

# Bellman Equation

# Objectives

- Derive the Bellman equation for state value functions
- Define the Bellman equation for action value functions
- Understand how Bellman equations relate current and future values.

# Bellman Equation

- The Bellman equation is a fundamental concept in dynamic programming and reinforcement learning.
- It expresses the relationship between the value of a state (or state-action pair) and the value of its successor states.
- The Bellman equation plays a crucial role in many RL algorithms, as it provides a recursive definition for computing value functions.

# Bellman Equation Types

- Bellman Expectation Equation:
  - The Bellman expectation equation expresses the relationship between the value of a state (or state-action pair) and the expected immediate reward plus the discounted value of the successor states.
  - $$V^\pi(s) = \sum_a \pi(a|s) \sum_{s',r} p(s', r|s, a)[r + \gamma V^\pi(s')]$$
  - $p(s',r|s,a)$  is the probability of transitioning to state  $s'$  and receiving reward  $r$  when taking action  $a$  in state  $s$ , and  $\pi(a|s)$  is the policy's probability of selecting action  $a$  in state  $s$ .  $\gamma$  is the discount factor which determines the importance of future rewards.

# Bellman Equation Types

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  - $$Q^\pi(s, a) = \sum_{s', r} p(s', r | s, a)[r + \gamma \sum_{a'} \pi(a' | s') Q^\pi(s', a')]$$
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# Bellman Equation Types

## Bellman Optimality Equation:

- The Bellman optimality equation expresses the optimal value of a state (or state-action pair) in terms of the maximum expected immediate reward plus the discounted value of the successor states.
- For the state value function  $V^*(s)$ , it is defined as:

$$V^*(s) = \max_a \sum_{s',r} p(s', r | s, a) [r + \gamma V^*(s')]$$

- $V^*(s)$  represents the optimal value of state  $s$  under the optimal policy

# Bellman Equation Types

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- For the action value function  $Q^*(s,a)$ , it is defined as:

$$Q^*(s, a) = \sum_{s', r} p(s', r | s, a) [r + \gamma \max_{a'} Q^*(s', a')]$$

- $Q^*(s, a)$  represents the optimal value of taking action  $a$  in state  $s$  under the optimal policy.

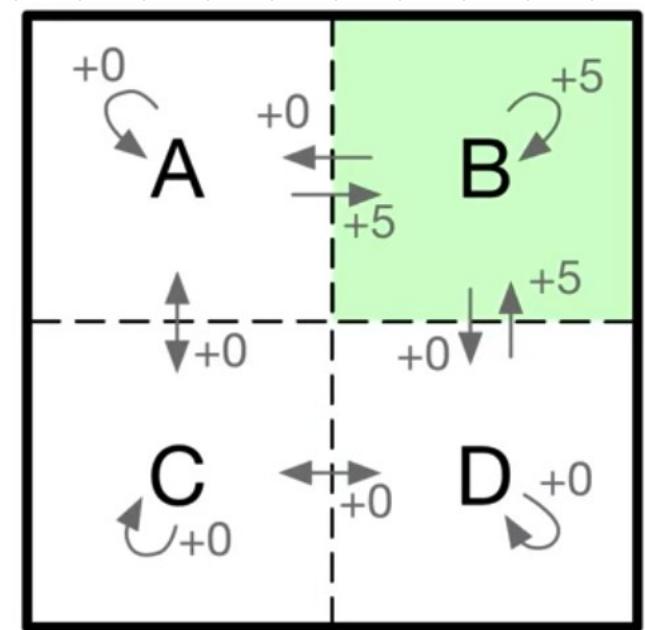
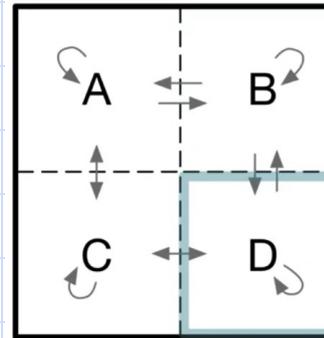
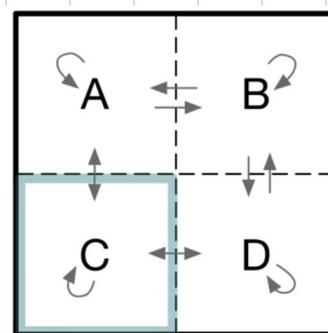
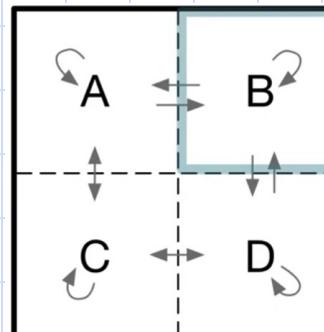
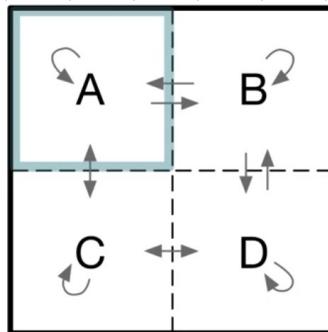
# Bellman Equation

