

1. Recursive Bellman equations

Prove the recursive Bellman expectation equations for the value function v_π and the action value function q_π using the state transition function \mathcal{P} and the reward function \mathcal{R} . You are allowed to use the equations from Theorem 1 in Section 4.

$$(a) \quad v_\pi(s) = \sum_a \pi(a|s) \left(\mathcal{R}(s, a) + \gamma \sum_{s'} \mathcal{P}(s'|s, a) v_\pi(s') \right)$$

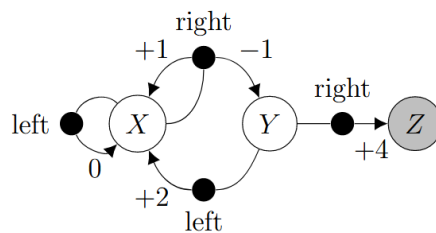
$$(b) \quad q_\pi(s, a) = \mathcal{R}(s, a) + \gamma \sum_{s'} \mathcal{P}(s'|s, a) \sum_{a'} \pi(a'|s') q_\pi(s', a')$$

$$\begin{aligned} (a) \quad v_\pi(s) &= E[R_{t+1} + \gamma v_\pi(S_{t+1}) | S_t = s] \\ &= \sum_a \pi(a|s) (R(s, a) + \gamma v_\pi(S_{t+1})) \\ &= \sum_a \pi(a|s) (R(s, a) + \gamma \sum_{s'} \mathcal{P}(s'|s, a) v_\pi(s')) \end{aligned}$$

$$\begin{aligned} (b) \quad q_\pi(s, a) &= E[R_{t+1} + \gamma q_\pi(S_{t+1}, A_{t+1}) | S_t = s, A_t = a] \\ &= R(s, a) + \gamma \underbrace{\sum_{s'} \sum_{a'} \mathcal{P}(s'|s, a) \overset{\pi}{q_\pi}(s', a')}_{\text{I don't get it.}} \end{aligned}$$

2. Action value functions

- (a) For any given MDP, policy π , *terminal state* E and action a , what is $q_\pi(E, a)$? All transitions from a terminal state are back to itself with a reward of 0.
- (b) Consider the MDP and policy π_1 from the previous exercise sets. Note that if action *right* is taken in state X , then the transitions to X and Y occur with probabilities 0.75 and 0.25, respectively. The deterministic policy π_1 is defined as $\pi_1(X) = \text{right}$, $\pi_1(Y) = \text{right}$.

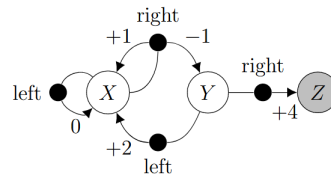


$$(a) \quad v_\pi(E) = 0$$

$$\begin{aligned} q_\pi(E, a) &= R(E, a) + \gamma \sum_{s'} \mathcal{P}(s'|s, a) v_\pi(s') \\ &= \underbrace{R(E, a)}_0 + \gamma \underbrace{v_\pi(E)}_0 = 0 \end{aligned}$$

(b)

- Consider the MDP and policy π_1 from the previous exercise sets. Note that if action *right* is taken in state X , then the transitions to X and Y occur with probabilities 0.75 and 0.25, respectively. The deterministic policy π_1 is defined as $\pi_1(X) = \text{right}$, $\pi_1(Y) = \text{right}$.



Compute the action value of state X and action *left* under policy π_1 , i.e. $q_{\pi_1}(X, \text{left})$, using *only* the action value function (don't use the values from the last exercise set). The discount factor is $\gamma = 0.9$.

$$\begin{aligned}
 q_{\pi_1}(X, \text{left}) &= R(X, \text{left}) + \gamma \sum_{s'} P(s'|s, a) \sum_{a'} \pi(a'|s') q_{\pi}(s', a') \\
 &= \underbrace{R(X, \text{left})}_0 + \gamma q_{\pi_1}(X, \text{right}) \quad \text{It doesn't care where it comes from} \\
 &= \gamma q_{\pi_1}(X, \text{right})
 \end{aligned}$$

$$\begin{aligned}
 q_{\pi_1}(X, \text{right}) &= R(X, \text{right}) + \gamma (P(X|X, \text{right}) q_{\pi_1}(X, \text{right}) \\
 &\quad + P(Y|X, \text{right}) q_{\pi_1}(Y, \text{right}))
 \end{aligned}$$

$$\begin{aligned}
 R(X, \text{right}) &= (+1) \cdot P(X, +1|X, \text{right}) + (-1) \cdot P(Y, -1|X, \text{right}) \\
 &= 0.75 - 0.25 = 0.5
 \end{aligned}$$

$$q_{\pi_1}(X, \text{right}) = 0.5 + \gamma q_{\pi_1}(X, \text{right}) \quad q_{\pi_1}(X, \text{right}) = 5$$

$$\text{then } q_{\pi_1}(X, \text{left}) = \gamma q_{\pi_1}(X, \text{right}) = 0.9 \cdot 0.5 = 0.45$$

- (c) In the lecture we defined the policy iteration algorithm to find the optimal policy using value functions. Write down a modified version of policy iteration that finds the optimal policy using action value functions (known as Q-Policy iteration).

pol eval:

$$q_{k+1}(s, a) = R(s, a) + \gamma \sum_{s'} P(s'|s, a) \sum_{a'} \pi(a'|s') q_k(s', a')$$

pol improve:

$$\pi'(s) = \arg\max_a (q_{\pi}(s, a))$$

$$v_{k+1}(s) = \sum_a \pi(a|s) q_k(s, a)$$

3. Value iteration

- (a) Perform two steps of value iteration for the MDP from exercise 2(b), i.e. calculate $v_1(s)$ and $v_2(s)$ for $s \in \{X, Y\}$. Initialize the values with $v_0(X) = 0$ and $v_0(Y) = 0$. You can assume that the value of the terminal state Z is zero in each step.

$$k=0: \quad v_0(X) = v_0(Y) = v_0(Z) = 0$$

$$v_1(X) = \max_a (R(X, a)) = R(X, \text{right}) = 0.5$$

$$v_1(Y) = \max_a (R(Y, a)) = R(Y, \text{right}) = 4$$

$$k=1 \quad v_1(X) = 0.5, \quad v_1(Y) = 4, \quad v_1(Z) = 0$$

$$v_2(X) = \max_a (R(X, a) + \gamma P(X|X, a) v_1(X) + \gamma P(Y|X, a) v_1(Y))$$

$$= \max_a (R(X, a) + 0.45 P(X|X, a) + 0.81 P(Y|X, a))$$

$$a = \text{left}: \quad 0 + 0.45 = 0.45$$

$$a = \text{right}: \quad 0.5 + 0.45 \cdot 0.75 + 0.81 \cdot 0.25 = 1.04, \quad \text{pick right}$$

$$v_2(X) = 1.04$$

$$v_2(Y) = \max_a (R(Y, a) + \gamma P(X|Y, a) v_1(X) + \underbrace{\gamma P(Z|Y, a) v_1(Z)}_0)$$

$$a = \text{left}: \quad 2 + 0.9 \times 0.5 = 2 + 0.45 = 2.45$$

$$a = \text{right}: \quad 4, \quad \text{pick right}$$