

Markov Decision Process

Announcements

TA office hours are posted

HW0 is due Wednesday

Programming assignment 1 will be out on Wednesday

Reading Materials: Reinforcement Learning: Theory & Algorithms

<https://rltheorybook.github.io/>

This is an extremely advanced RL book, so we will pick **specific subsections** for you to read

Please let us know if you find any typos or mistakes in the book

Outlines:

1. Definitions of Markov Decision Process
2. Value functions (V and Q functions)
3. Bellman equations

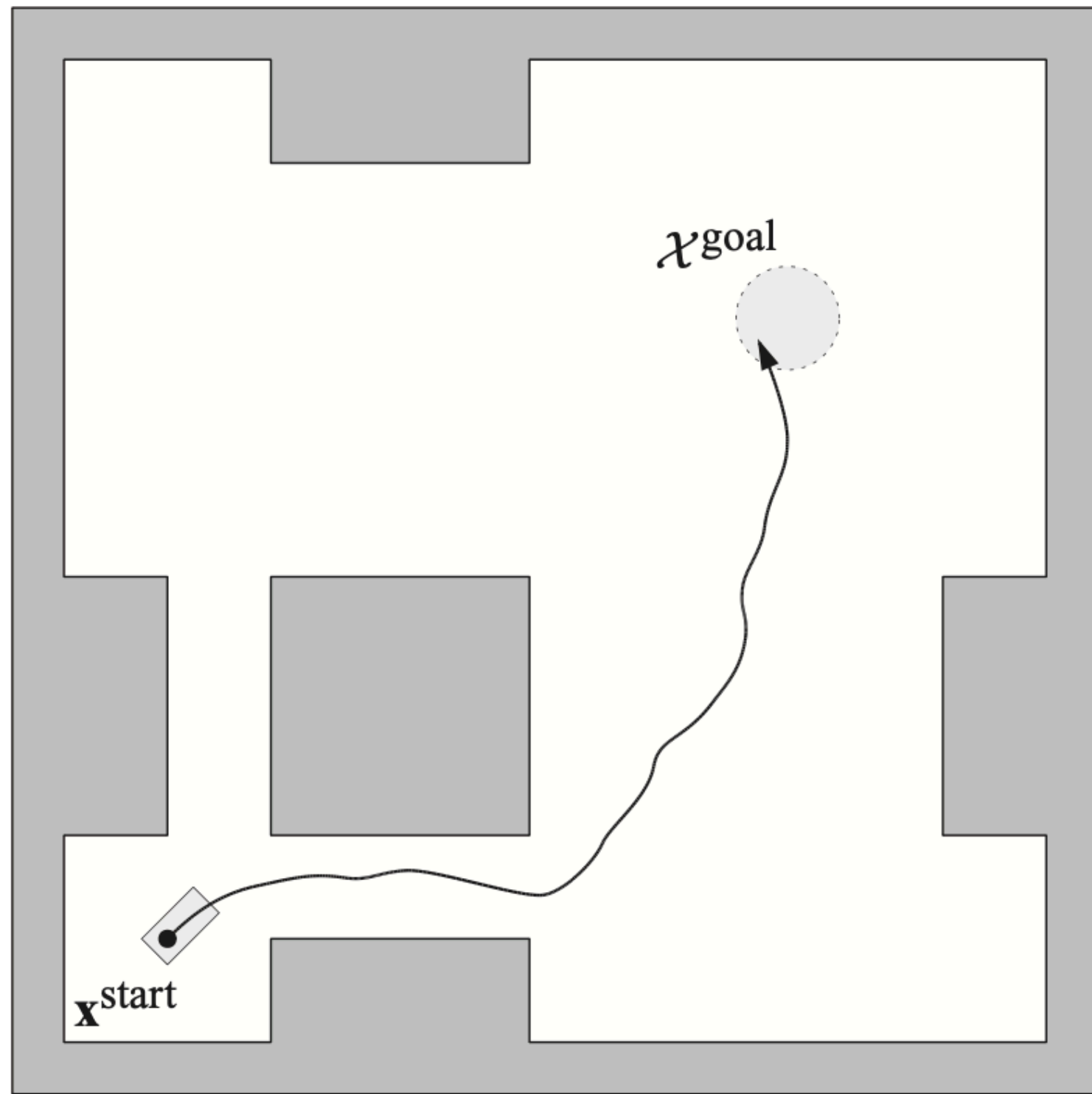
The Mathematical framework: Infinite horizon **Markov Decision Process**



