Dynamic Programming

Practice Quiz, 14 questions

14/14 points (100%)

Congratulations! You passed!

Next Item

1 / 1
point

1.
The value of any state under an optimal policy is ___ the value of that state under a non-optimal policy. [Select all that apply]

- [ ] Strictly greater than

Un-selected is correct

- [ ] Greater than or equal to

Correct
Correct! This follows from the policy improvement theorem.

- [ ] Strictly less than

Un-selected is correct

- [ ] Less than or equal to

Un-selected is correct

---

1 / 1
point

2.
If a policy is greedy with respect to the value function for the equiprobable random policy, then it is **guaranteed** to be an optimal policy.

- ( ) True
- ( ) False

Correct

Correct! Only policies greedy with respect to the optimal value function are guaranteed to be optimal.

---

1 / 1
point

3.
If a policy π is greedy with respect to its own value function v_π, then it is an optimal policy.

- False
- True

Correct

Correct! If a policy is greedy with respect to its own value function, it follows from the policy improvement theorem and the Bellman optimality equation that it must be an optimal policy.

---

1 / 1
point

4.
Let v_π be the state-value function for the policy π. Let π' be greedy with respect to v_π. Then $v_{\pi'} \geq v_\pi$.

- False
- True

Correct

Correct! This is a consequence of the policy improvement theorem.

---

1 / 1
point

5.
Let v_π be the state-value function for the policy π. Let $v_{\pi'}$ be the state-value function for the policy π'. Assume $v_\pi = v'_\pi$. Then this means that $\pi = \pi'$.

- True
- False

Correct

Correct! For example, two policies might share the same value function, but differ due to random tie breaking.

Dynamic Programming

Practice Quiz, 14 questions

14/14 points (100%)

1 / 1
point

6.
What is the relationship between value iteration and policy iteration? [Select all that apply]

- [ ] Value iteration is a special case of policy iteration.

Un-selected is correct

- [ ] Policy iteration is a special case of value iteration.

Un-selected is correct

- [ ] Value iteration and policy iteration are both special cases of generalized policy iteration.

Correct
Correct!

---

1 / 1
point

7.
The word synchronous means "at the same time". The word asynchronous means "not at the same time". A dynamic programming algorithm is: [Select all that apply]

- [ ] Asynchronous, if it does not update all states at each iteration.

Correct
Correct! Only algorithms that update every state exactly once at each iteration are synchronous.

- [ ] Asynchronous, if it updates some states more than others.

Correct
Correct! Only algorithms that update every state exactly once at each iteration are synchronous.

- [ ] Synchronous, if it systematically sweeps the entire state space at each iteration.

Correct
Correct! Only algorithms that update every state exactly once at each iteration are synchronous.

Dynamic Programming

Practice Quiz, 14 questions

14/14 points (100%)

1 / 1
point

8.
All Generalized Policy Iteration algorithms are synchronous.

- True
- False

Correct
Correct! A Generalized Policy Iteration algorithm can update states in a non-systematic fashion.

---

1 / 1
point

9.
Policy iteration and value iteration, as described in chapter four, are synchronous.

- True

Correct
Correct! As described in lecture, policy iteration and value iteration update all states systematic sweeps.

- False

---

1 / 1
point

10.
Which of the following is true?

- Synchronous methods generally scale to large state spaces better than asynchronous methods.
- Asynchronous methods generally scale to large state spaces better than synchronous methods.

Correct
Correct! Asynchronous methods can focus updates on more relevant states, and update less relevant states less often. If the state space is very large, asynchronous methods may still be able to achieve good performance whereas even just one synchronous sweep of the state space may be intractable.

---

1 / 1

1 / 1
point

Dynamic Programming

Practice Quiz, 14 questions

14/14 points (100%)

Why are dynamic programming algorithms considered planning methods? [Select all that apply]

- [ ] They compute optimal value functions.

