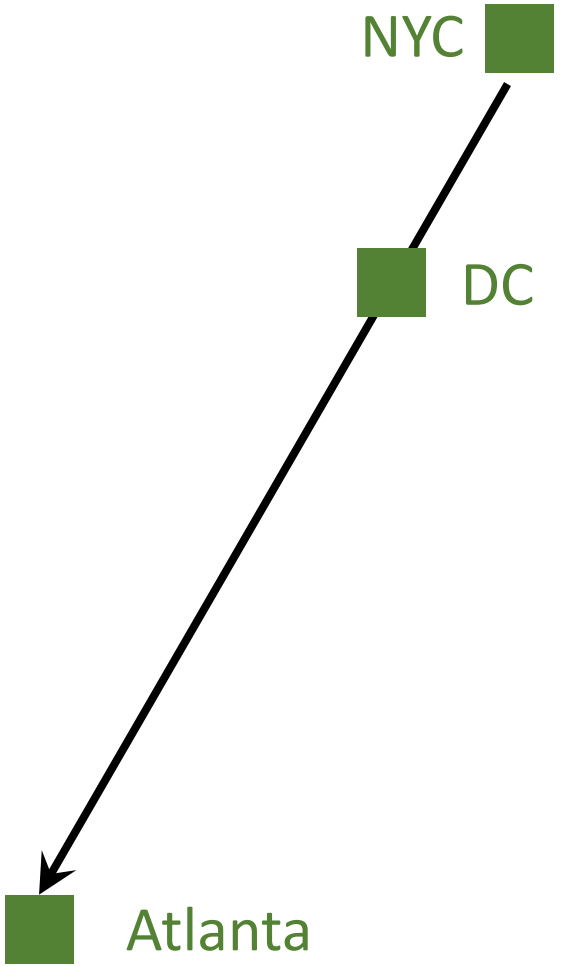


Example

- I want to drive from NYC to Atlanta (via DC).
- Model $Q(\mathbf{w})$ estimates the time cost, e.g., 1000 minutes.

Question: How do I update the model?

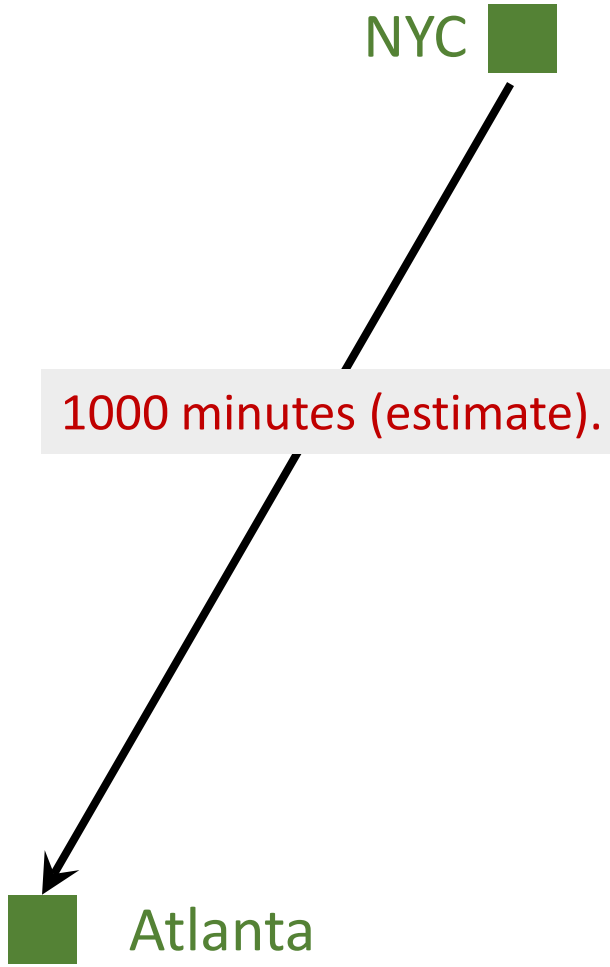
- Can I update the model before finishing the trip?
- Can I get a better $\mathbf{w}$ as soon as I arrived at DC?



