

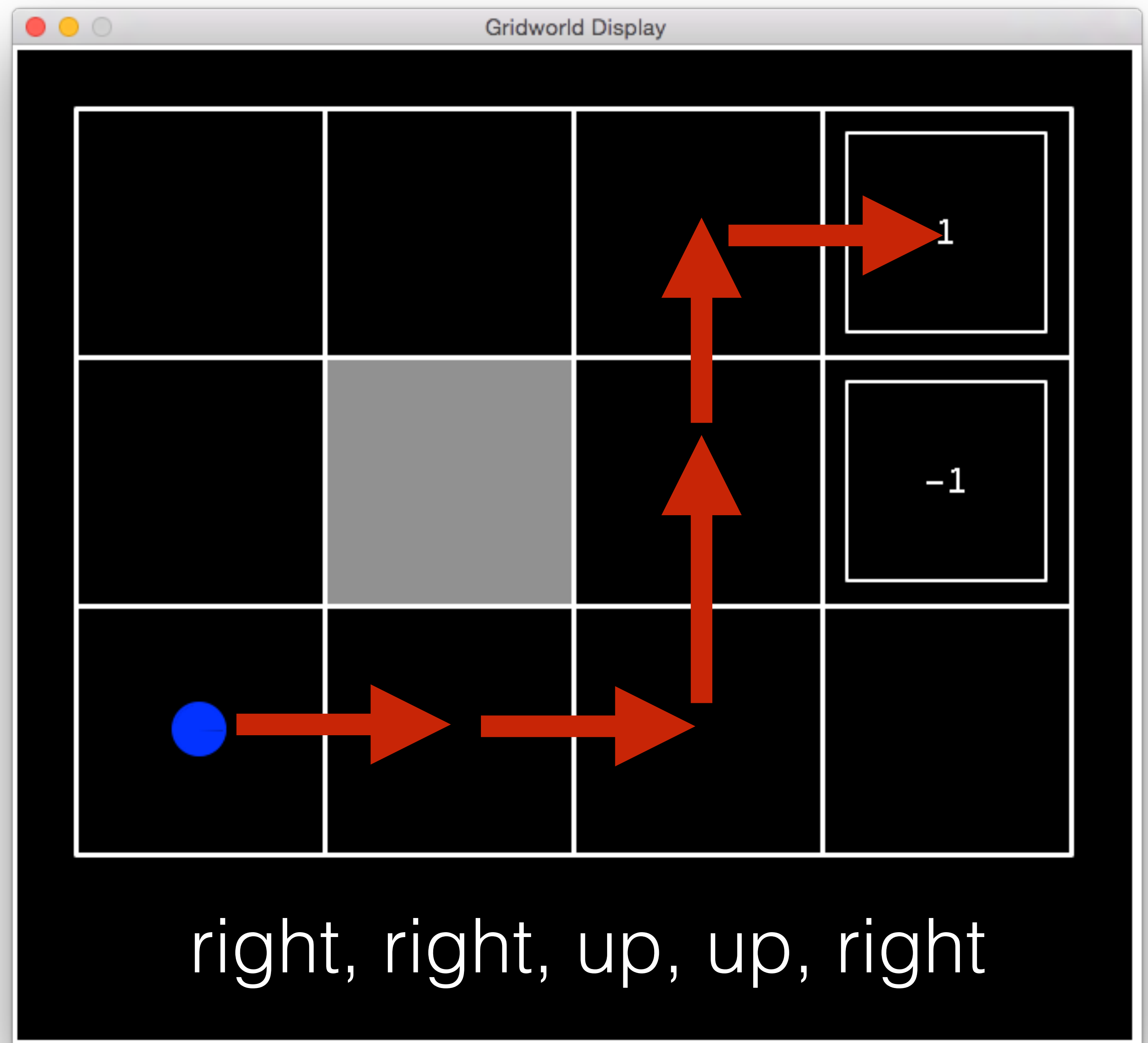
# Markov Decision Processes

CS4804

# Outline

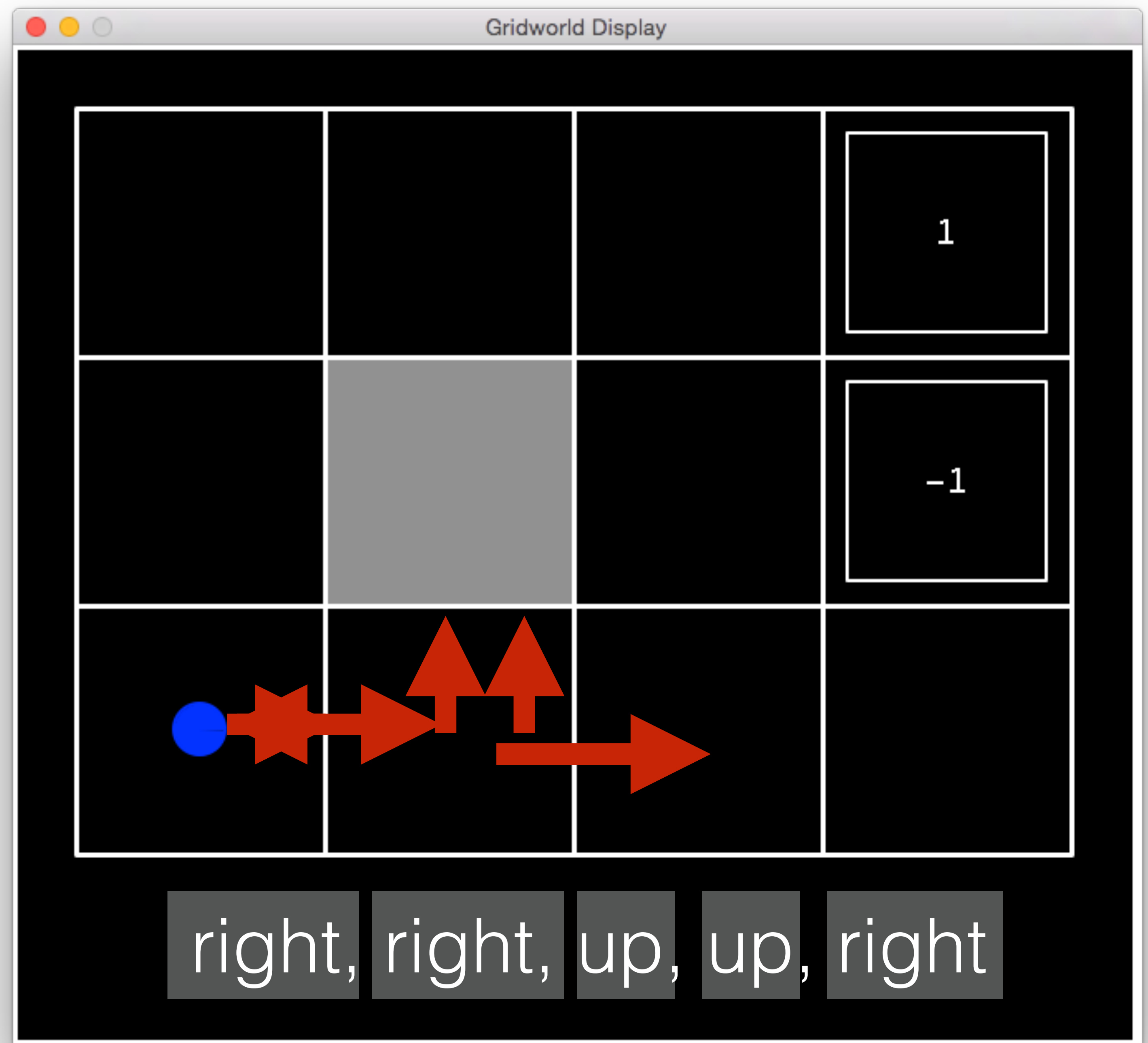
- Markov decision process: richer environment representation
- Reward functions
- Optimizing policies via value iteration

