Value

CISC 7404 - Decision Making

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Review

Policy-Conditioned Returns

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Trajectory optimization is model-based algorithm

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Guaranteed optimal policy, given infinite compute

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Today, we will look at new algorithms based on the notion of **value**

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Expensive to train, but very cheap to use

Policy-Conditioned Returns

Recall the return from trajectory optimization

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$$[\mathcal{G}(\boldsymbol{\tau}) \mid s_0, a_0, a_1, ...] = \sum_{t=0}^{\infty} \gamma^t \mathbb{E}[\mathcal{R}(s_{t+1}) \mid s_0, a_0, a_1, ...]$$

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This is an **action-conditioned** discounted return

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- Random
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- Random
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- Maximize $\mathcal{G}$

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$$\pi : S \times \Theta \mapsto \Delta A$$

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$$\pi(a_t \mid s_t; \theta_\pi) = \begin{cases} 1 \text{ if } a_t = \arg\max_{a_t \in A} \mathbb{E}[\mathcal{G}(\boldsymbol{\tau}) \mid s_0, a_0, a_1, ...] \\ 0 \text{ otherwise} \end{cases}$$

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Conditioning the return on actions is annoying

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Must compute infinitely many actions and outcomes for the return

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What if we condition on a policy, instead of specific actions?

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$$a_0 \sim \pi(\cdot \mid s_0; \theta_\pi), \quad a_1 \sim \pi(\cdot \mid s_1; \theta_\pi), \quad a_2 \sim \pi(\cdot \mid s_2; \theta_\pi), \quad ...$$

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Condition on a function parameterized by θ_π instead of many actions

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The function outputs a distribution over the action space $\pi(a \mid s; \theta_\pi)$

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How does $\mathbb{E}[\mathcal{R}(s_{t+1})]$ change when we condition on θ_π?

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Question: What changes when we condition on θ_π?

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$$\Pr(s_{t+1} \mid s_0; \theta_\pi)$$

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Answer: State transition function

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Combine the policy distribution with next state distribution

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Write out the first few timesteps

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$$\Pr(s_2 \mid s_0; \theta_\pi) = \sum_{s_1 \in S} \sum_{a_1 \in A} \mathrm{Tr}(s_2 \mid s_1, a_1) \cdot \pi(a_1 \mid s_1; \theta_\pi)$$

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Derive a general form for $\Pr(s_{n+1} \mid s_0; \theta_\pi)$

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Derive a general form for $\Pr(s_{n+1} \mid s_0; \theta_\pi)$

$$\Pr(s_{n+1} \mid s_0; \theta_\pi) = \sum_{s_1, \dots, s_n \in S} \prod_{t=0}^{n} \left(\sum_{a_t \in A} \mathrm{Tr}(s_{t+1} \mid s_t, a_t) \cdot \pi(a_t \mid s_t; \theta) \right)$$

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Plug back into our expected reward

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Plug back into our expected reward

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Discounted return is discounted sum of rewards

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Goal: find the θ_π (policy parameters) to maximize the expected return

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It is a critical part of decision making

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We can compute

$$V(s_a, \theta_\pi), V(s_b, \theta_\pi), V(s_c, \theta_\pi)$$

To find the value of any state

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We call the following equation the **Monte Carlo** value function

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- Or build the infinite decision tree

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Infinite sums make things difficult and intractable

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Let us try to delete the infinite sum

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This is a huge finding!

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Evaluate infinite-depth decision tree with a single function call

TD Value Functions

To summarize, we can represent the value function in two ways:

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They produce the same result, but with different computation

Q Functions

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We saw two forms of the value function

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We can use the value function to find an optimal policy

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What if we wanted a mix of both?

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Q Functions

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Means:

- Take a specific action a_0 (trajectory optimization)
- Follow $\pi(a \mid s; \theta_\pi)$ for all future actions $a_1, a_2, \ldots$ (value function)

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The Q function tells us:

- The value of an action a_0

Q Functions

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The Q function tells us:

