12/14 Questions Answered
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HW 4

Q1 Numerical Answer Formatting

0 Points

Many of the questions in this homework have answers that are decimal numbers. Due to current limitations of Gradescope, your answers must be an exact string match to ours. In order to ensure an exact match, please carefully follow the following formatting for your numerical answers.

- Do not round decimals. None of the answers are infinite decimals, so include full precision (all answers should be less than 5 places after the decimal).
- Do not include any leading or trailing 0s unless they are necessary to show the location of the decimal
- If the number is an integer, do not include a decimal

Examples:

`.1234`

`-.001`

`10.4`

`-10`

`0`

Note: If you use the Python interpreter to do your math, floating point error may lead to inexact decimal numbers. It is probably best to use another calculator, but if you do use Python you may need to adjust its output to get the actual exact answer.

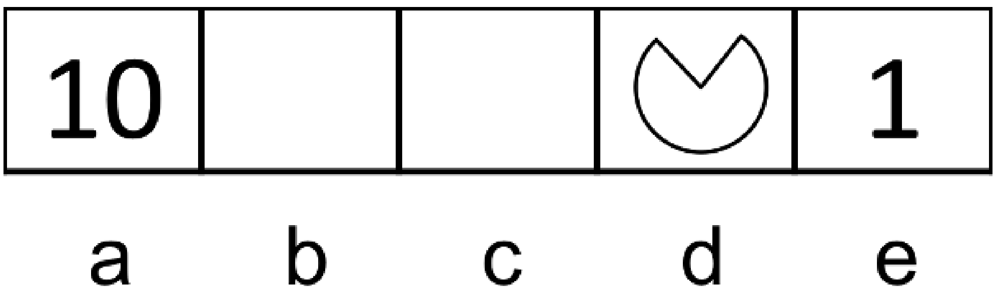
Save Answer

Q2 Solving MDPs

9 Points

Consider the gridworld MDP for which
Left and Right actions are 100% successful.

Specifically, the available actions in each state are to move to the neighboring grid squares. From state a, there is also an exit action available, which results in going to the terminal state and collecting a reward of 10. Similarly, in state e, the reward for the exit action is 1. Exit actions are successful 100% of the time.



Let the discount factor $\gamma = 1$. Fill in the following quantities.

$V_0(d) =$

0

EXPLANATION

When value iteration is initialized, the V_0 value of each state is 0.

$V_1(d) =$

0

EXPLANATION

At the first iteration, each state knows about the V_0 values of successor states. Because $V_0(e) = 0$, the state d will not know about the exit reward at state e.

Call t the terminal state. Notice the transition probabilities do not show up in our equation, because the transitions are all deterministic.

$$V_1(a) = R(a, exit, t) + V_0(t) = 10$$

$$V_1(b) = max(V_0(a), V_0(c)) = 0$$

$$V_1(c) = max(V_0(b), V_0(d)) = 0$$

$$V_1(d) = max(V_0(c), V_0(e)) = 0$$

$$V_1(e) = R(e, exit, t) + V_0(t) = 1$$

$V_2(d) =$

1

EXPLANATION

At the second iteration, each state knows about the V_1 values of successor states. State d will now know about the exit reward of state e, and $V_1(d)$ will be updated to 1.

$$V_2(a) = 10$$

$$V_2(b) = max(V_1(a), V_1(c)) = 10$$

$$V_2(c) = max(V_1(b), V_1(d)) = 0$$

$$V_2(d) = max(V_1(c), V_1(e)) = 1$$

$$V_2(e) = 1$$

$V_3(d) =$

1

EXPLANATION

$V_3(a) = 10$

$V_3(b) = max(V_2(a), V_2(c)) = 10$

$V_3(c) = max(V_2(b), V_2(d)) = 10$

$V_3(d) = max(V_2(c), V_2(e)) = 1$

$V_3(e) = 1$

$V_4(d) =$

10

EXPLANATION

At the fourth iteration, state d will see the exit reward of state a, so $V_4(d)$ will be updated to 10. $V_4(a) = 10$

$V_4(b) = max(V_3(a), V_3(c)) = 10$

$V_4(c) = max(V_3(b), V_3(d)) = 10$

$V_4(d) = max(V_3(c), V_3(e)) = 10$

$V_4(e) = 1$

$V_5(d) =$

10

EXPLANATION

Nothing will change between the fourth and fifth iteration.