collect reward



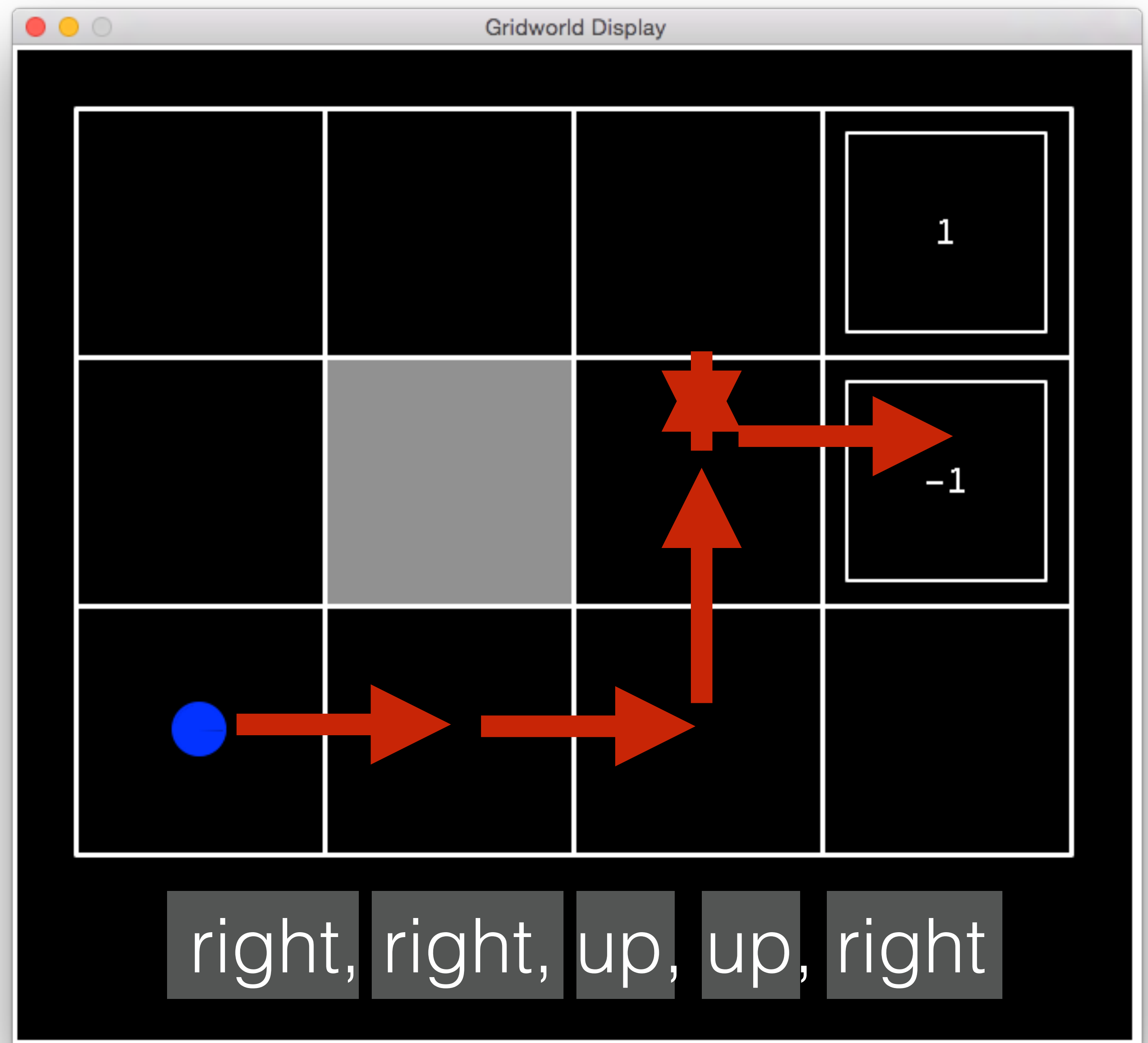
collect reward

stochastic transitions



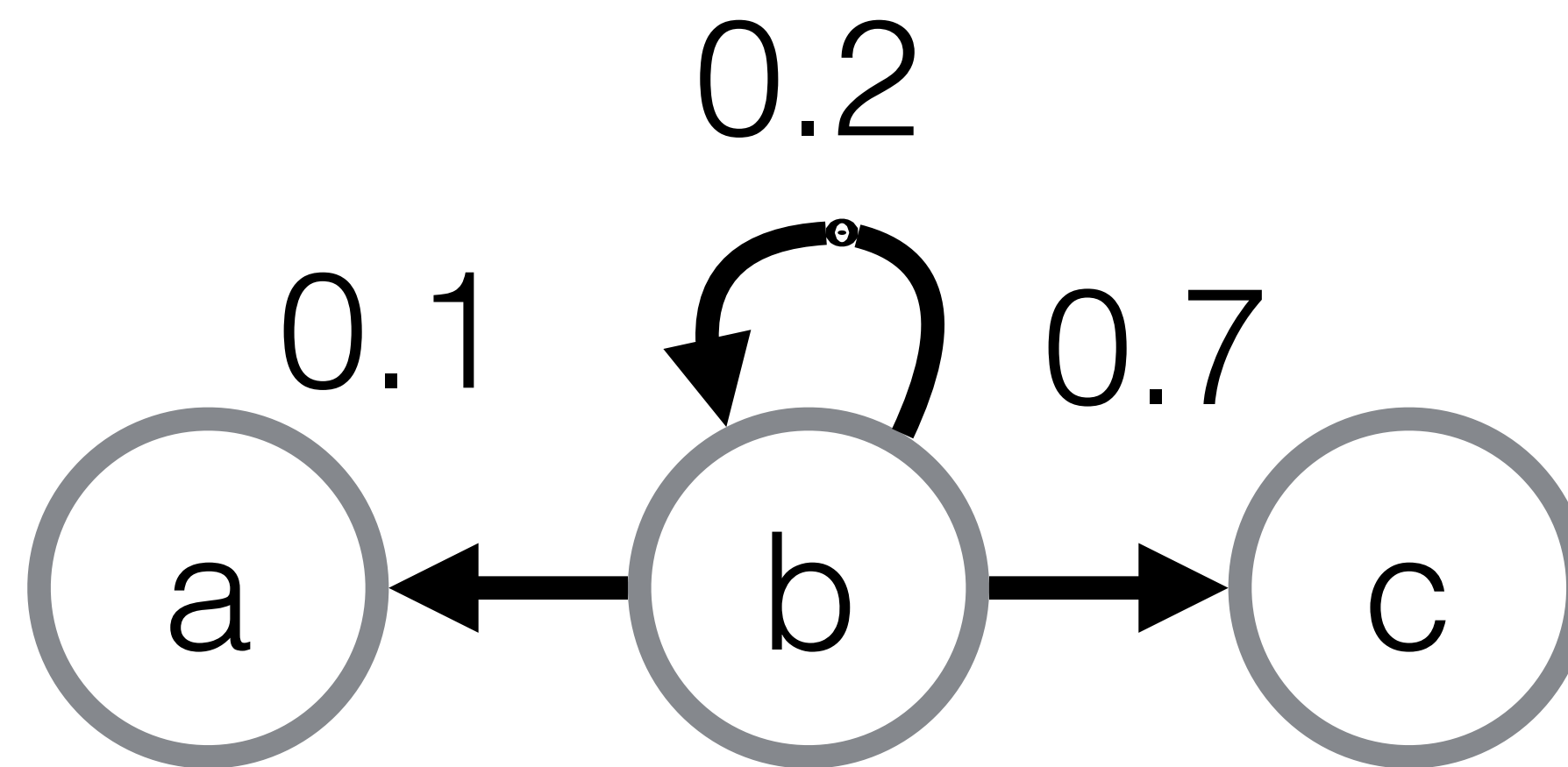
collect reward

stochastic transitions



# Actions and Transitions

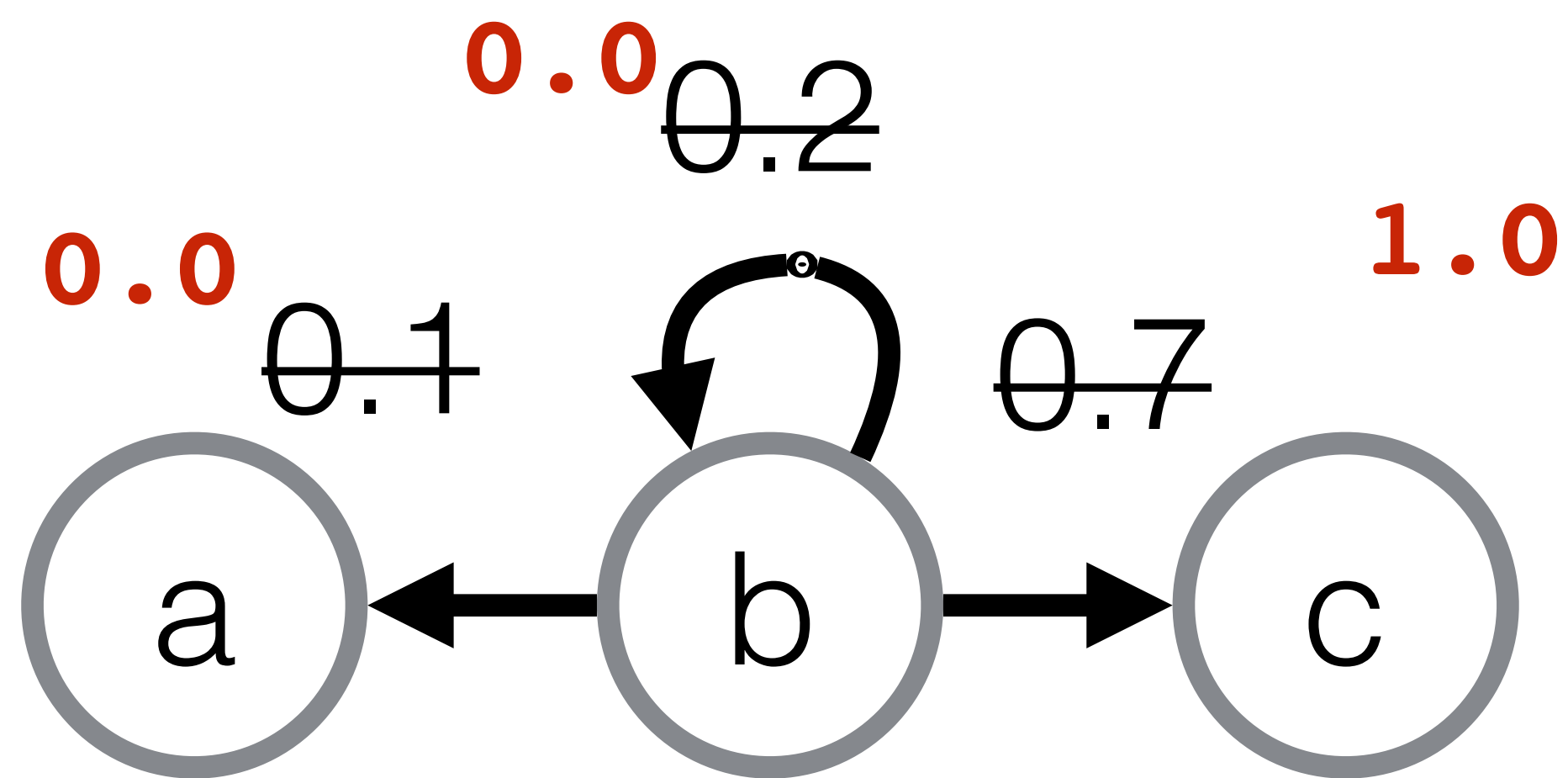
- $\Pr(\mathbf{s}' \mid \mathbf{s}, \mathbf{a})$ 
  - Probability we **transition** to  $\mathbf{s}'$  if we choose **action**  $\mathbf{a}$  in state  $\mathbf{s}$