Un-selected is correct

- [ ] They learn from trial and error interaction.

Un-selected is correct

- [ ] They use a model to improve the policy.

Correct

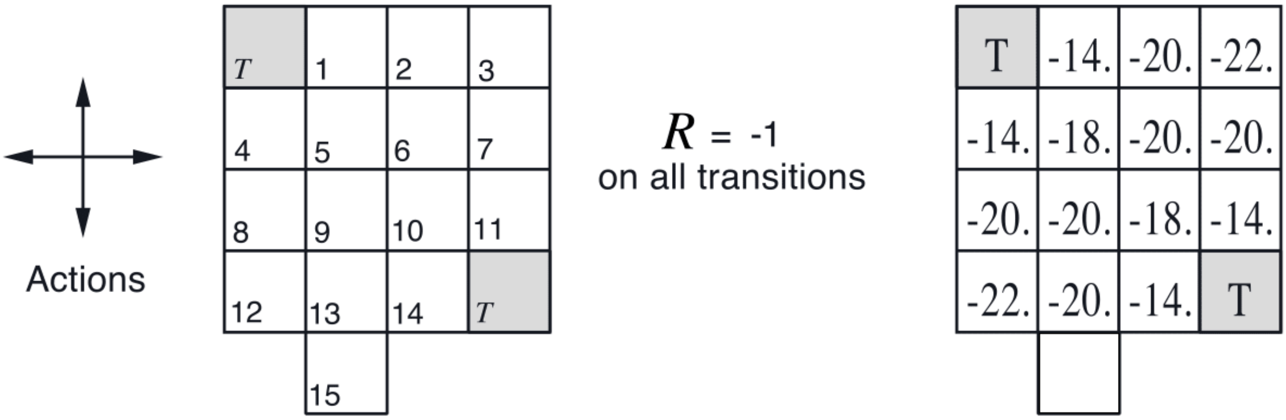
Correct! This is the definition of a planning method.

---

1 / 1
point

12.

Consider the undiscounted, episodic MDP below. There are four actions possible in each state, A = {up, down, right, left}, which deterministically cause the corresponding state transitions, except that actions that would take the agent off the grid in fact leave the state unchanged. The right half of the figure shows the value of each state under the equiprobable random policy. If π is the equiprobable random policy, what is $q(11, \text{down})$?



- ( ) $q(11, \text{down}) = -14$
- ( ) $q(11, \text{down}) = -1$

Correct

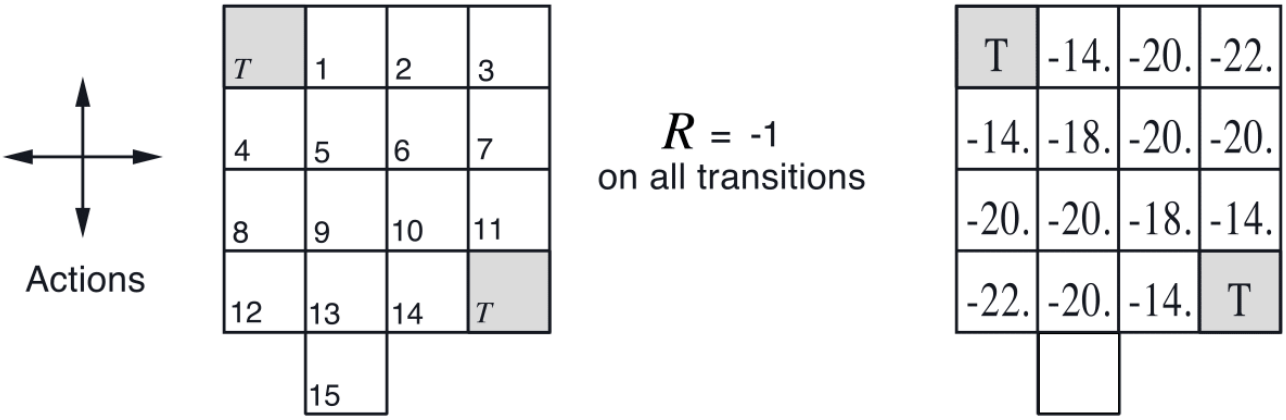
Correct! Moving down incurs a reward of -1 before reaching the terminal state, after which the episode is over.