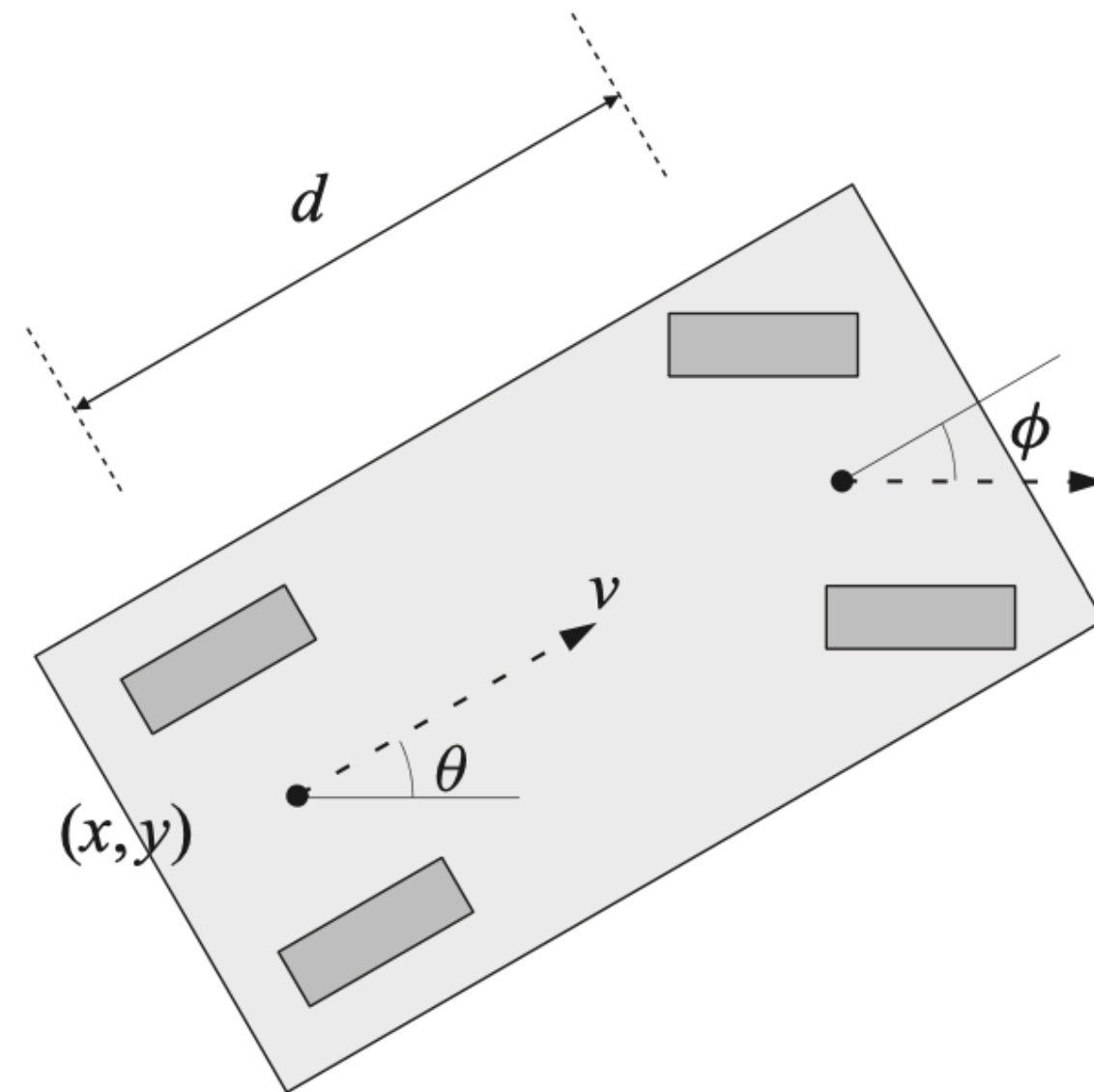
$$r(s, a), s' \sim P(\cdot | s, a)$$

$P(\cdot | s, a)$: distribution over the next state

Example: 2-D simple car navigation



(a)