Alternatively, for a simple MDP like this one, the values could also be computed directly from the meaning of $V_i(d)$, which is the expected discounted sum of rewards if acting optimally for i time steps, starting from state d. With $i = 0$ and $i = 1$, no reward can be obtained from state d, so $V_0(d) = V_1(d) = 0$. With $i = 2$ and $i = 3$, a reward of 1 can be obtained through "Right", "Exit" from state d, so $V_2(d) = V_3(d) = 1$. Because it takes four steps to obtain the reward of 10 ("Left", "Left", "Left", "Exit"), $V_i(d) = 10$ for $i \geq 4$.

✔ Correct

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Q3 Value Iteration Convergence Values

9 Points

Consider the gridworld where Left and Right actions are successful 100% of the time.

Specifically, the available actions in each state are to move to the neighboring grid squares. From state a, there is also an exit action available, which results in going to the terminal state and collecting a reward of 10. Similarly, in state e, the reward for the exit action is 1. Exit actions are successful 100% of the time.

10				1
a	b	c	d	e

Let the discount factor $\gamma = 0.2$. Fill in the following quantities.

$V^*(a) = V_\infty(a) =$

10

EXPLANATION

The optimal action from a is to take the exit action.

Call t the terminal state.

$V^*(a) = R(a, exit, t) + \gamma V^*(t) = 10$

$V^*(b) = V_\infty(b) =$

2

EXPLANATION

From state b, it is quite clear that you should move toward the closer, larger reward at state a.

$V^*(b) = R(b, left, a) + \gamma V^*(a) = 2$

$V^*(c) = V_\infty(c) =$

.4

EXPLANATION

From state c, you are equally close to both rewards, so the optimal action is to move toward the larger reward in state a.

$$V^*(c) = R(c, left, b) + \gamma V^*(b) = .4$$

$V^*(d) = V_\infty(d) =$

.2

EXPLANATION

It is not immediately obvious which way we should go from state d, so we must do some calculations first.

$$V^*(d) = max(R(d, left, c) + \gamma V^*(c), R(d, right, e) + \gamma V^*(e)) = max(.08, .2) = .2$$

Notice that from d, we prefer the closer, smaller reward to the farther, larger reward. This is because our discount factor (0.2) is low enough for us to prefer the closer reward. If our discount factor was higher, we might prefer the farther reward instead.

$V^*(e) = V_\infty(e) =$

1

EXPLANATION

In state e, we have a similar situation as state d, where we could go for the closer, smaller reward or the farther, larger reward. However, because we know the correct action from state d is "Right", we know that state e will also prefer the closer reward.

$$V^*(e) = R(e, exit, t) + \gamma V^*(t) = 1$$

✔ Correct

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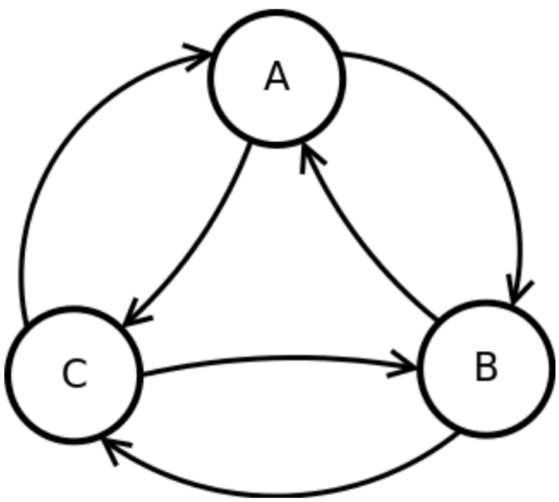
Q4 Value Iteration: Cycle

12 Points

We recommend you work out the solutions to the following questions on a sheet of scratch paper, and then enter your results into the answer boxes.

Consider the following transition diagram, transition function and reward function for an MDP.



Discount Factor, $\gamma = 0.5$

s	a	s'	T(s,a,s')	R(s,a,s')
A	Clockwise	B	1.0	0.0
A	Counterclockwise	C	1.0	-2.0
B	Clockwise	A	0.4	-1.0
B	Clockwise	C	0.6	2.0
B	Counterclockwise	A	0.6	2.0
B	Counterclockwise	C	0.4	-1.0
C	Clockwise	A	0.6	2.0
C	Clockwise	B	0.4	2.0
C	Counterclockwise	A	0.4	2.0
C	Counterclockwise	B	0.6	0.0

Suppose that after iteration k of value iteration we end up with the following values for V_k :

$V_k(A)$	$V_k(B)$	$V_k(C)$
0.400	1.400	2.160

What is $V_{k+1}(A)$?