Temporal Difference (TD) Learning

- Model's estimate:

  NYC to Atlanta: 1000 minutes (estimate).



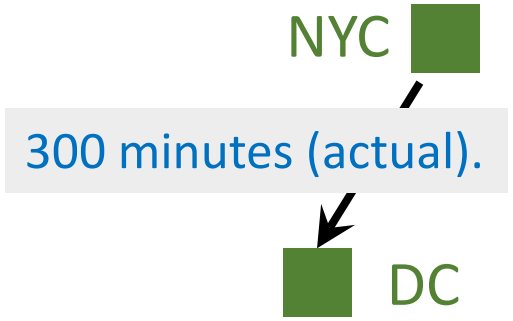
Temporal Difference (TD) Learning

- Model's estimate:

  NYC to Atlanta: 1000 minutes (estimate).

- I arrived at DC; actual time cost:

  NYC to DC: 300 minutes (actual).



Temporal Difference (TD) Learning

- Model's estimate:

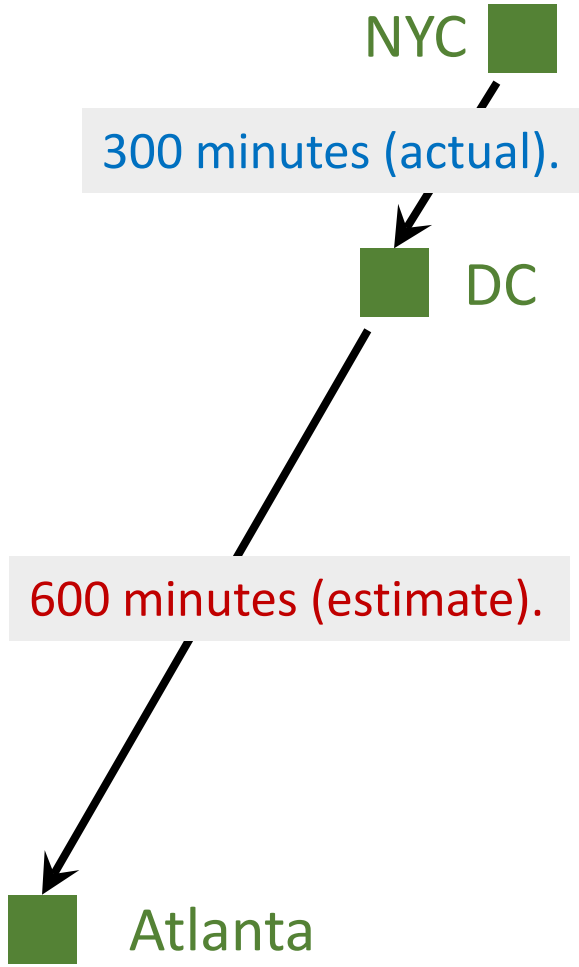
  NYC to Atlanta: 1000 minutes (estimate).

- I arrived at DC; actual time cost:

  NYC to DC: 300 minutes (actual).

- Model now updates its estimate:

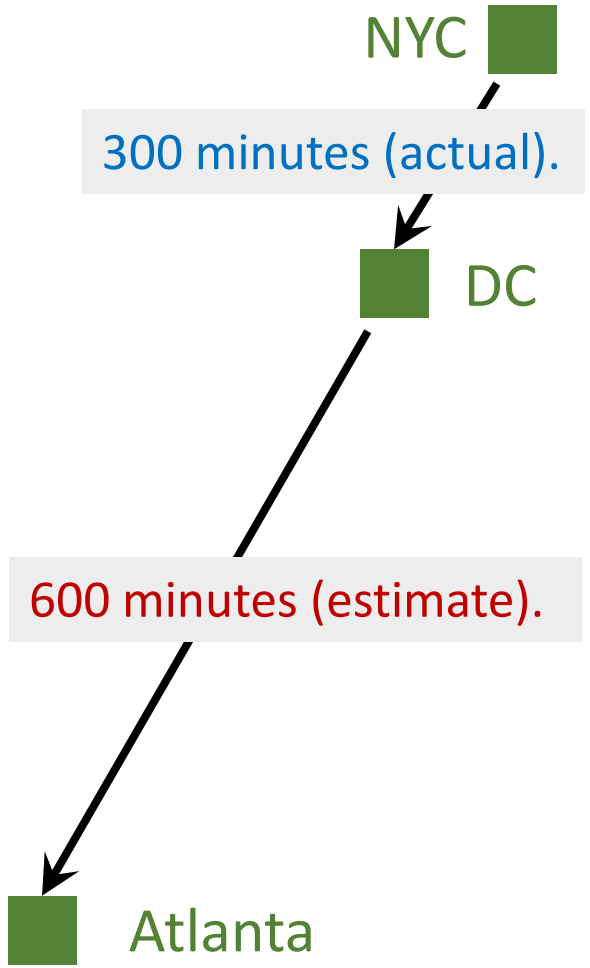
  DC to Atlanta: 600 minutes (estimate).



