

## Your grade: 100%

Your latest: 100% • Your highest: 100% • To pass you need at least 80%. We keep your highest score.

[Next item →](#)

1. A policy is a function which maps \_\_\_\_ to \_\_\_\_.

1 / 1 point

- ☐ Actions to probability distributions over values.
- ☐ States to actions.
- ☐ Actions to probabilities.
- ☐ States to values.
- ☒ States to probability distributions over actions.

✓ **Correct**  
Correct!

2. The term “backup” most closely resembles the term \_\_\_\_ in meaning.

1 / 1 point

- ☐ Value
- ☒ Update
- ☐ Diagram

✓ **Correct**  
Correct!

3. At least one deterministic optimal policy exists in every Markov decision process.

1 / 1 point

- ☐ False
- ☒ True

✓ **Correct**  
Correct! Let's say there is a policy  $\pi_1$  which does well in some states, while policy  $\pi_2$  does well in others. We could combine these policies into a third policy  $\pi_3$ , which always chooses actions according to whichever of policy  $\pi_1$  and  $\pi_2$  has the highest value in the current state.  $\pi_3$  will necessarily have a value greater than or equal to both  $\pi_1$  and  $\pi_2$  in every state! So we will never have a situation where doing well in one state requires sacrificing value in another. Because of this, there always exists some policy which is best in every state. This is of course only an informal argument, but there is in fact a rigorous proof showing that there must always exist at least one optimal deterministic policy.

4. The optimal state-value function:

1 / 1 point

- ☐ Is not guaranteed to be unique, even in finite Markov decision processes.
- ☒ Is unique in every finite Markov decision process.

✓ **Correct**  
Correct! The Bellman optimality equation is actually a system of equations, one for each state, so if there are  $N$  states, then there are  $N$  equations in  $N$  unknowns. If the dynamics of the environment are known, then in principle one can solve this system of equations for the optimal value function using any one of a variety of methods for solving systems of nonlinear equations. All optimal policies share the same optimal state-value function.

5. Does adding a constant to all rewards change the set of optimal policies in episodic tasks?

1 / 1 point

- ☒ Yes, adding a constant to all rewards changes the set of optimal policies.
- ☐ No, as long as the relative differences between rewards remain the same, the set of optimal policies is the same.

✔ Correct

Correct! Adding a constant to the reward signal can make longer episodes more or less advantageous (depending on whether the constant is positive or negative).

6. Does adding a constant to all rewards change the set of optimal policies in continuing tasks?

1 / 1 point

- ☐ Yes, adding a constant to all rewards changes the set of optimal policies.
- ☒ No, as long as the relative differences between rewards remain the same, the set of optimal policies is the same.

✔ Correct

Correct! Since the task is continuing, the agent will accumulate the same amount of extra reward independent of its behavior.

7. Select the equation that correctly relates  $v_*$  to  $q_*$ . Assume  $\pi$  is the uniform random policy.

1 / 1 point

- ☐  $v_*(s) = \sum_{a,r,s'} \pi(a|s)p(s',r|s,a)q_*(s')$
- ☐  $v_*(s) = \sum_{a,r,s'} \pi(a|s)p(s',r|s,a)[r + \gamma q_*(s')]$
- ☐  $v_*(s) = \sum_{a,r,s'} \pi(a|s)p(s',r|s,a)[r + q_*(s')]$
- ☒  $v_*(s) = \max_a q_*(s,a)$

✔ Correct

Correct!

8. Select the equation that correctly relates  $q_*$  to  $v_*$  using four-argument function  $p$ .

1 / 1 point

- ☐  $q_*(s,a) = \sum_{s',r} p(s',r|a,s)[r + v_*(s')]$
- ☐  $q_*(s,a) = \sum_{s',r} p(s',r|a,s)\gamma[r + v_*(s')]$
- ☒  $q_*(s,a) = \sum_{s',r} p(s',r|a,s)[r + \gamma v_*(s')]$

✔ Correct

Correct!

9. Write a policy  $\pi_*$  in terms of  $q_*$ .

1 / 1 point

- ☐  $\pi_*(a|s) = q_*(s,a)$
- ☐  $\pi_*(a|s) = \max_{a'} q_*(s,a')$
- ☒  $\pi_*(a|s) = 1$  if  $a = \operatorname{argmax}_{a'} q_*(s,a')$ , else 0

✔ Correct

Correct!

10. Give an equation for some  $\pi_*$  in terms of  $v_*$  and the four-argument  $p$ .

1 / 1 point

- ☒  $\pi_*(a|s) = 1$  if  $v_*(s) = \sum_{s',r} p(s',r|s,a)[r + \gamma v_*(s')]$ , else 0
- ☐  $\pi_*(a|s) = \sum_{s',r} p(s',r|s,a)[r + \gamma v_*(s')]$
- ☐  $\pi_*(a|s) = 1$  if  $v_*(s) = \max_{a'} \sum_{s',r} p(s',r|s,a')[r + \gamma v_*(s')]$ , else 0
- ☐  $\pi_*(a|s) = \max_{a'} \sum_{s',r} p(s',r|s,a')[r + \gamma v_*(s')]$

✔ Correct  
Correct!