.7

EXPLANATION

$V_{k+1}(A) =$
$\max(Q_{k+1}(A, clockwise), Q_{k+1}(A, counterclockwise))$

$Q_{k+1}(A, clockwise) =$
$T(A, clockwise, B)[R(A, clockwise, B) + \gamma V_k(B)] = .7$

$Q_{k+1}(A, counterclockwise) =$
$T(A, counterclockwise, C)[R(A, counterclockwise, C) +$
$\gamma V_k(C)] = -.92$

Note that in general, we would have to sum over all possible s' for each action, but actions from A are deterministic in this problem.

Now, suppose that we ran value iteration to completion and found the following value function, V^*.

$V^*(A)$	$V^*(B)$	$V^*(C)$
0.881	1.761	2.616

What is Q^*(A, clockwise)?

.8805

EXPLANATION

$Q^*(A, clockwise) =$
$T(A, clockwise, B)[R(A, clockwise, B) + \gamma V^*(B)] =$
$.8805$

What is Q^*(A, counterclockwise)?

-.692

EXPLANATION

$Q^*(A, counterclockwise) = T(A, counterclockwise, C)[R(A, counterclockwise, C) + \gamma V^*(C)] = -.692$

What is the optimal action from state A?

- (x) Clockwise
- ( ) Counterclockwise

EXPLANATION

The optimal action from A is the one that gives us the highest Q^* value.

✔ Correct

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Q5 Value Iterations Properties

7 Points

Which of the following are true about value iteration? We assume the MDP has a finite number of actions and states, and that the discount factor satisfies $0 < \gamma < 1$.

- [x] Value iteration is guaranteed to converge.
- [x] Value iteration will converge to the same vector of values (V^*) no matter what values we use to initialize V.
- [ ] None of the above

EXPLANATION

1. For discount less than 1, value iteration is guaranteed to converge.
2. At convergence, the following equation must be satisfied for all states:

$$V^*(s) = max_a \sum_{s'} T(s,a,s')[R(s,a,s') + \gamma V^*(s')]$$

There will only be one set of values that satisfies this condition, so no matter where we start value iteration, we will always arrive at the same set of values on convergence.

✔ Correct

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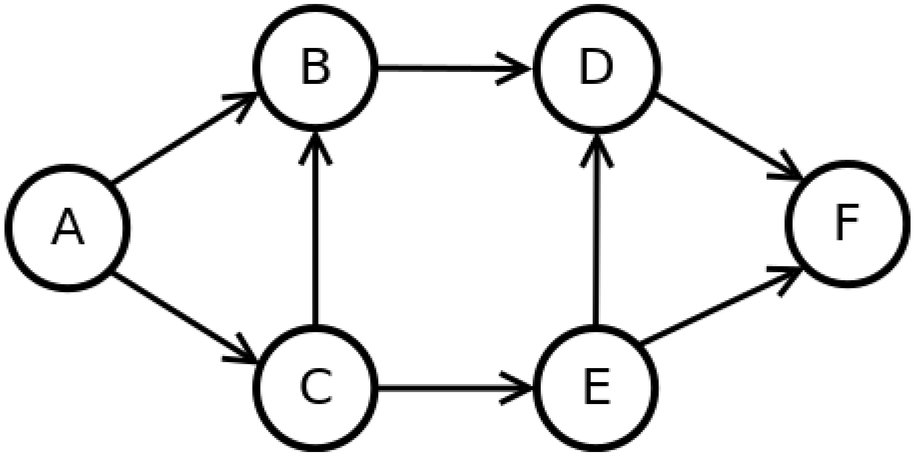
Q6 Value Iteration Convergence

6 Points

We will consider a simple MDP that has six states, A, B, C, D, E, and F. Each state has a
single action, go. An arrow from a state x to a state y indicates that it is possible
to transition from state x to next state y when go is taken. If there are multiple
arrows leaving a state x, transitioning to each of the next states is equally likely.
The state F has no outgoing arrows: once you arrive in F, you stay in F for all future
times. The reward is one for all transitions, with one exception: staying in F gets a
reward of zero. Assume a discount factor = 0.5. We assume that we initialize the value of each state to 0. (Note: you should not need to explicitly run value
iteration to solve this problem.)