Temporal Difference (TD) Learning

- Model's estimate: $Q(\mathbf{w}) = 1000$ minutes.
- Updated estimate: $300 + 600 = 900$ minutes.

TD target.



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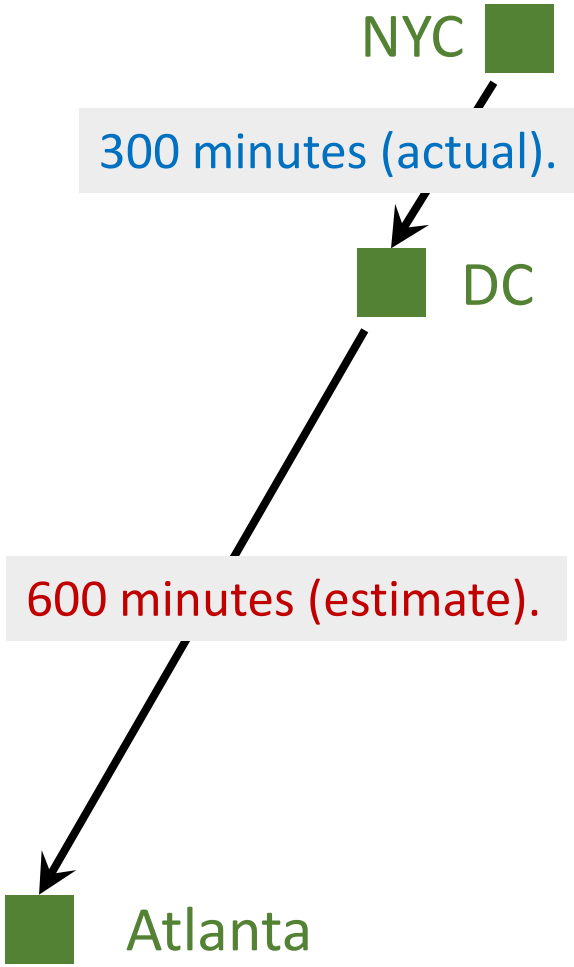
TD target.

- TD target $y = 900$ is a more reliable estimate than 1000.



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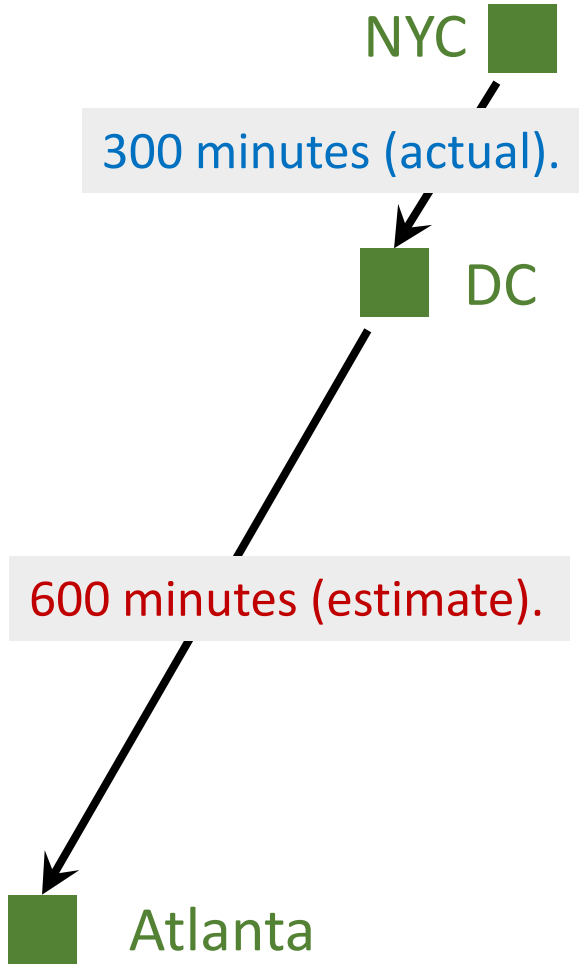
- Loss: $L = \frac{1}{2}(Q(\mathbf{w}) - y)^2$.