- $q(11, \text{down}) = -15$
- $q(11, \text{down}) = 0$

---

1 / 1
point

13.
Consider the undiscounted, episodic MDP below. There are four actions possible in each state, A = {up, down, right, left}, which deterministically cause the corresponding state transitions, except that actions that would take the agent off the grid in fact leave the state unchanged. The right half of the figure shows the value of each state under the equiprobable random policy. If π is the equiprobable random policy, what is $q(7, \text{down})$?



- $q(7, \text{down}) = -14$
- $q(7, \text{down}) = -15$

Correct
Correct! Moving down incurs a reward of -1 before reaching state 11, from which the expected future return is -14.

- $q(7, \text{down}) = -21$
- $q(7, \text{down}) = -20$

---

1 / 1
point

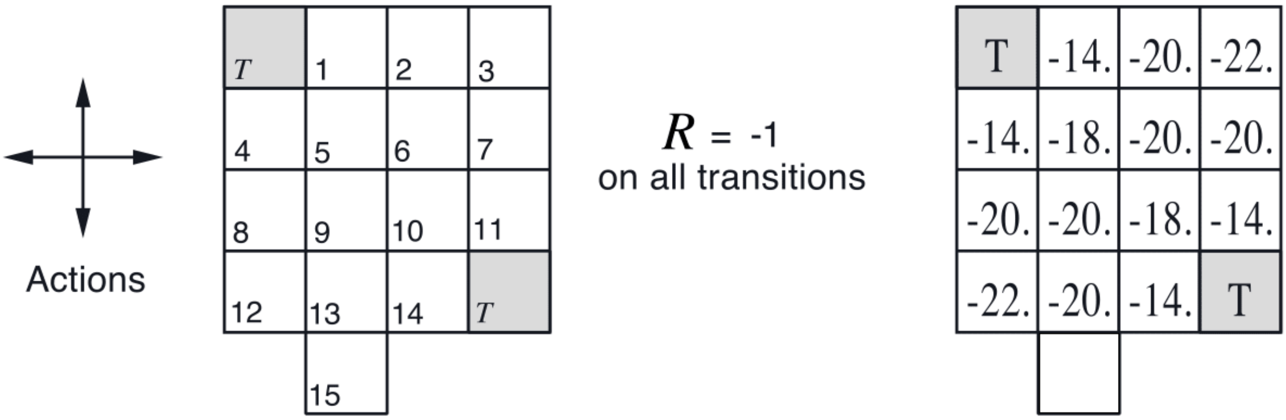
14.

Dynamic Programming

Practice Quiz, 14 questions

14/14 points (100%)

Consider the undiscounted, episodic MDP below. There are four actions possible in each state, A = {up, down, right, left}, which deterministically cause the corresponding state transitions, except that actions that would take the agent off the grid in fact leave the state unchanged. The right half of the figure shows the value of each state under the equiprobable random policy. If π is the equiprobable random policy, what is $v(15)$? Hint: Recall the Bellman equation $v(s) = \sum_a \pi(a|s) \sum_{s',r} p(s', r|s, a)[r + \gamma v(s')]$



- $v(15) = -25$
- $v(15) = -23$
- $v(15) = -21$
- $v(15) = -24$

Correct

Correct! We can get this by solving for the unknown variable $v(15)$. Let's call this unknown x. We solve for x in the equation $x = 1/4(-21) + 3/4(-1 + x)$. The first term corresponds to transitioning to state 13. The second term corresponds to taking one of the other three actions, incurring a reward of -1 and staying in state x.

- $v(15) = -22$