**a** = right

# Actions and Transitions

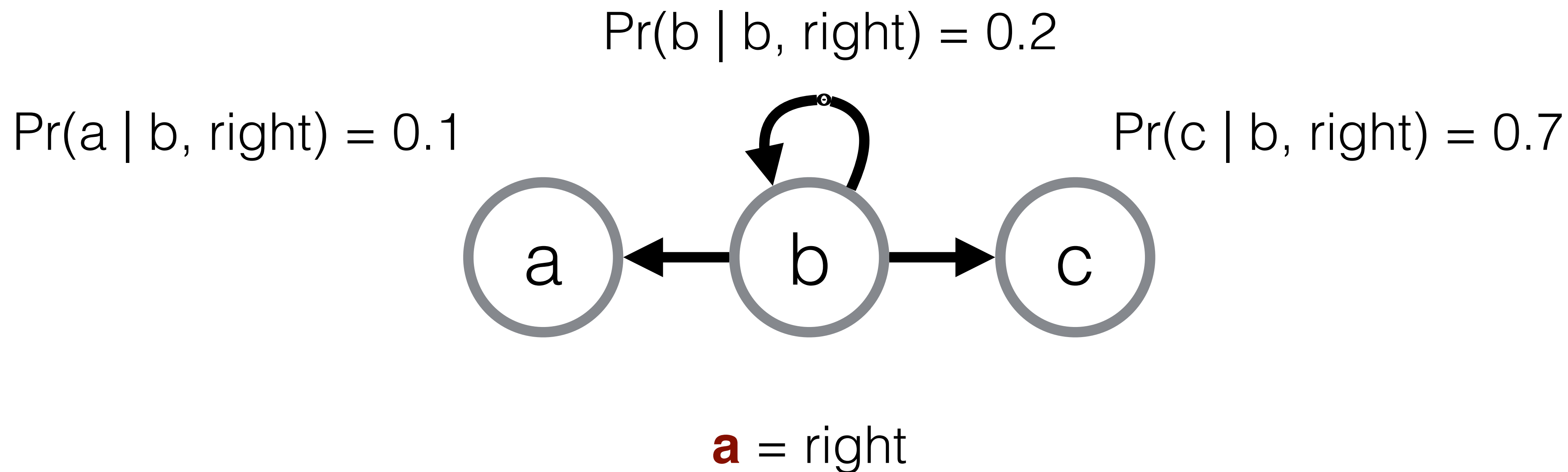
- $\Pr(\mathbf{s}' \mid \mathbf{s}, \mathbf{a})$ 
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$\mathbf{a}$  = right

# Actions and Transitions

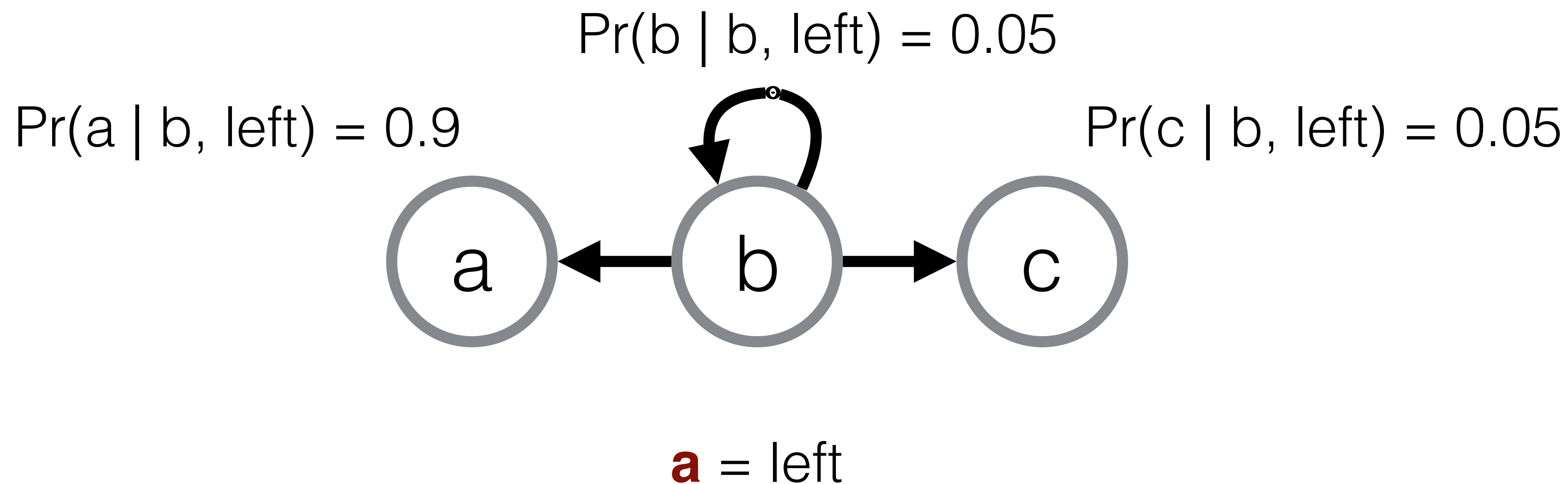
- $\Pr(\mathbf{s}' \mid \mathbf{s}, \mathbf{a})$ 
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# Actions and Transitions

- $\Pr(\mathbf{s}' \mid \mathbf{s}, \mathbf{a})$ 
  - Probability we **transition** to  $\mathbf{s}'$  if we choose **action**  $\mathbf{a}$  in state  $\mathbf{s}$