TD error



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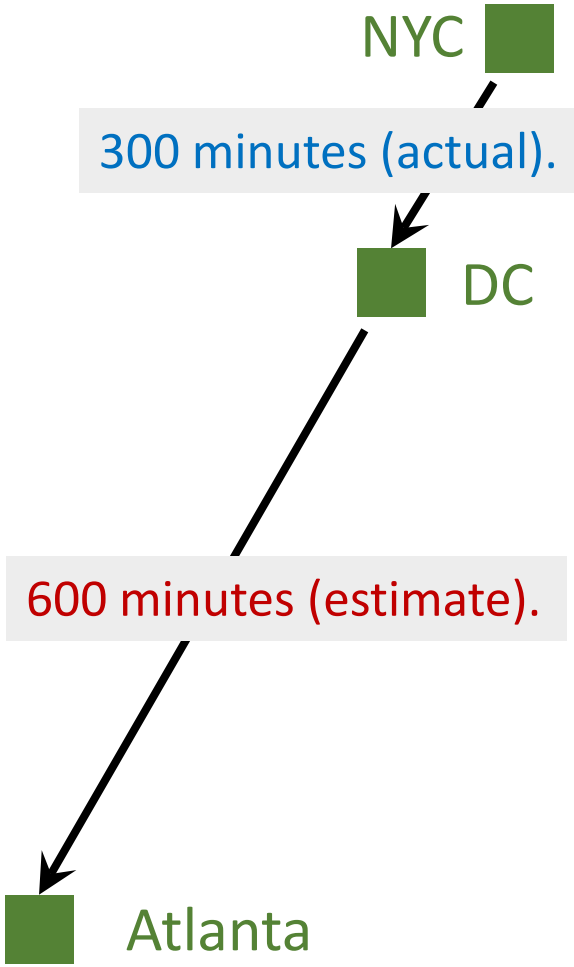
TD target.

- TD target $y = 900$ is a more reliable estimate than 1000.
- Loss: $L = \frac{1}{2}(Q(\mathbf{w}) - y)^2$.
- Gradient: $\frac{\partial L}{\partial \mathbf{w}} = (1000 - 900) \cdot \frac{\partial Q(\mathbf{w})}{\partial \mathbf{w}}$.

TD error



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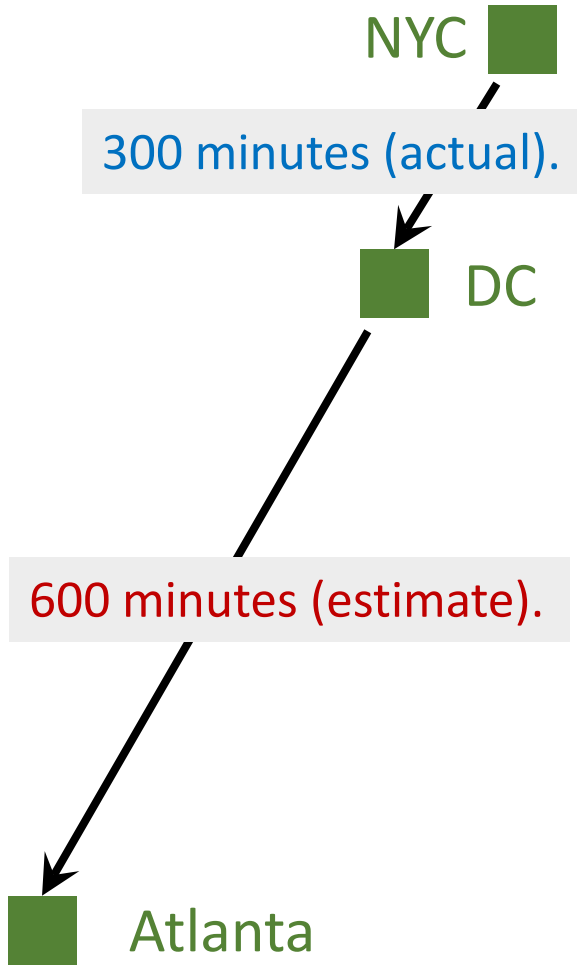
- Updated estimate: $300 + 600 = 900$ minutes.