- It defines how the value functions relate to each other and to the dynamics of the environment.
- RL algorithms leverage these equations to iteratively improve value function estimates and derive optimal policies.
- Bellman equations to compute value functions.

# Bellman Equation

## □ Example

- Start from C → A → B → D. The reward is 0 everywhere except for any time the agent lands in state B.

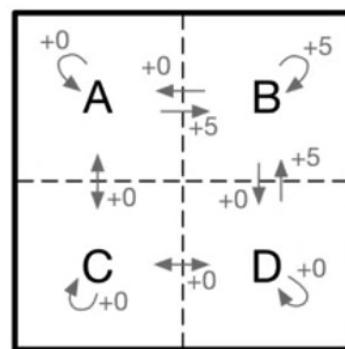


Bellman Equation

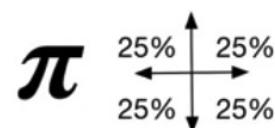
# Bellman Equation

## □ Example

- Using the Bellman equation, we can write down an expression for the value of state A in terms of the sum of the four possible actions and the resulting possible



$$V_{\pi}(s) = \sum_a \pi(a | s) \sum_r \sum_{s'} p(s', r | s, a) [r + \gamma V_{\pi}(s')]$$

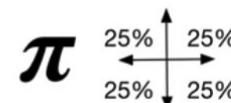
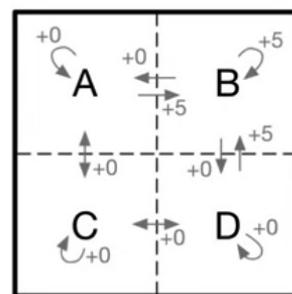


# Bellman Equation

## □ Example

- The expression further in this case, because for each action there's only one possible associated next state and reward.
- That's the sum over s prime and r reduces to a single value (s prime and r do still depend on the selected action, and the current state s).

current state



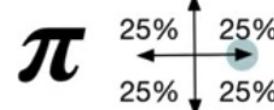
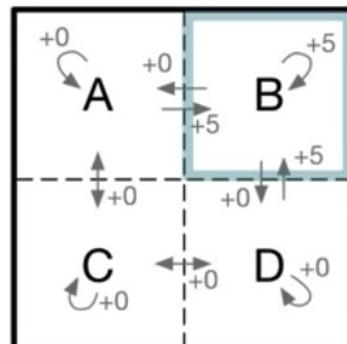
$$V_{\pi}(s) = \sum_a \pi(a | s) \sum_r \sum_{s'} p(s', r | s, a) [r + \gamma V_{\pi}(s')]$$

$$V_{\pi}(A) = \sum_a \pi(a | A) (r + 0.7V_{\pi}(s'))$$

# Bellman Equation

## □ Example

- If we go right from state A, we land in state B, and receive a reward of +5. This happens one quarter of the time under the random policy.



$$V_{\pi}(s) = \sum_a \pi(a | s) \sum_r \sum_{s'} p(s', r | s, a) [r + \gamma V_{\pi}(s')]$$

