

## ✓ Congratulations! You passed!

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1. A function which maps \_\_\_ to \_\_\_ is a value function. [Select all that apply]

1 / 1 point

- ☐ Values to actions.
- ☐ Values to states.
- ☒ State-action pairs to expected returns.

✓ Correct

Correct! A function that takes a state-action pair and outputs an expected return is a value function.

- ☒ States to expected returns.

✓ Correct

Correct! A function that takes a state and outputs an expected return is a value function.

2. Consider the continuing Markov decision process shown below. The only decision to be made is in the top state, where two actions are available, left and right. The numbers show the rewards that are received deterministically after each action. There are exactly two deterministic policies,  $\pi_{\text{left}}$  and  $\pi_{\text{right}}$ . Indicate the optimal policies if  $\gamma = 0$ ? If  $\gamma = 0.9$ ? If  $\gamma = 0.5$ ? [Select all that apply]

1 / 1 point

- ☒ For  $\gamma = 0$ ,  $\pi_{\text{left}}$

✓ Correct

Correct! Since both policies return to the top state every two time steps, to determine the optimal policy, it suffices to consider the reward accumulated over the first two time steps. For the policy left, this is equal to 1; for the policy right, this is equal to 0.

- ☒ For  $\gamma = 0.9$ ,  $\pi_{\text{right}}$

✓ Correct

Correct! Since both policies return to the top state every two time steps, to determine the optimal policy, it suffices to consider the reward accumulated over the first two time steps. For the policy left, this is equal to 1; for the policy right, this is equal to 1.8.

- ☒ For  $\gamma = 0.5$ ,  $\pi_{\text{left}}$

✓ Correct

Correct! Since both policies return to the start state every two time steps, to determine the optimal policy, it suffices to consider the reward accumulated over the first two time steps. For the policy left, this is equal to 1; for the policy right, this is equal to 1.

- ☐ For  $\gamma = 0.9$ ,  $\pi_{\text{left}}$

- ☒ For  $\gamma = 0.5$ ,  $\pi_{\text{right}}$

✓ Correct

Correct! Since both policies return to the start state every two time steps, to determine the optimal policy, it suffices to consider the reward accumulated over the first two time steps. For the policy left, this is equal to 1; for the policy right, this is equal to 1.

- ☐ For  $\gamma = 0$ ,  $\pi_{\text{right}}$

3. Every finite Markov decision process has \_\_\_. [Select all that apply]

1 / 1 point

- ☐ A unique optimal policy
- ☒ A deterministic optimal policy

✓ 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.

- ☒ A unique optimal value function

✓ 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