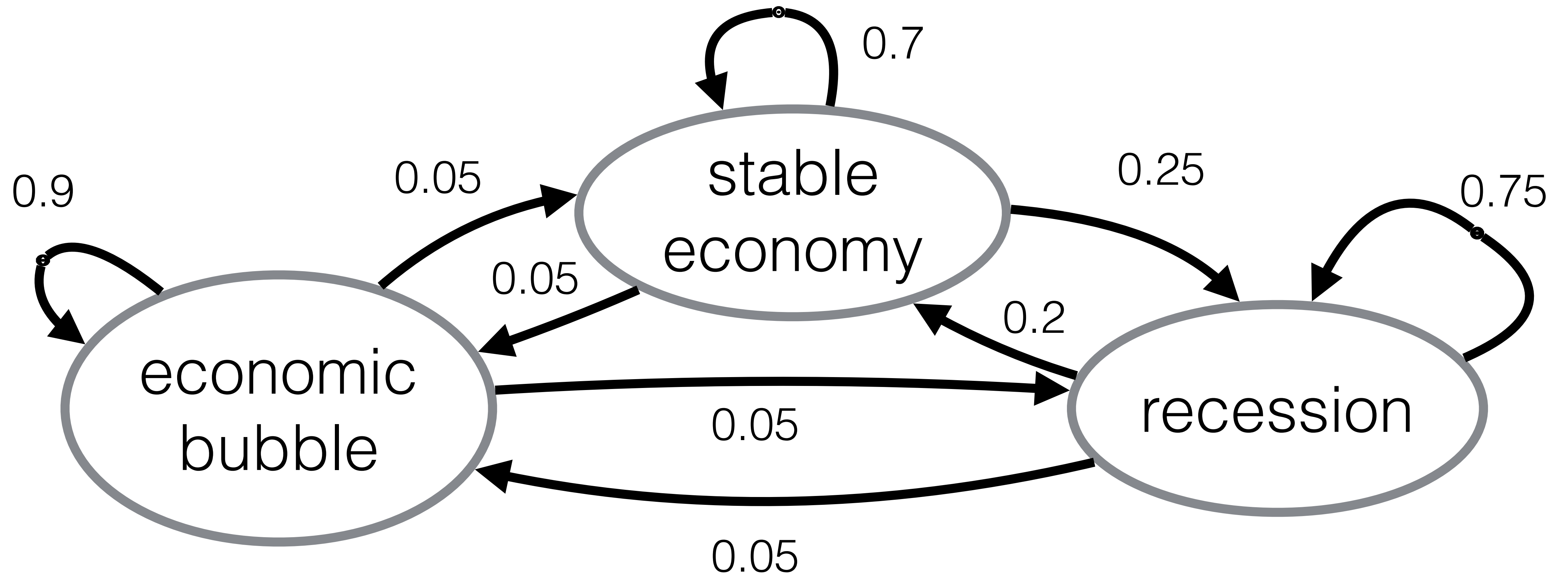


# Preview: Markov Models

Markov Decision Process:  $\Pr(\mathbf{s}' \mid \mathbf{s}, \mathbf{a})$

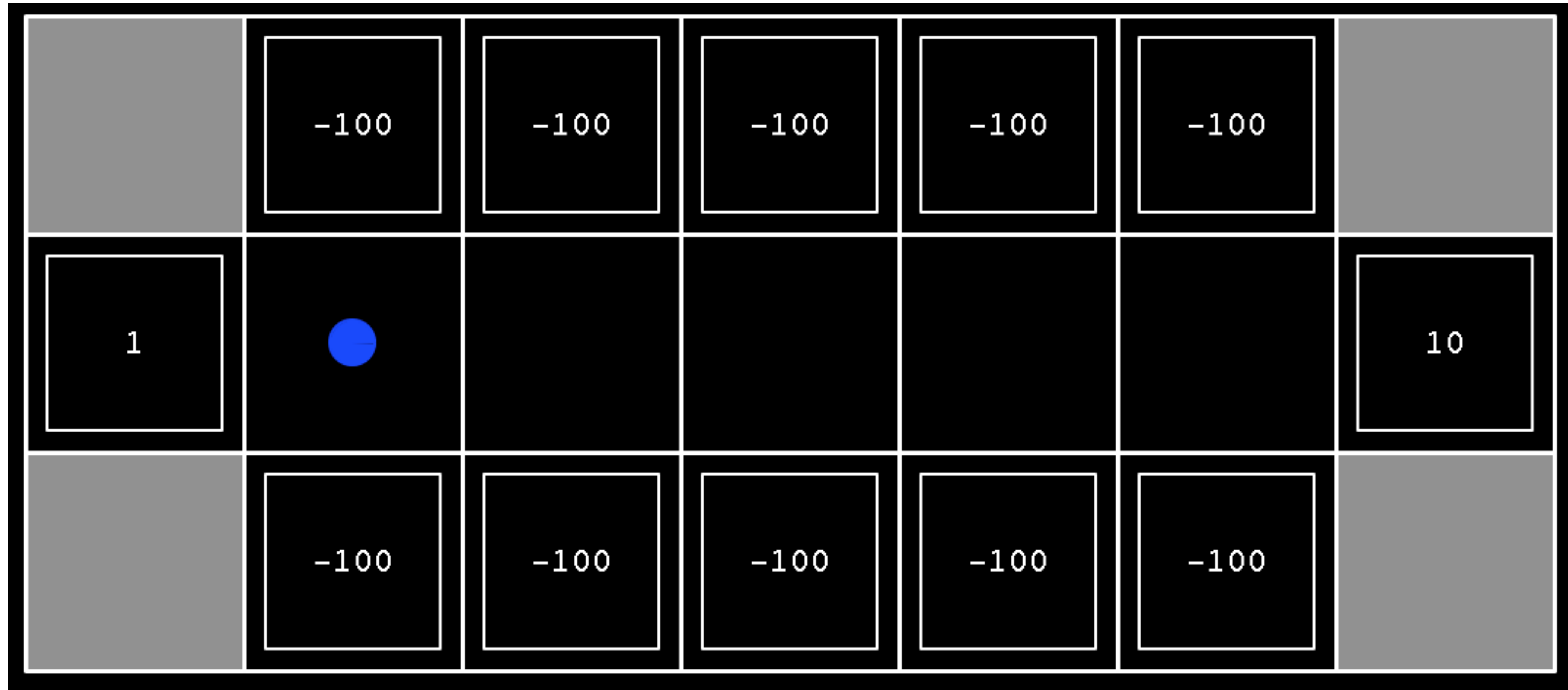
Markov Process  $\Pr(\mathbf{s}' \mid \mathbf{s})$

# Preview: Markov Models



Markov Process  $\Pr(\mathbf{s}' | \mathbf{s})$

# Reward function $R(s)$



# Policy $\pi(s)$

	<b>down</b> -100	<b>down</b> -100	<b>down</b> -100	<b>down</b> -100	<b>down</b> -100	
<b>right</b> 1	<b>right</b>	<b>right</b>	<b>right</b>	<b>right</b>	<b>right</b>	<b>stay</b> 10
	<b>up</b> -100	<b>up</b> -100	<b>up</b> -100	<b>up</b> -100	<b>up</b> -100	

# Policy $\pi(s)$

	<b>down</b> -100	<b>down</b> -100	<b>down</b> -100	<b>down</b> -100	<b>down</b> -100	
<b>stay</b> 1	<b>left</b>	<b>left</b>	<b>right</b>	<b>right</b>	<b>right</b>	<b>stay</b> 10
	<b>up</b> -100	<b>up</b> -100	<b>up</b> -100	<b>up</b> -100	<b>up</b> -100	

# How Good is a Policy?

$$U([s_0, s_1, \dots, s_T]) = \sum_{t=0}^T R(s_t)$$

$$U([s_0, s_1, \dots, s_T]) = \sum_{t=0}^T \gamma^t R(s_t) \quad \gamma \in (0, 1]$$

# How Good is a Policy?

$$U([s_0, s_1, \dots, s_T]) = \sum_{t=0}^{\infty} \gamma^t R(s_t) \quad \gamma \in (0, 1]$$

$$U^\pi(s) = \mathbb{E}_{\text{Pr}([s_0, s_1, \dots] | s_0=s, \pi)} \left[ \sum_{t=0}^{\infty} \gamma^t R(S_t) \right]$$

$$\pi_s^* = \arg \max_{\pi} U^\pi(s)$$



$$U([s_0, s_1, \dots, s_T]) = \sum_{t=0}^{\infty} \gamma^t R(s_t) \quad \gamma \in (0, 1]$$

$$U^\pi(s) = \mathbb{E}_{\text{Pr}([s_0, s_1, \dots] | s_0=s, \pi)} \left[ \sum_{t=0}^{\infty} \gamma^t R(s_t) \right]$$