(b)

$$s = [x, y, \theta, v]^T \in \mathbb{R}^4$$

$$a = [\alpha, \phi]^T \in \mathbb{R}^2$$

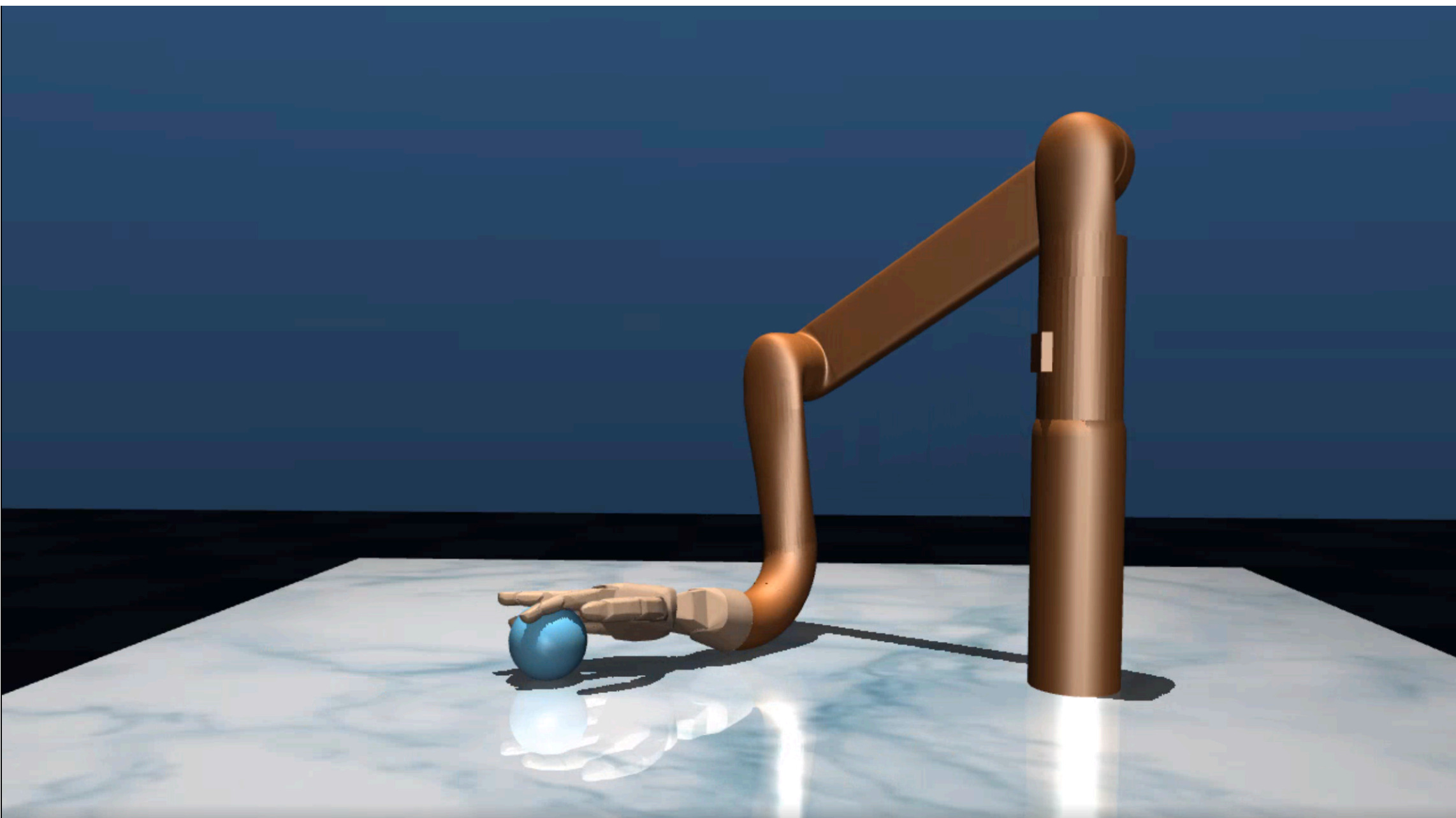
$$r(s, a) = \begin{cases} 100 & (x, y) \in \mathcal{X}_{\text{goal}} \\ -1 & \text{hit obstacles} \\ 0 & \text{else} \end{cases}$$

$$s' = f(s, a) + \epsilon, \text{ where } \epsilon \sim \mathcal{N}(0, I)$$

$$f(s, a) = \begin{bmatrix} x + \tau v \cos \theta \\ y + \tau v \sin \theta \\ \theta + \tau v \tan(\phi) / d \\ v + \tau \alpha \end{bmatrix}$$