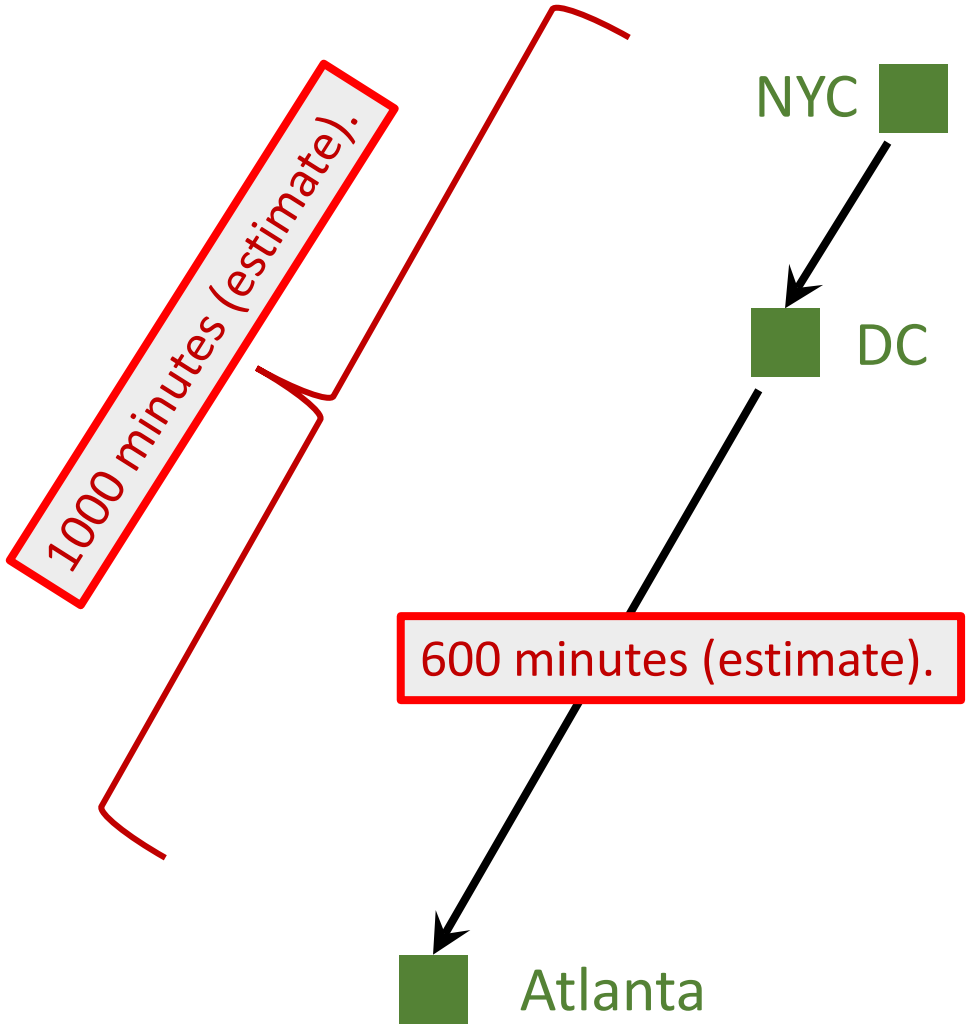
TD target.