Part 1

After how many iterations of value iteration will the value for state E have become exactly equal to the true optimum? (Enter inf if the values will never become equal to the true optimal but only converge to the true optimal.)

2

Part 2

How many iterations of value iteration will it take for the values of all states to converge to the true optimal values? (Enter inf if the values will never become equal to the true optimal but only converge to the true optimal.)

4

EXPLANATION

Because there are no moves from state F, we have the optimal value of F upon initializing. Since all the rewards are earned from transitions, finding the optimal value of a state amounts to finding the longest path from that state to F. For example, state D, whose longest path to F is only length 1, will find its optimal value after only one iteration.

$$V^*(D) = V_1(D) = R(D, go, F) + \gamma V^*(F) = 1$$

Similarly, the state A will find its optimal value after four iterations, because it will find out about its length 4 path to F after four iterations. Because A's length 4 path is the longest of the graph, it will take four iterations for all states to converge to their optimal values.

✔ Correct

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Q7 Policy Evaluation

10 Points

Consider the gridworld where

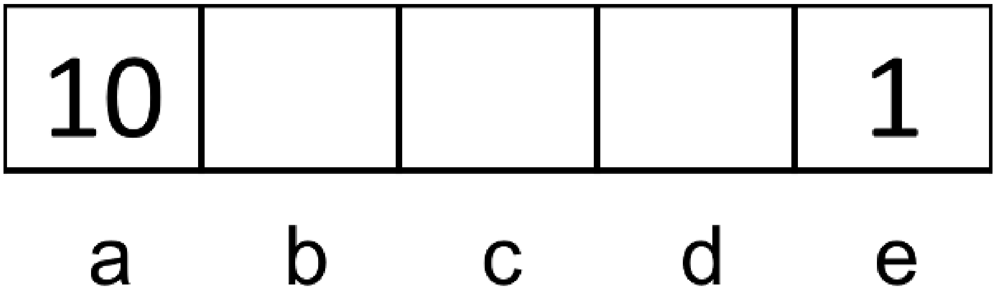
Left and Right actions are successful 100% of the time.

Specifically, the available actions in each state are to move to the neighboring grid squares. From state a, there is also an exit action available, which results in going to the terminal state and collecting

a

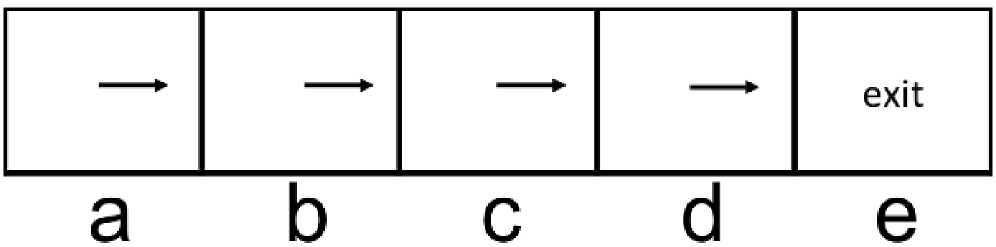
reward of 10. Similarly, in state e, the reward for the exit action is 1. Exit actions are successful 100% of the time.

The discount factor (γ) is 1.



Part 1

Consider the policy π_1 shown below, and evaluate the following quantities
for this policy.



$V^{\pi_1}(a) =$

1

$V^{\pi_1}(b) =$

1

$V^{\pi_1}(c) =$

1

$V^{\pi_1}(d) =$

1

$V^{\pi_1}(e) =$

1

Part 2

Consider the policy π_2 shown below, and evaluate the following quantities
for this policy.

exit	←	←	→	exit
a	b	c	d	e

$V^{\pi_2}(a) =$

10

$V^{\pi_2}(b) =$

10

$V^{\pi_2}(c) =$

10

$V^{\pi_2}(d) =$

1

$V^{\pi_2}(e) =$

1

EXPLANATION

Because there is no discounting and the only reward you receive is for taking an exit action, the value of a state is determined only by which exit will be taken from that state according to the policy.

Part 1: Because you will exit at state e from every state, the value of every state will be 1.

Part 2: From states a, b, and c, you will exit from state a, so the value from these states is 10. From states d and e, you will exit from state e, so the value of these states is 1.

✔ Correct

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Q8 Policy Iteration

9 Points

Consider the gridworld where
Left and Right actions are successful 100% of the time.