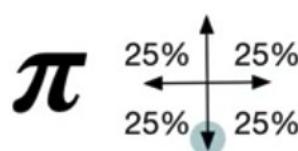
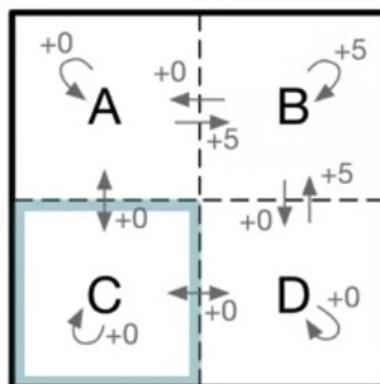
$$V_{\pi}(A) = \sum_a \pi(a | A) (r + 0.7V_{\pi}(s'))$$

$$V_{\pi}(A) = \frac{1}{4} (5 + 0.7V_{\pi}(B))$$

# Bellman Equation

## □ Example

- If we go down, we land in state C, and receive no immediate reward. → this occurs one-quarter of the time



$$V_{\pi}(s) = \sum_a \pi(a | s) \sum_r \sum_{s'} p(s', r | s, a) [r + \gamma V_{\pi}(s')]$$

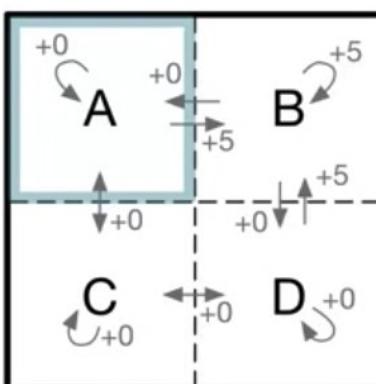
$$V_{\pi}(A) = \sum_a \pi(a | A) (r + 0.7V_{\pi}(s'))$$

$$V_{\pi}(A) = \frac{1}{4}(5 + 0.7V_{\pi}(B)) + \frac{1}{4}0.7V_{\pi}(C)$$

# Bellman Equation

## □ Example:

- If you go either up or left, we will land back in state A again. Each of the actions, up and left, again, occur one-



$$V_{\pi}(s) = \sum_a \pi(a | s) \sum_r \sum_{s'} p(s', r | s, a) [r + \gamma V_{\pi}(s')]$$

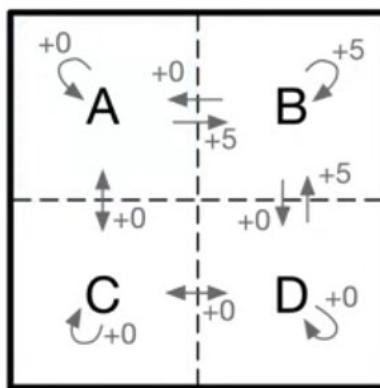
$$V_{\pi}(A) = \sum_a \pi(a | A) (r + 0.7V_{\pi}(s'))$$

$$V_{\pi}(A) = \frac{1}{4}(5 + 0.7V_{\pi}(B)) + \frac{1}{4}0.7V_{\pi}(C) + \frac{1}{2}0.7V_{\pi}(A)$$

# Bellman Equation

## □ Example

□ Finally, we arrived at the expression shown here for the value of state A.



$$V_{\pi}(s) = \sum_a \pi(a | s) \sum_r \sum_{s'} p(s', r | s, a) [r + \gamma V_{\pi}(s')]$$

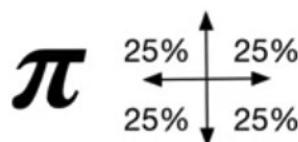
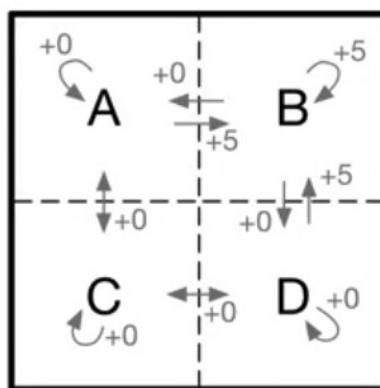
$$V_{\pi}(A) = \frac{1}{4}(5 + 0.7V_{\pi}(B)) + \frac{1}{4}0.7V_{\pi}(C) + \frac{1}{2}0.7V_{\pi}(A)$$