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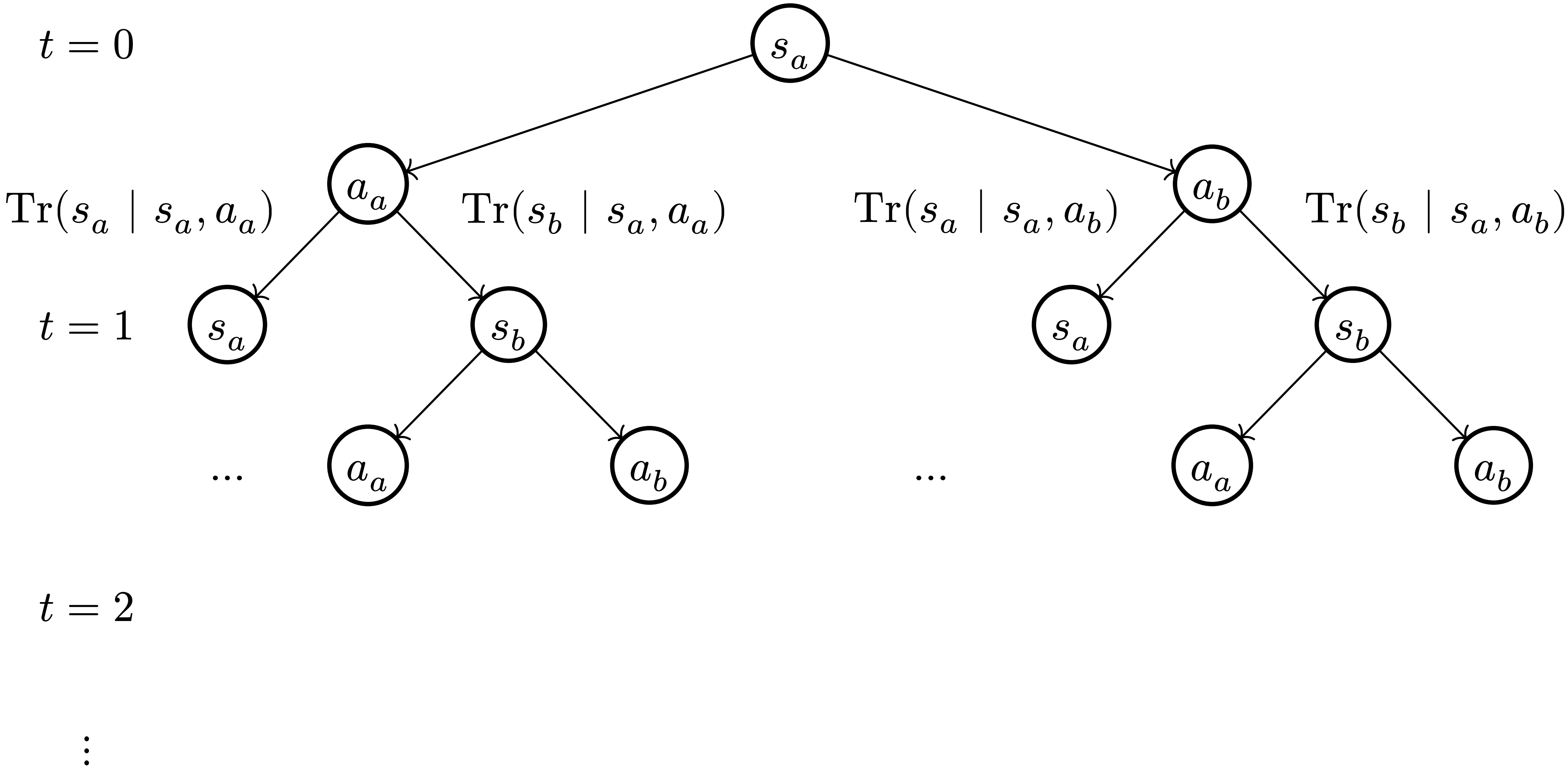
We collapsed the infinite decision tree into a single level

Q Functions



$t = 0$
s_a
a_a
a_b
$\mathrm{Tr}(s_a \mid s_a, a_a)$
$\mathrm{Tr}(s_b \mid s_a, a_a)$
$\mathrm{Tr}(s_a \mid s_a, a_b)$
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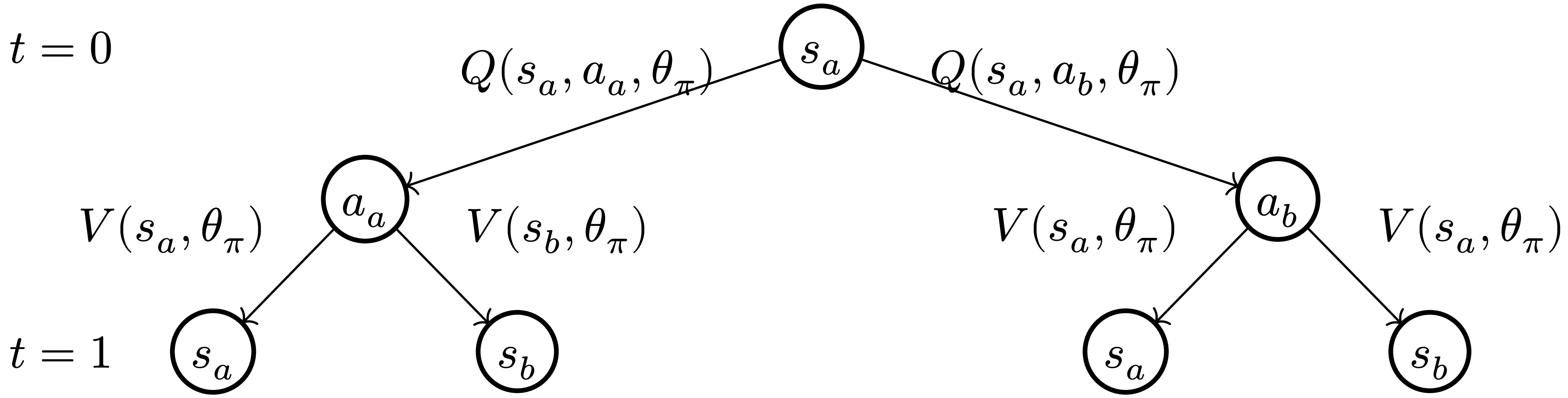
$t = 1$
s_a
s_b
s_a
s_b
$\dots$
a_a
a_b
$\dots$
a_a
a_b
$t = 2$
$\vdots$