Example:

robot hand needs to pick the ball and hold it in a goal (x,y,z) position



State s : robot configuration (e.g., joint angles) and the ball's position

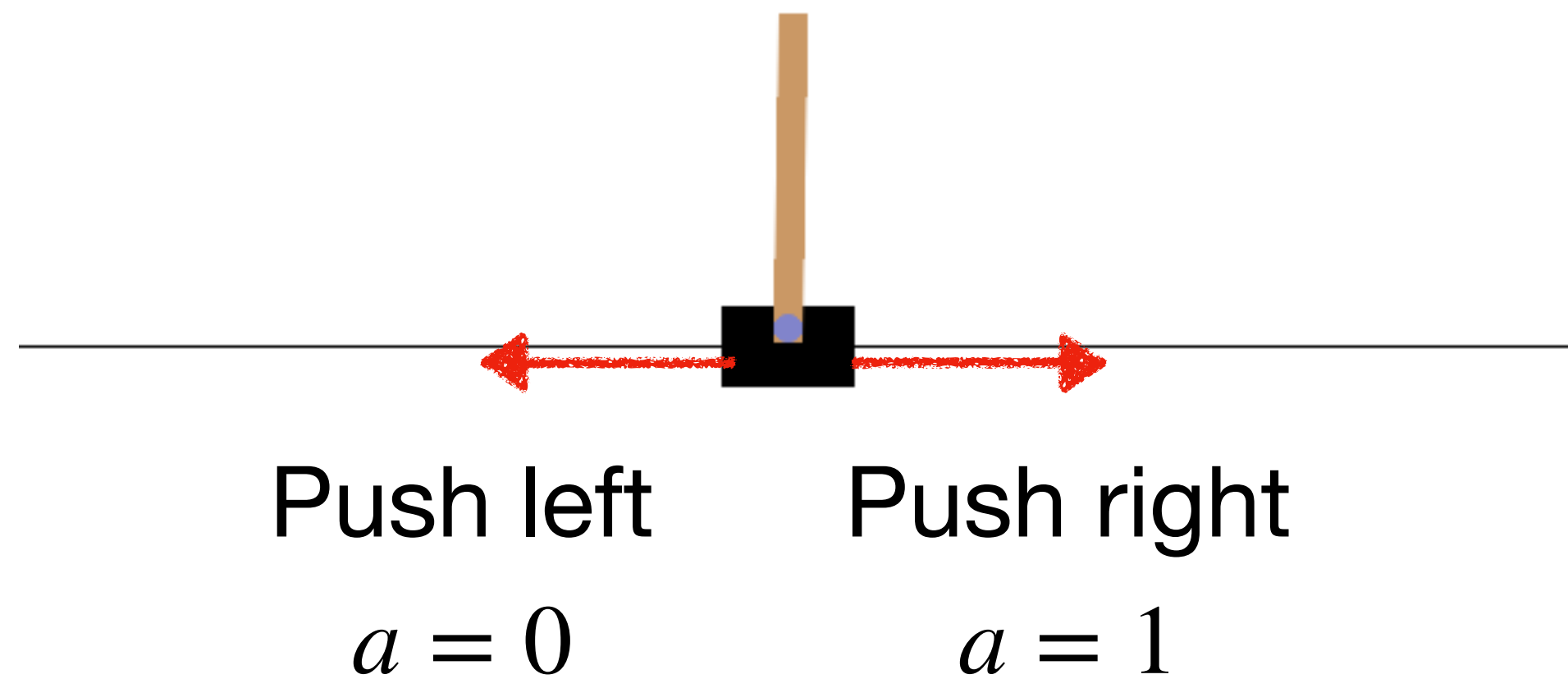
Action a : Torque on joints in arm & fingers

Transition $s' \sim P(\cdot | s, a)$: physics + some noise

Cost $c(s, a)$: torque magnitude + dist to goal

Example: OpenAI Gym demonstrations

State = [cart pos, cart velocity,
pole angle, pole angular velocity]



$$r(s, a) = \begin{cases} 1 & \text{pole angle} \in [-12^\circ, 12^\circ], \\ 0 & \text{else} \end{cases}$$

Policy

$$\mathcal{S} \rightarrow \mathcal{A}$$

A mapping from state to action (what action should I take if I'm in this state...)