- TD target $y = 900$ is a more reliable estimate than 1000.
- Loss: $L = \frac{1}{2}(Q(\mathbf{w}) - y)^2$.
- Gradient: $\frac{\partial L}{\partial \mathbf{w}} = (1000 - 900) \cdot \frac{\partial Q(\mathbf{w})}{\partial \mathbf{w}}$.
- Gradient descent: $\mathbf{w}_{t+1} = \mathbf{w}_t - \alpha \cdot \frac{\partial L}{\partial \mathbf{w}} \Big|_{\mathbf{w}=\mathbf{w}_t}$.

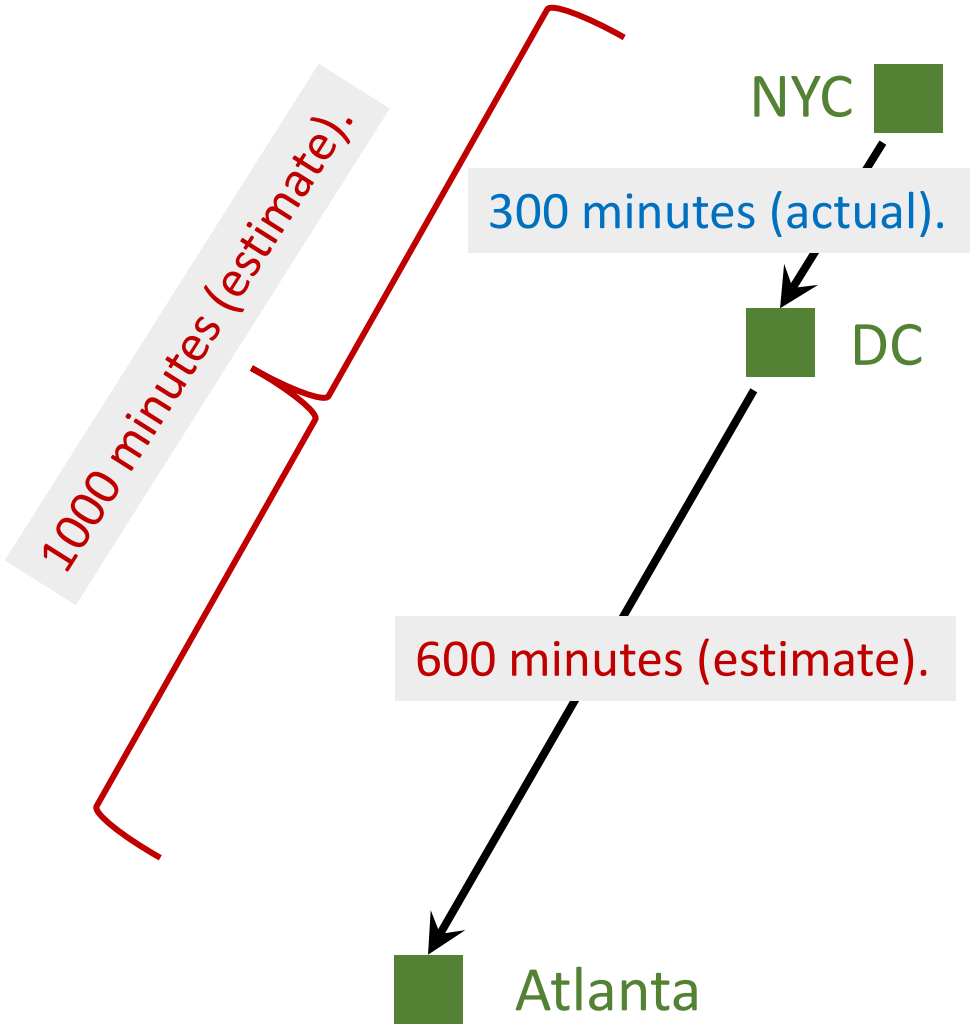
Why does TD learning work?

- Model's estimates:
  - NYC to Atlanta: 1000 minutes.
  - DC to Atlanta: 600 minutes.
  - ➔ NYC to DC: 400 minutes.