Specifically, the available actions in each state are to move to the neighboring grid squares. From state a, there is also an exit action available, which results in going to the terminal state and collecting
a
reward of 10. Similarly, in state e, the reward for the exit action is 1. Exit actions are successful 100% of the time.

The discount factor (γ) is 0.9.

a	b	c	d	e
10				1

We will execute one round of policy iteration.

Consider the policy π_i shown below, and evaluate the following quantities
for this policy.

a	b	c	d	e
exit	←	→	←	exit

$V^{\pi_i}(a) =$

10

EXPLANATION

From a, we take the exit action with reward 10. Thus, the value of state a is 10.

$V^{\pi_i}(b) =$

9

EXPLANATION

$V^{\pi_i}(b) = \gamma V^{\pi_i}(a) = 9$

$V^{\pi_i}(c) =$

0

EXPLANATION

From c, we will never reach an exit state, according to the policy. Therefore, the value for this state is 0.

$V^{\pi_i}(d) =$

0

EXPLANATION

0, by the same reasoning as for state c.

$V^{\pi_i}(e) =$

1

EXPLANATION

From e, we take the exit action with reward 1.

✔ Correct

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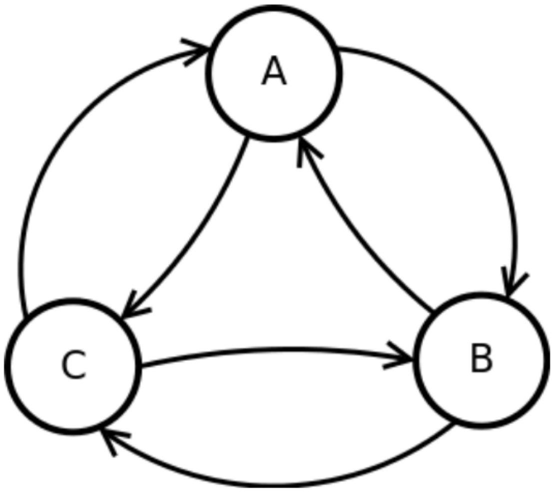
Q9 Policy Iteration: Cycle

14 Points

Consider the following transition diagram, transition function and reward function for an MDP.



Discount Factor, γ = 0.5

s	a	s'	T(s,a,s')	R(s,a,s')
A	Clockwise	B	0.8	0.0
A	Clockwise	C	0.2	2.0
A	Counterclockwise	B	0.4	1.0
A	Counterclockwise	C	0.6	0.0
B	Clockwise	C	1.0	-1.0
B	Counterclockwise	A	0.6	-2.0
B	Counterclockwise	C	0.4	1.0
C	Clockwise	A	1.0	-2.0
C	Counterclockwise	A	0.2	0.0
C	Counterclockwise	B	0.8	-1.0

Suppose we are doing policy evaluation, by following the policy given by the left-hand side table below. Our current estimates (at the end of some iteration of policy evaluation) of the value of states when following the current policy is given in the right-hand side table.

A	B	C
Counterclockwise	Counterclockwise	Counterclockwise

$V_k^\pi(A)$	$V_k^\pi(B)$	$V_k^\pi(C)$
0.000	-0.840	-1.080

We recommend you work out the solutions to the following questions on a sheet of scratch paper, and then enter your results into the answer boxes.

Part 1

What is $V_{k+1}^\pi(A)$?

-.092

EXPLANATION

$V^{\pi}_{k+1}(A) =$
$T(A, counterclockwise, B)[R(A, counterclockwise, B) + \gamma V^{\pi}_{k}(B)] +$

$T(A, counterclockwise, C)[R(A, counterclockwise, C) + \gamma V^{\pi}_{k}(C)] = -.092$

We only take into account the counterclockwise action from A, because that is the action according to our policy.

Suppose that policy evaluation converges to the following value function, V^{π}_{∞}.

$V^{\pi}_{\infty}(A)$	$V^{\pi}_{\infty}(B)$	$V^{\pi}_{\infty}(C)$
-0.203	-1.114	-1.266

Now let's execute policy improvement.

Part 2

What is Q^{π}_{∞}(A, clockwise)?

-.1722

EXPLANATION

$Q^{\pi}_{\infty}(A, clockwise) =$
$T(A, clockwise, B)[R(A, clockwise, B) + \gamma V^{\pi}_{\infty}(B)] +$

$T(A, clockwise, C)[R(A, clockwise, C) + \gamma V^{\pi}_{\infty}(C)] = -.1722$

Part 3: What is Q^{π}_{∞}(A, counterclockwise)?