$$a \sim \pi(\cdot | s)$$

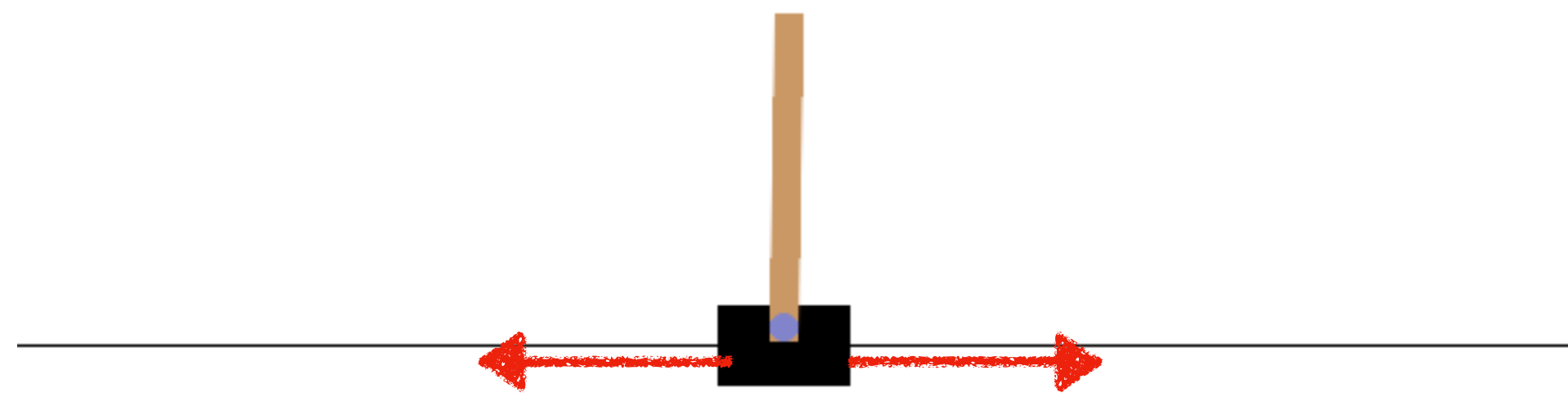
conditional
distribution over all
actions

Deterministic vs stochastic?

Q: Assume \mathcal{S} state and \mathcal{A} actions, how many different deterministic policies we can have?

Example: OpenAI Gym demonstrations

State = [cart pos, cart velocity,
pole angle, pole angular velocity]



Push left

$$a = 0$$

Push right

$$a = 1$$


$$r(s, a) = \begin{cases} 1 & \text{pole angle} \in [-12^\circ, 12^\circ], \\ 0 & \text{else} \end{cases}$$

Policy 1: uniform random
 $\pi(0 | s) = \pi(1 | s) = 0.5, \forall s$

Policy 2: adaptive

$$\pi(s) = \begin{cases} 0(\text{left}) & \text{if pole angle} < 0 \\ 1(\text{right}) & \text{else} \end{cases}$$

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Performance of a policy π

Expected total reward of a policy π :

$$V^\pi(s) = \mathbb{E} \left[r_0 + \gamma r_1 + \gamma^2 r_2 + \dots + \gamma^h r_h + \dots \mid s_0 = s, \pi \right]$$

$\gamma \in [0,1)$: discount factor (value future reward less and less)

Q: think about the CartPole example, is there a way we can estimate $V^\pi(s)$ at a given s ?

Optimal policy

π^\star : the policy that maximizes expected future reward at all states

$$V^\star(s) \geq V^\pi(s), \forall s, \forall \pi$$

Fact: such optimal policy does exist for any infinite horizon discounted MDP

Q: what is the optimal policy when $\gamma = 0$?