Why does TD learning work?

- Model's estimates:
  - NYC to Atlanta: 1000 minutes.
  - DC to Atlanta: 600 minutes.
  - ➔ NYC to DC: 400 minutes.
- Ground truth:
  - NYC to DC: 300 minutes.
- TD error: $\delta = 400 - 300 = 100$



TD Learning for DQN

How to apply TD learning to DQN?

- In the “driving time” example, we have the equation:

$$T_{\mathrm{NYC}\to\mathrm{ATL}} \approx T_{\mathrm{NYC}\to\mathrm{DC}} + T_{\mathrm{DC}\to\mathrm{ATL}} .$$

Model’s estimate

Actual time

Model’s estimate

How to apply TD learning to DQN?

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Model's estimate | Actual time | Model's estimate

- In deep reinforcement learning:

$$Q(s_t, a_t; \mathbf{w}) \approx r_t + \gamma \cdot \max_a Q(s_{t+1}, a; \mathbf{w}).$$

How to apply TD learning to DQN?

Identity: $U_t = R_t + \gamma \cdot U_{t+1}$.

TD learning for DQN:

- DQN's output, $Q(s_t, a_t; \mathbf{w})$, is an estimate of U_t.
- DQN's output, $Q(s_{t+1}, a_{t+1}; \mathbf{w})$, is an estimate of U_{t+1}.
- Thus, $\underbrace{Q(s_t, a_t; \mathbf{w})}_{\text{estimate of } U_t} \approx \mathbb{E}\left[R_t + \gamma \cdot \underbrace{\max_a Q(S_{t+1}, a; \mathbf{w})}_{\text{estimate of } U_{t+1}}\right]$.

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- Thus, $\underbrace{Q(s_t, a_t; \mathbf{w})}_{\text{Prediction}} \approx \underbrace{r_t + \gamma \cdot \max_a Q(s_{t+1}, a; \mathbf{w})}_{\text{TD target}}$.

Train DQN using TD learning

- Prediction: $Q(s_t, a_t; \mathbf{w}_t)$.
- TD target:

$$y_t = r_t + \gamma \cdot \max_a Q(s_{t+1}, a; \mathbf{w}_t).$$

Train DQN using TD learning

- Prediction: $Q(s_t, a_t; \mathbf{w}_t)$.
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$$y_t = r_t + \gamma \cdot \max_a Q(s_{t+1}, a; \mathbf{w}_t).$$

- Loss: $L_t = \frac{1}{2}[Q(s_t, a_t; \mathbf{w}) - y_t]^2$.
- Gradient descent: $\mathbf{w}_{t+1} = \mathbf{w}_t - \alpha \cdot \frac{\partial L_t}{\partial \mathbf{w}} \Big|_{\mathbf{w}=\mathbf{w}_t}$.

Explore the Environment

- **ε-greedy policy:**
  - With probability **ε**, the agent chooses a random action (exploration).
  - With probability **1 - ε**, the agent chooses the action that has the highest predicted Q-value (exploitation).
- **Decaying ε:** Often, DQN uses an **annealing strategy** where ε starts high (favoring exploration) and gradually decreases over time (favoring exploitation as the agent learns more).

Summary

Value-Based Reinforcement Learning

Definition: Optimal action-value function.

- $Q^\star(s_t, a_t) = \max_\pi \mathbb{E}\left[U_t | S_t = s_t, A_t = a_t\right]$.

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DQN: Approximate $Q^\star(s, a)$ using a neural network (DQN).

- $Q(s, a; \mathbf{w})$ is a neural network parameterized by $\mathbf{w}$.
- Input: observed state s.
- Output: scores for all the action $a \in \mathcal{A}$.

Temporal Difference (TD) Learning

Algorithm: One iteration of TD learning.

1. Observe state $S_t = s_t$ and perform action $A_t = a_t$.
2. Predict the value: $q_t = Q(s_t, a_t; \mathbf{w}_t)$.
3. Differentiate the value network: $\mathbf{d}_t = \frac{\partial\, Q(s_t, a_t; \mathbf{w})}{\partial\, \mathbf{w}} \Big|_{\mathbf{w}=\mathbf{w}_t}$.