-.2026

EXPLANATION

$Q^{\pi}_{\infty}(A, counterclockwise) =$
$T(A, counterclockwise, B)[R(A, counterclockwise, B) +$
$\gamma V^{\pi}_{\infty}(B)]+$

$T(A, counterclockwise, C)[R(A, counterclockwise, C) +$
$\gamma V^{\pi}_{\infty}(C)] = -.2026$

Part 4: What is the updated action for state A?

- (selected) Clockwise
- Counterclockwise

EXPLANATION

The updated action for state A will be the action that results in the higher Q^{π}_{∞}.

✔ Correct

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Q10 Wrong Discount Factor

7 Points

Bob notices value iteration converges more quickly with smaller γ and rather than using the true discount factor γ, he decides to use a discount factor of $\alpha\gamma$ with $0 < \alpha < 1$ when running value iteration. Mark each of the following that are guaranteed to be true:

- [ ] While Bob will not find the optimal value function, he could simply rescale the values he finds by $\frac{1-\gamma}{1-\alpha}$ to find the optimal value function.
- [x] If the MDP's transition model is deterministic and the MDP has zero rewards everywhere, except for a single transition at the goal with a positive reward, then Bob will still find the optimal policy.
- [ ] If the MDP's transition model is deterministic, then Bob will still find the optimal policy.
- [x] Bob's policy will tend to more heavily favor short-term rewards over long-term rewards compared to the optimal policy.
- [ ] None of the above.

EXPLANATION

Option 1: False. If Bob simply rescales all the values, the policy that he finds will be exactly the same.

Option 2: True. When the transitions are deterministic and there is a single reward at the goal, the optimal policy will be the shortest path to the goal both for discount factor γ and factor $\alpha\gamma$. Therefore, the optimal policy will not change.

Option 3: False. Consider the MDP from Question 8 for $\alpha = .1$ and $\gamma = .9$. The optimal policy in this MDP is to go left at state d. However, Bob's policy will tell you to go right at state d.

Option 4: True. Bob's policy is the optimal policy from running value iteration with a lower discount factor. The lower discount factor favors short term rewards.

✔ Correct

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Q11 MDP Properties

10 Points

Q11.1

5 Points

Which of the following statements are true for an MDP?

- [ ] If the only difference between two MDPs is the value of the discount factor then they must have the same optimal policy.
- [x] For an infinite horizon MDP with a finite number of states and actions and with a discount factor γ that satisfies $0 < \gamma < 1$, value iteration is guaranteed to converge.
- [ ] When running value iteration, if the policy (the greedy policy with respect to the values) has converged, the values must have converged as well.
- [ ] None of the above

EXPLANATION

Option 1: False. Consider the MDP for Question 8 with two discount factors $\gamma_1 = .9$ and $\gamma_2 = .2$. For γ_1, the optimal policy will be to go left at state d. For γ_2, the optimal policy will be to go right at state d.

Option 2: True. With a discount factor less than 1, value iteration is guaranteed to converge, as shown in lecture.

Option 3: False. Consider an MDP with three states A, B, and C. There are deterministic transitions from A to B, B to C, and C to A. The reward for each transition is 1. For this MDP, we will know from the beginning what the policy is, because there is only one action from each state, and so there is only one possible policy. However, value iteration only converge much later.

✔ Correct

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Q11.2
5 Points

Which of the following statements are true for an MDP?

- [x] If one is using value iteration and the values have converged, the policy must have converged as well.
- [ ] Expectimax will generally run in the same amount of time as value iteration on a given MDP.
- [x] For an infinite horizon MDP with a finite number of states and actions and with a discount factor γ that satisfies $0 < \gamma < 1$, policy iteration is guaranteed to converge.
- [ ] None of the above

EXPLANATION

Option 1: True. If value iteration has converged, the values of each state will not change anymore. This means that the policy from iteration to iteration will not change either.

Option 2: False. Let's consider the cost of computing the value of a single state s, where a horizon H is needed for the values to converge. With expectimax, we will construct a tree with a maximum branching factor of AS, for every (a, s') pair, and a depth of H, for the horizon, so the complexity of expectimax will be $(AS)^H$. Now consider value iteration. For every step of value iteration, we will look at AS^2 values, for every (s, a, s') tuple. There will be a total of H iterations, so complexity of value iteration is AS^2H. Thus, expectimax will generally run much slower than value iteration.