$$\pi_s^* = \arg \max_{\pi} U^\pi(s) = \pi_{s'}^* \text{ for any } s'$$

$$U(s) = U^{\pi^*}(s)$$

$$\pi^*(s) = \arg \max_{a \in A(s)} \sum_{s'} P(s' | s, a) U(s')$$

$$\pi^*(s) = \arg \max_{a \in A(s)} \sum_{s'} P(s'|s, a) U(s')$$

$U(s')$  = expected utility given optimal play from  $s'$

$$U(s) = R(s) + \gamma \max_{a \in A(s)} \sum_{s'} P(s'|s, a) U(s')$$

**Bellman equation**

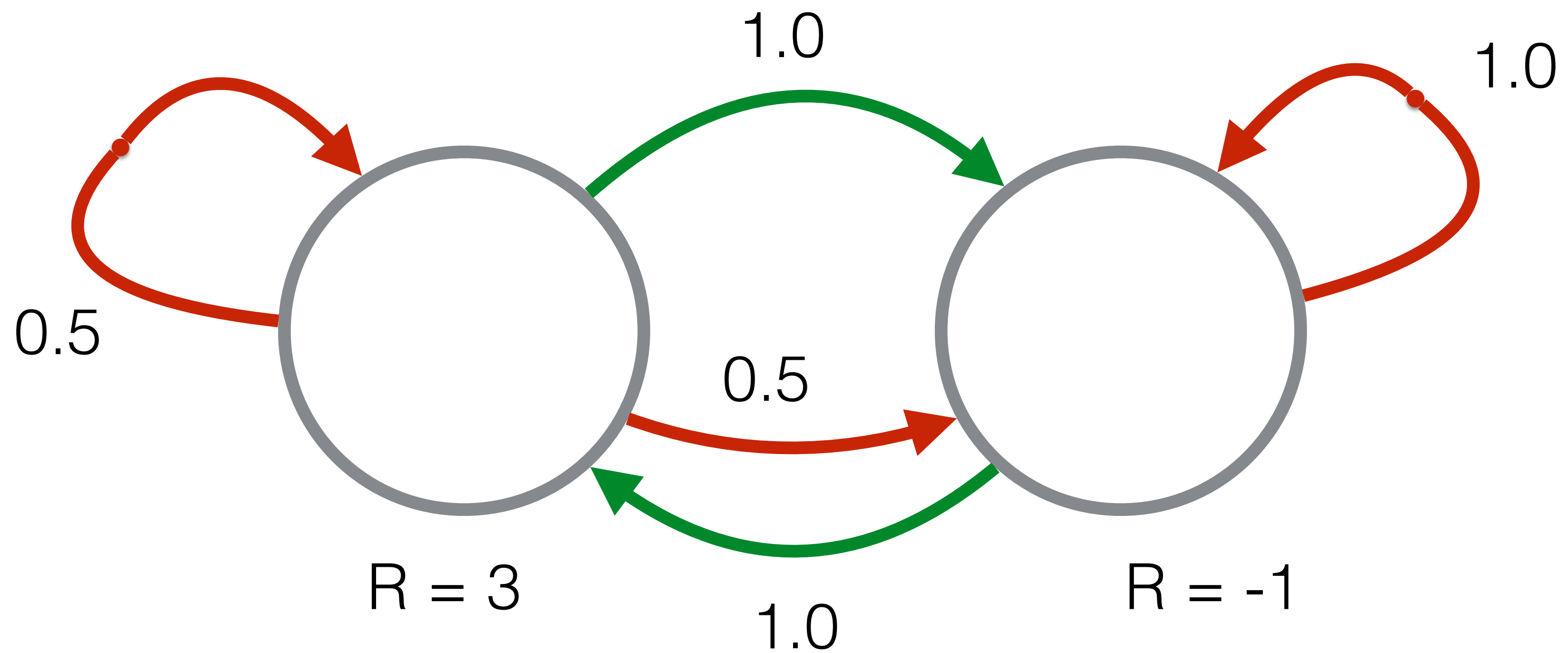
# Value Iteration

$$U_{i+1}(s) \leftarrow R(s) + \gamma \max_{a \in A(s)} \sum_{s'} P(s'|s, a) U_i(s')$$

$$U(s) = R(s) + \gamma \max_{a \in A(s)} \sum_{s'} P(s'|s, a) U(s')$$

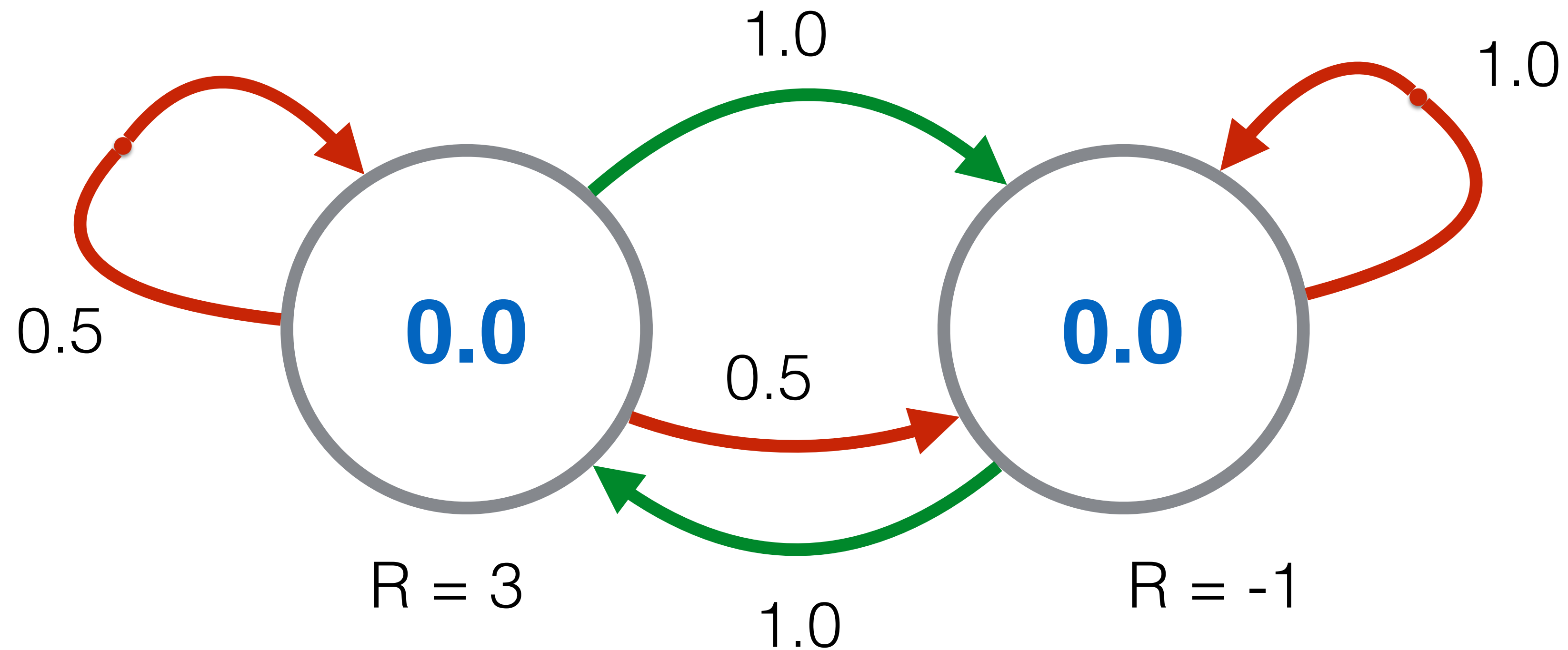
**Bellman equation**

# Value Iteration Example



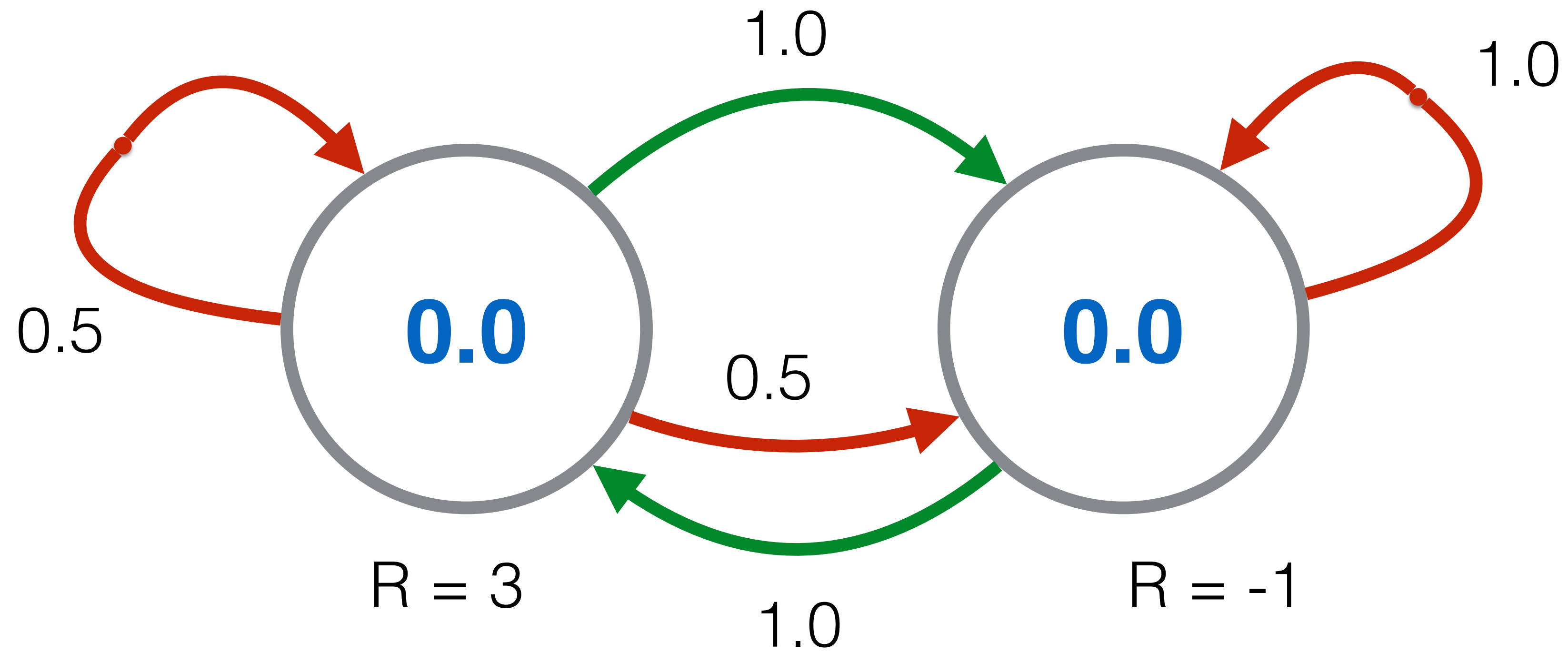
# Value Iteration Example

$$U_{i+1}(s) \leftarrow R(s) + \gamma \max_{a \in A(s)} \sum_{s'} P(s'|s, a) U_i(s') \quad \gamma = 0.5$$



$$U_{i+1}(s) \leftarrow R(s) + \gamma \max_{a \in A(s)} \sum_{s'} P(s'|s, a) U_i(s')$$