State-action Q function

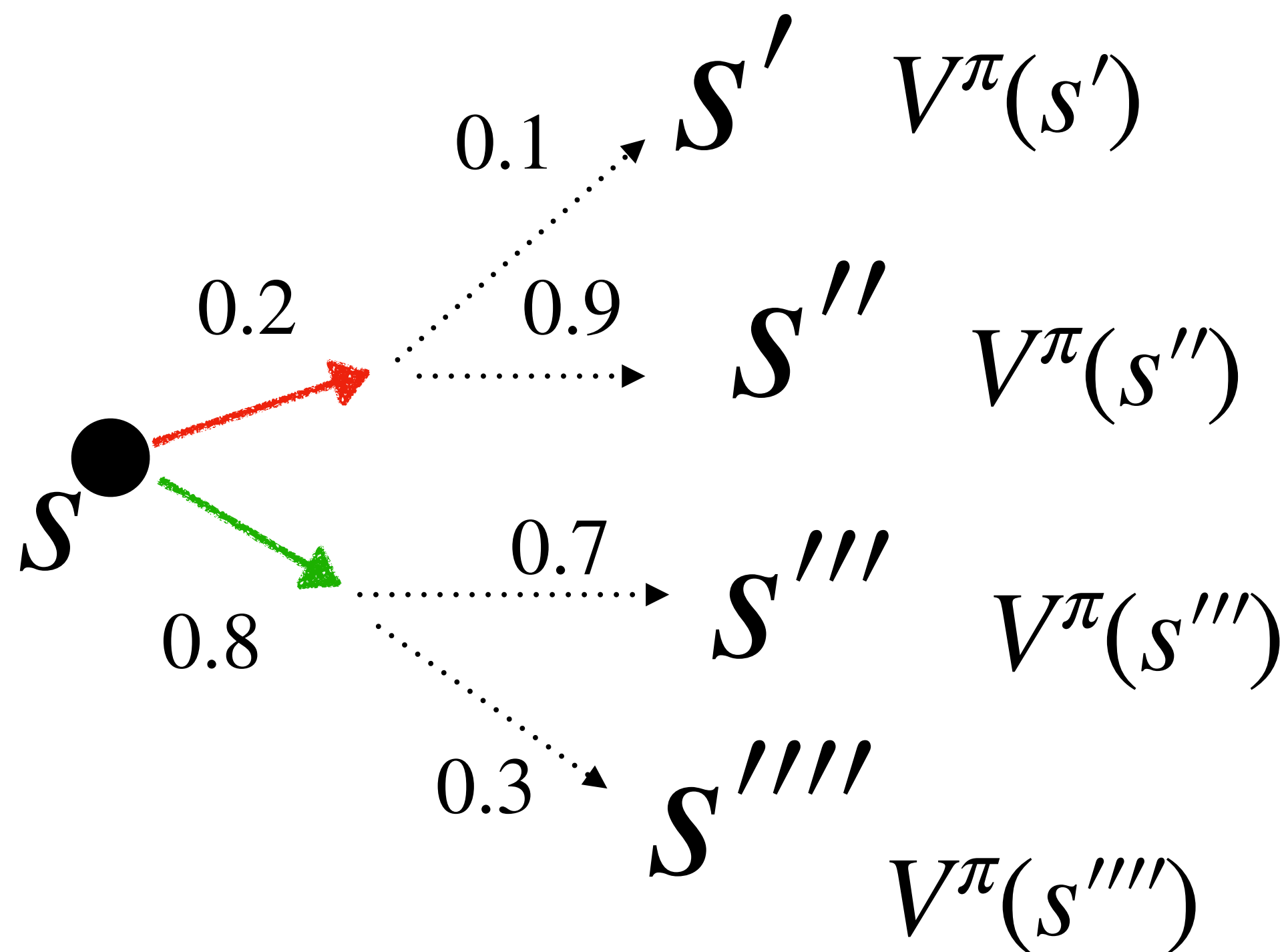
$$Q^\pi(s, a) = \mathbb{E} \left[r_0 + \gamma r_1 + \gamma^2 r_2 + \dots + \gamma^h r_h + \dots \mid s_0 = s, a_0 = a, \pi \right]$$

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- ✓ 1. Definitions of Markov Decision Process
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Can we quantify V / Q using one-step transition?

$$V^\pi(s) = \mathbb{E} \left[r_0 + \gamma r_1 + \gamma^2 r_2 + \dots + \gamma^h r_h + \dots \mid s_0 = s, a \sim \pi \right]$$



$$V^\pi(s) = \mathbb{E}_{a \sim \pi(\cdot|s)} \left[r(s, a) + \gamma \mathbb{E}_{s' \sim P(\cdot|s, a)} [V^\pi(s')] \right]$$

Bellman equation for value function

Can we quantify V / Q using one-step transition?

Your homework: understand the one-step relationship between V and Q

$$Q^\pi(s, a) = r(s, a) + \gamma \mathbb{E}_{s' \sim P(\cdot | s, a)} [V^\pi(s')]$$

$$V^\pi(s) = \mathbb{E}_{a \sim \pi(\cdot | s)} Q^\pi(s, a)$$

Summary:

- **Discounted infinite horizon MDP:**
 - State, action, policy, transition, reward (or cost), discount factor
 - **V function and Q function**
 - Key concept: **Bellman equation**