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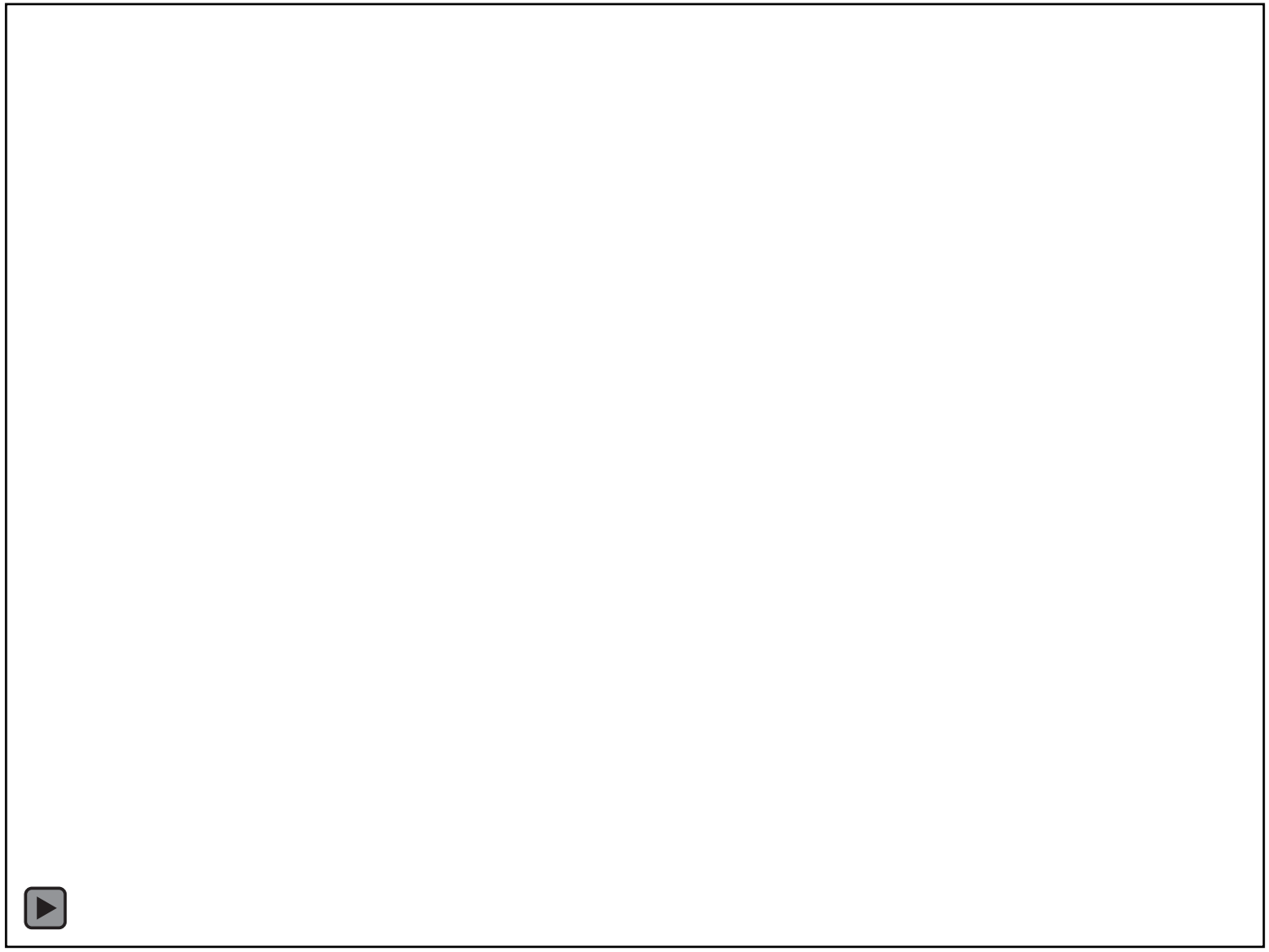
Play Breakout using DQN



(The video was posted on YouTube by DeepMind)

Thank you!

http://wangshusen.github.io/