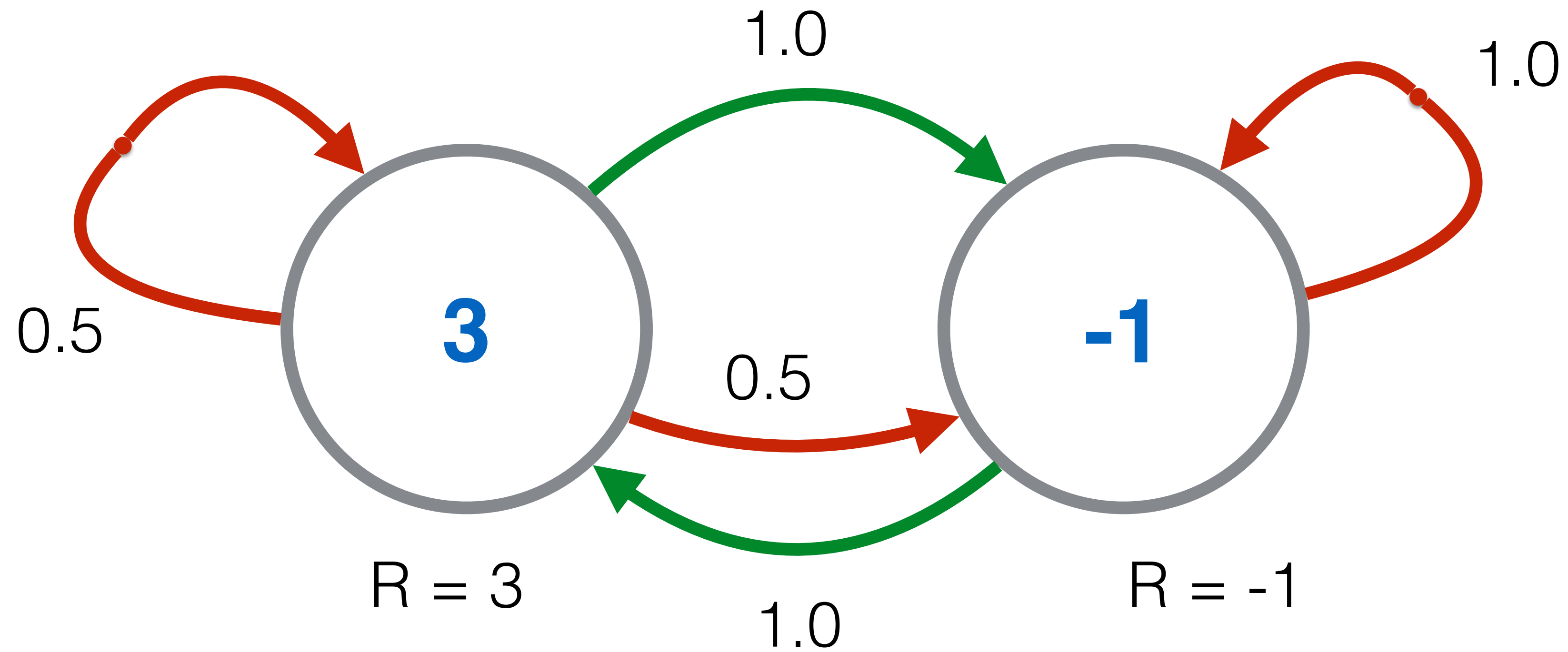
$$\gamma = 0.5$$



$$3 + 0.5 \max\{ 1.0 * 0.0, 0.5 * 0.0 + 0.5 * 0.0 \} = 3$$

$$-1 + 0.5 \max\{ 1.0 * 0.0, 1.0 * 0.0 \} = -1$$

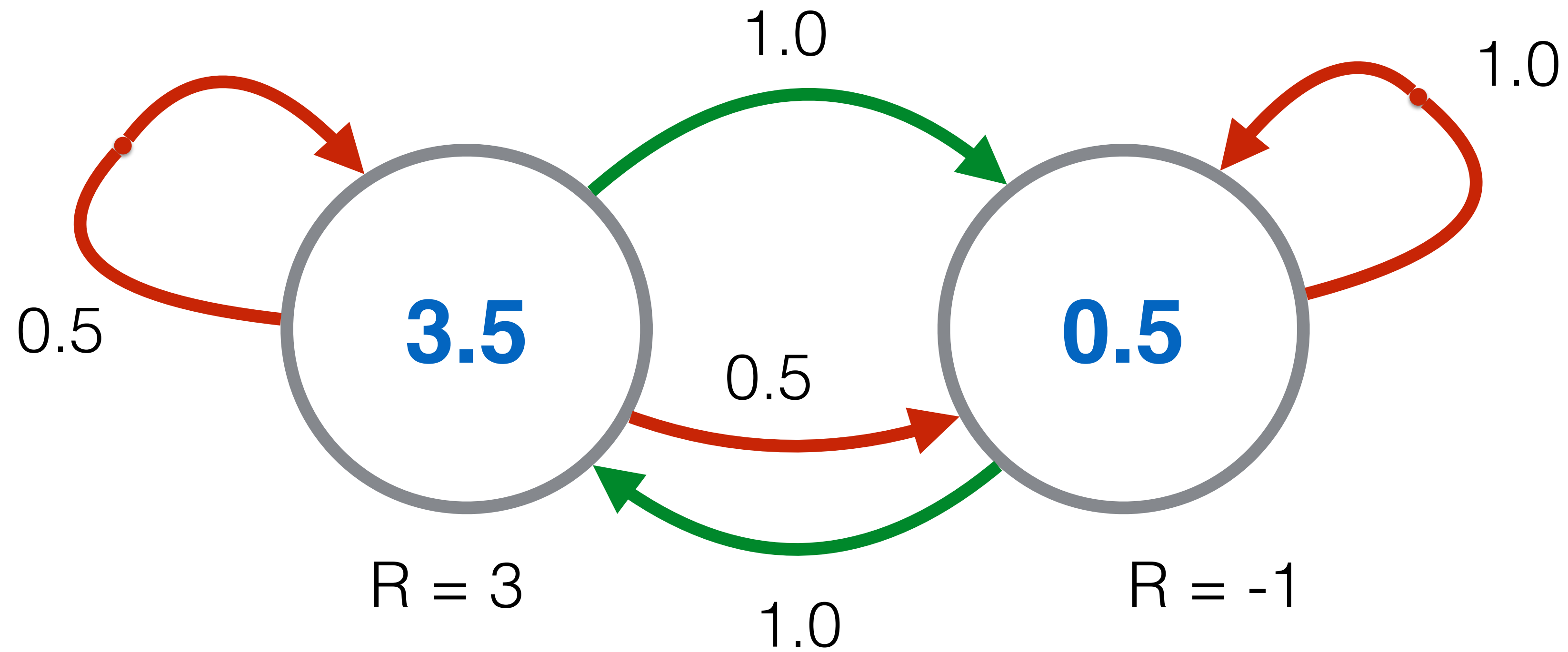
$$U_{i+1}(s) \leftarrow R(s) + \gamma \max_{a \in A(s)} \sum_{s'} P(s'|s, a) U_i(s') \quad \gamma = 0.5$$



$$3 + 0.5 \max\{ 1.0 * (-1), \quad 0.5 * 3 + 0.5 * (-1) \} = 3 + 0.5 \max\{ -1, 1 \} = 3.5$$

$$-1 + 0.5 \max\{ 1.0 * 3, 1.0 * (-1) \} = 0.5$$

$$U_{i+1}(s) \leftarrow R(s) + \gamma \max_{a \in A(s)} \sum_{s'} P(s'|s, a) U_i(s') \quad \gamma = 0.5$$