Q Functions



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We now have all the information we need to implement Q learning

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The Q function uses the policy (using the value function)

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Question: How do we find these terms?

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$$\boldsymbol{E} = \begin{bmatrix} s_0 & s_1 & s_2 & \dots \\ a_0 & a_1 & a_2 & \dots \\ r_0 & r_1 & r_2 & \dots \end{bmatrix}^\top$$

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$$\boldsymbol{E} = \begin{bmatrix} s_0 & s_1 & s_2 & \dots \\ a_0 & a_1 & a_2 & \dots \\ r_0 & r_1 & r_2 & \dots \end{bmatrix}^\top$$

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We know the right hand side, use it to learn the left hand side

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$$Q_{i+1}(s, a, \theta_\pi) = Q_i(s, a, \theta_\pi) - \eta$$

Improve convergence with a learning rate α

$$Q_{i+1}(s, a, \theta_\pi) = \alpha(Q_i(s, a, \theta_\pi) - \eta)$$

Q Learning

Monte Carlo update:

Q Learning

Monte Carlo update:

$$Q_{i+1}(s_0, a_0, \theta_\pi) =$$

$$\alpha \left(\hat{\mathbb{E}}[\mathcal{R}(s_1) \mid s_0, a_0] + \sum_{t=1}^{\infty} \gamma^t \hat{\mathbb{E}}[\mathcal{R}(s_{t+1}) \mid s_1; \theta_\pi] - Q_i(s_0, a_0, \theta_\pi) \right)$$

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Temporal Difference update:

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Temporal Difference update:

$$Q_{i+1}(s_0, a_0, \theta_\pi) = \alpha \left(\hat{\mathbb{E}}[\mathcal{R}(s_1) \mid s_0, a_0] + d\gamma \max_{a \in A} Q_i(s_1, a, \theta_\pi) - Q_i(s_0, a_0, \theta_\pi) \right)$$

Updates guarantee convergence to the true Q function ($\lim_{i \to \infty} \eta = 0$)

Q Learning

Last thing, we must collect episodes to train Q!

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Can run policy in environment to create episodes

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Can run policy in environment to create episodes

```
states, next_states, rewards, terminateds = [], [], [], []
state = environment.reset()
while not terminated:
    action = policy.sample(state)
    next_state, reward, terminated = environment.step(action)

    states.append(state), next_states.append(next_state), ...
    state = next_state

episode = (states, next_states, rewards, terminateds)
```

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What policy do we sample actions from?

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$$\pi(a_0 \mid s_0; \theta_\pi) = \begin{cases} 1 \text{ if } a_0 = \arg\max_{a \in A} Q(s_0, a, \theta_\pi) \\ 0 \text{ otherwise} \end{cases}$$

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Epsilon greedy policy!

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$$\pi(a_0 \mid s_0; \theta_\pi) = \begin{cases} (1 - \varepsilon) \text{ if } a_0 = \arg\max_{a \in A} Q(s_0, a, \theta_\pi) \\ \frac{\varepsilon}{|A|} \text{ for } a \in A \end{cases}$$

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Sample random action with probability ε

In the limit, sample all possible actions in all states

Q Learning

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Today and for homework, use a simple matrix

Q Learning

Each state is a row, each action is a column in a matrix

Q Learning

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$$\begin{bmatrix} Q(s_a, a_a) & Q(s_b, a_b) & \dots & \\ Q(s_b, a_a) & Q(s_b, a_b) & \dots & \\ \vdots & \vdots & \vdots & \vdots \end{bmatrix}$$

Q Learning

Each state is a row, each action is a column in a matrix

$$\begin{bmatrix} Q(s_a, a_a) & Q(s_b, a_b) & \dots & \\ Q(s_b, a_a) & Q(s_b, a_b) & \dots & \\ \vdots & \vdots & \vdots & \vdots \end{bmatrix}$$

$Q_{i,j}$ gives Q value for state $s = i$ and action $a = j$

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https://colab.research.google.com/drive/1xtBxAaVc3ax6_j59RC3NLQQPFcIEoau-?usp=sharing