# Bellman Equation

- Example

- Equation for each of the other states, B, C, and D.



$$V_\pi(s) = \sum_a \pi(a | s) \sum_r \sum_{s'} p(s', r | s, a) [r + \gamma V_\pi(s')]$$

$$V_\pi(A) = \frac{1}{4}(5 + 0.7V_\pi(B)) + \frac{1}{4}0.7V_\pi(C) + \frac{1}{2}0.7V_\pi(A)$$

$$V_\pi(B) = \frac{1}{2}(5 + 0.7V_\pi(B)) + \frac{1}{4}0.7V_\pi(A) + \frac{1}{4}0.7V_\pi(D)$$

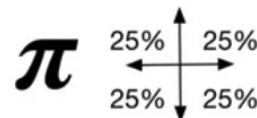
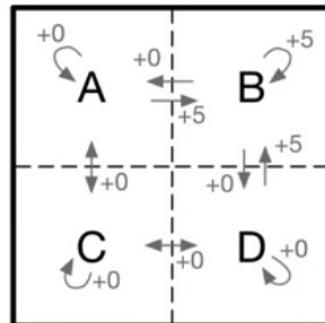
$$V_\pi(C) = \frac{1}{4}0.7V_\pi(A) + \frac{1}{4}0.7V_\pi(D) + \frac{1}{2}0.7V_\pi(C)$$

$$V_\pi(D) = \frac{1}{4}(5 + 0.7V_\pi(B)) + \frac{1}{4}0.7V_\pi(C) + \frac{1}{2}0.7V_\pi(D)$$

# Bellman Equation

## □ Example

- The unique solution is shown here.
- Bellman equation reduced an unmanageable infinite sum over possible futures, to a simple linear algebra problem.



$$V_{\pi}(s) = \sum_a \pi(a | s) \sum_r \sum_{s'} p(s', r | s, a) [r + \gamma V_{\pi}(s')]$$

$$V_{\pi}(A) = 4.2$$

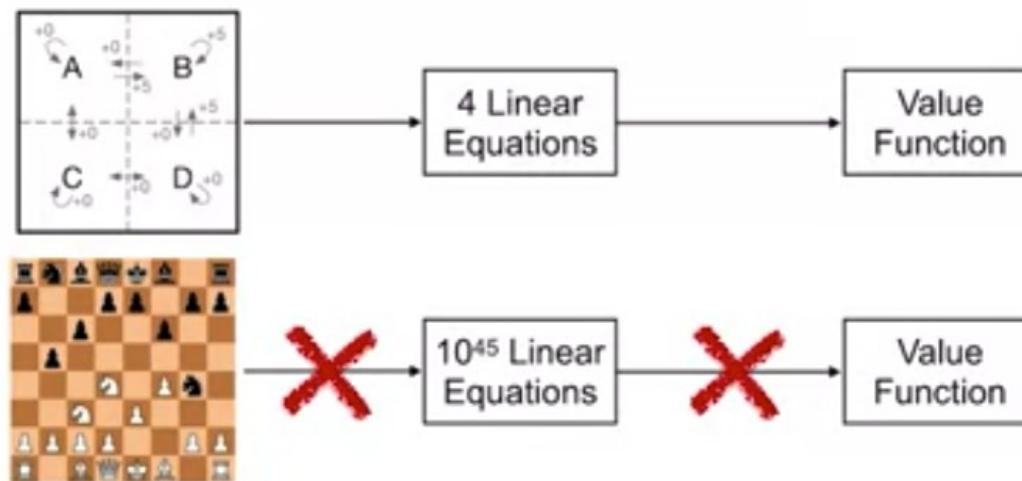
$$V_{\pi}(B) = 6.1$$

$$V_{\pi}(C) = 2.2$$

$$V_{\pi}(D) = 4.2$$

# Bellman Equation

- Bellman equations to compute value functions
- The Bellman equation to directly write down a system of equations for the state values
- More complex problems, this won't always be practical



# Summary

- Derive the Bellman equation for state value functions
- Define the Bellman equation for action value functions
- Understand how Bellman equations relate current and future values.

# Q & A