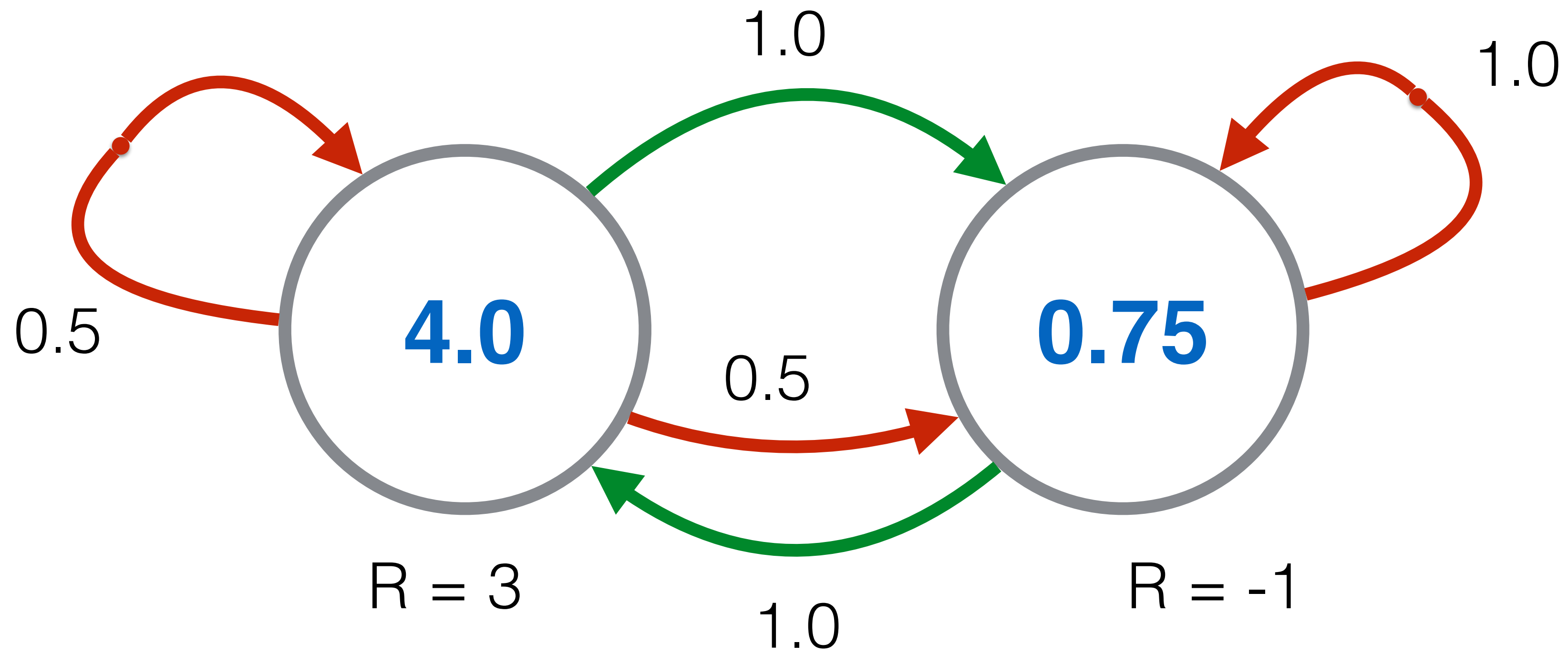
$$3 + 0.5 \max\{ 1.0 * \mathbf{0.5}, \quad 0.5 * \mathbf{3.5} + 0.5 * \mathbf{0.5} \} = 3 + 0.5 \max\{ 0.5, 2 \} = 4$$

$$-1 + 0.5 \max\{ 1.0 * \mathbf{3.5}, 1.0 * \mathbf{0.5} \} = 0.75$$

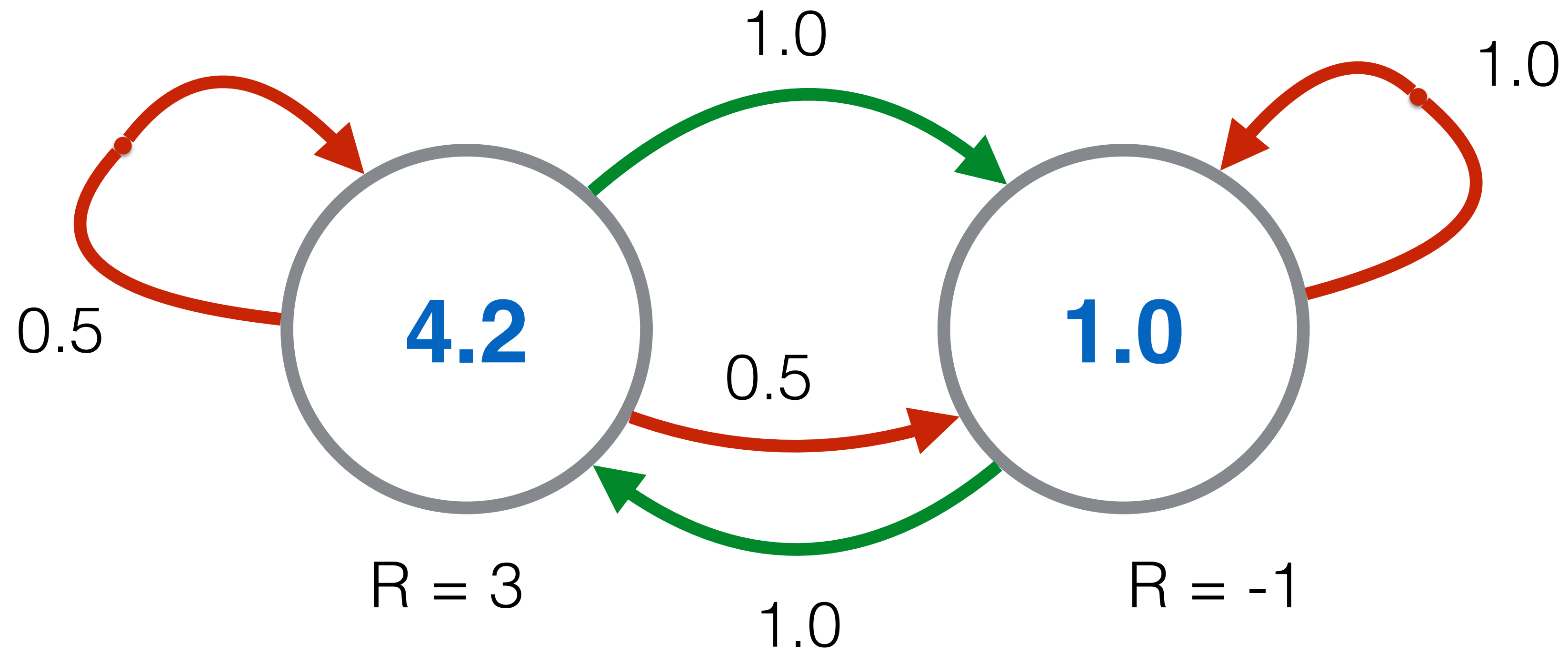


$$U_{i+1}(s) \leftarrow R(s) + \gamma \max_{a \in A(s)} \sum_{s'} P(s'|s, a) U_i(s')$$

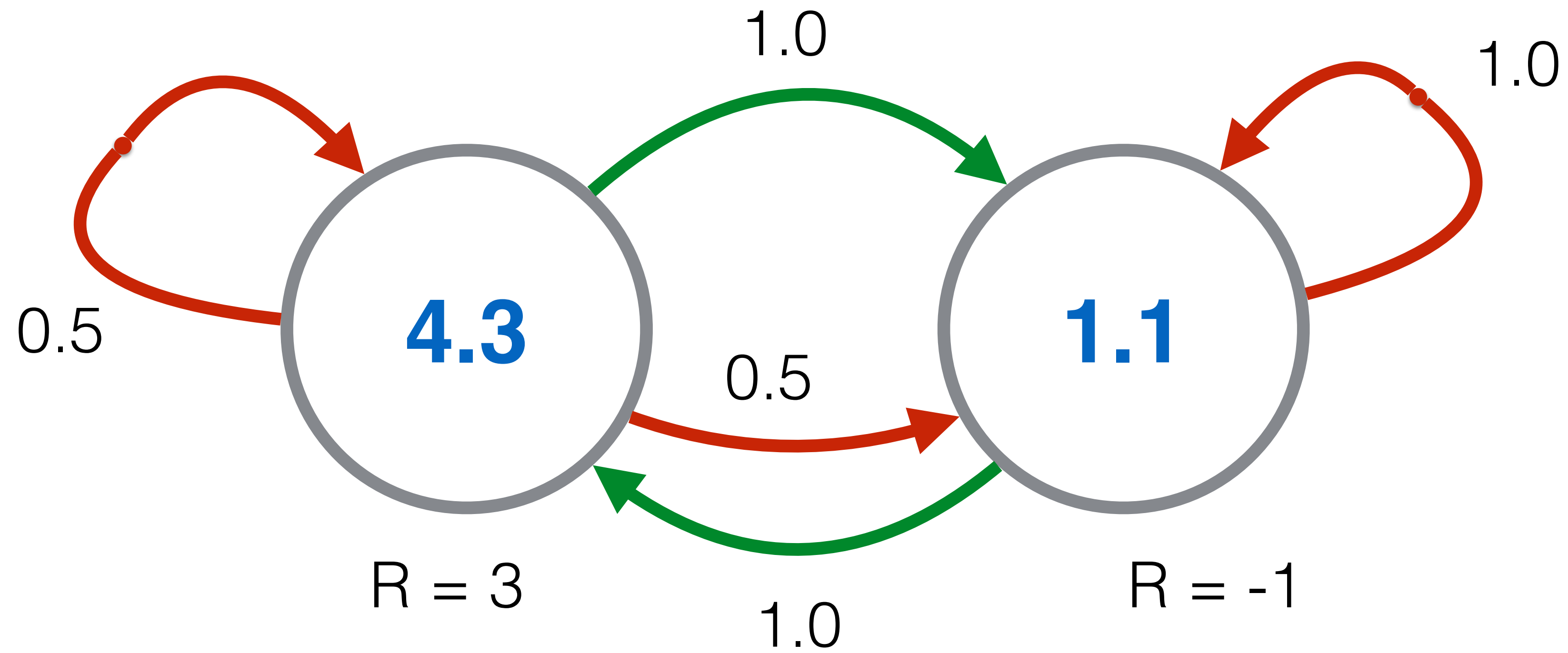
$$\gamma = 0.5$$



$$U_{i+1}(s) \leftarrow R(s) + \gamma \max_{a \in A(s)} \sum_{s'} P(s'|s, a) U_i(s') \quad \gamma = 0.5$$

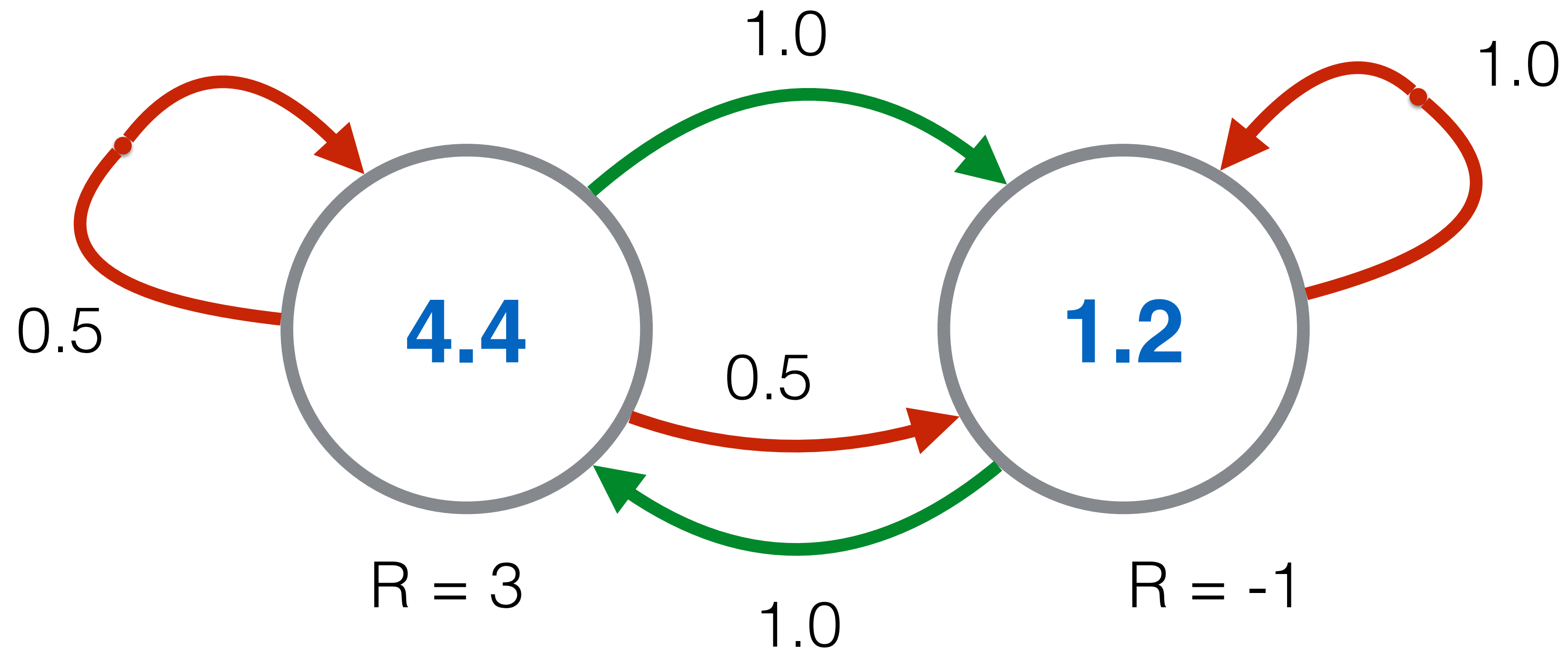


$$U_{i+1}(s) \leftarrow R(s) + \gamma \max_{a \in A(s)} \sum_{s'} P(s'|s, a) U_i(s') \quad \gamma = 0.5$$



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$$\gamma = 0.5$$

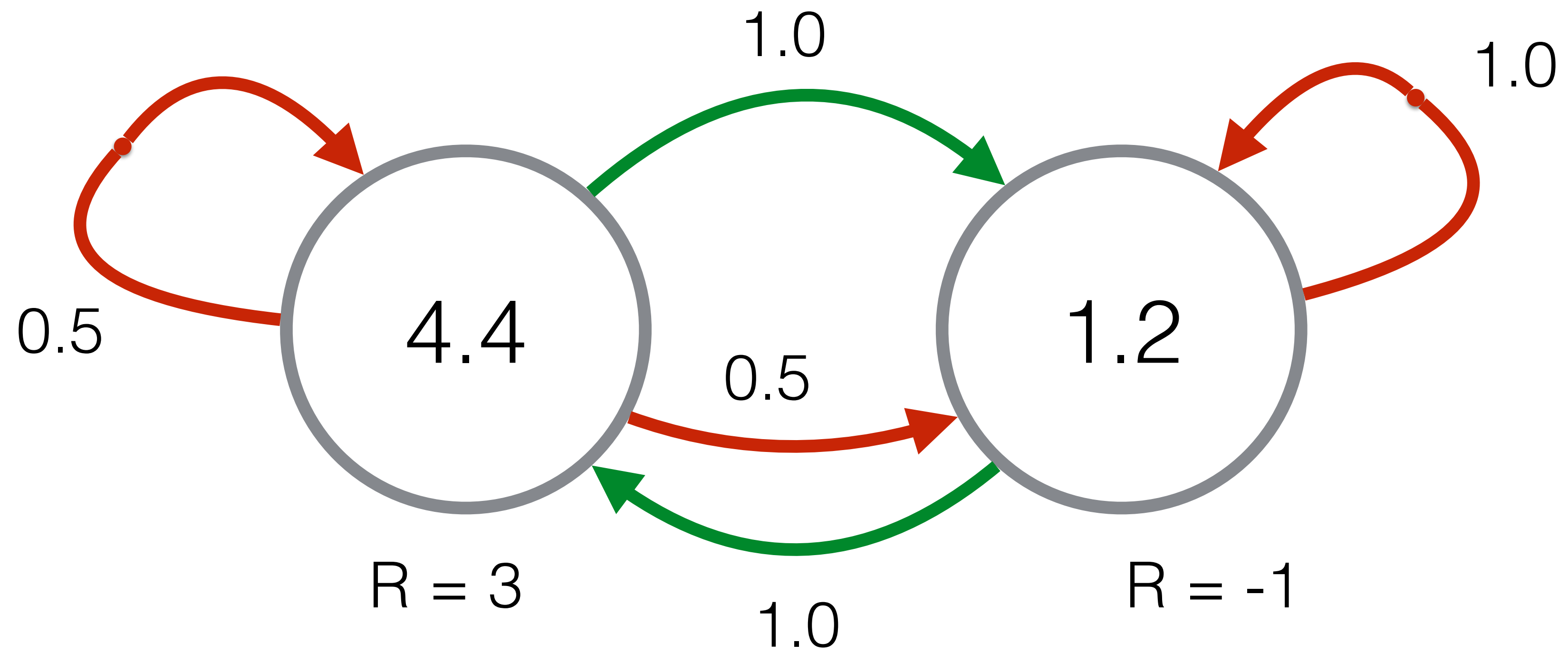


$$3 + 0.5 \max \{ 1.0 * \mathbf{1.2}, \quad 0.5 * \mathbf{4.4} + 0.5 * \mathbf{1.2} \}$$

$$3 + 0.5 \max \{ 1.2, \quad 2.2 + 0.6 \}$$

$$3 + 0.5 \max \{ 1.2, \quad 2.8 \}$$

$$3 + 0.5 * 2.8 = 4.4$$



$$\pi^*(s) = \arg \max_{a \in A(s)} \sum_{s'} P(s'|s, a) U(s')$$

# Summary

- Markov decision processes
  - actions have probabilistic state transitions
- Discounted reward function
- Optimal policy maximizes expected reward
- Value iteration
- Chapter 17 to end of 17.2