Option 3: True. For policy iteration, we are guaranteed to find a better policy every iteration until we converge. Because we improve the policy every iteration, and there are a finite number of policies for a given MDP, we are guaranteed to eventually converge.

✔ **Correct**

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Q12 Policies

7 Points

John, James, Alvin and Michael all get to act in an MDP $(S, A, T, \gamma, R, s_0)$.

John runs value iteration until he finds V^* which satisfies $\forall s \in S$: $V^*(s) = \max_{a \in A} \sum_{s'} T(s,a,s')(R(s,a,s') + \gamma V^*(s'))$ and acts according to $\pi_{\text{John}} = \arg\max_{a \in A} \sum_{s'} T(s,a,s')(R(s,a,s') + \gamma V^*(s'))$.

James acts according to an arbitrary policy π_{James}.

Alvin takes James's policy π_{James} and runs one round of policy iteration to find his policy π_{Alvin}.

Michael takes John's policy and runs one round of policy iteration to find his policy π_{Michael}.

Note: One round of policy iteration =
performing policy evaluation followed by performing policy improvement.

Mark all of the following that are guaranteed to be true:

- [ ] It is guaranteed that $\forall s \in S : V^{\pi_{\text{James}}}(s) \geq V^{\pi_{\text{Alvin}}}(s)$
- [x] It is guaranteed that $\forall s \in S : V^{\pi_{\text{Michael}}}(s) \geq V^{\pi_{\text{Alvin}}}(s)$
- [ ] It is guaranteed that $\forall s \in S : V^{\pi_{\text{Michael}}}(s) > V^{\pi_{\text{John}}}(s)$
- [ ] It is guaranteed that $\forall s \in S : V^{\pi_{\text{James}}}(s) > V^{\pi_{\text{John}}}(s)$
- [ ] None of the above.

EXPLANATION

Option 1: False. Actually, the reverse is true. In policy iteration, we are guaranteed to improve every step until convergence.

Option 2: True. Because John's policy is optimal, running policy iteration on it will return the same optimal policy. Therefore, Michael's policy is optimal, while Alvin's may not be optimal.

Option 3: False. John and Michael have the same policy.

Option 4: False. John's policy is optimal, so there cannot be a policy that is better than it.

✔ **Correct**

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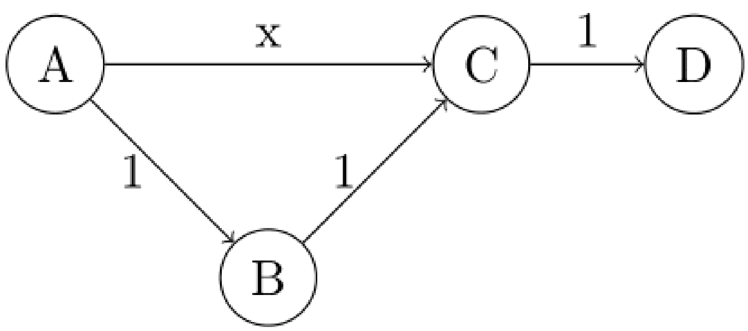
Q13 Challenge Question (MDP)

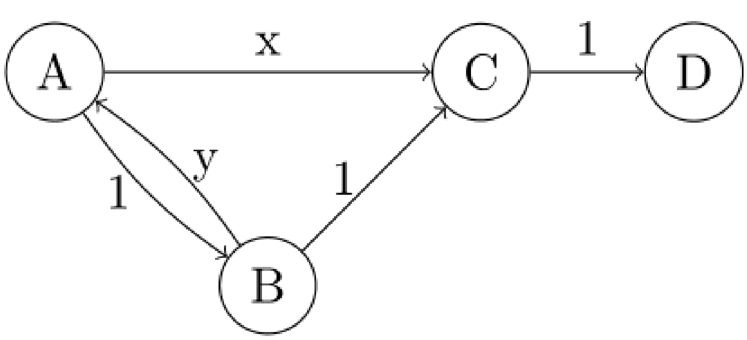
20 Points

13.1) (5 pts) Consider the following deterministic MDP with four states A, B, C and D:



The edges designate actions between states, the weights on those edges are the rewards, and the discount factor is $\gamma = 1$. Let k be the first iteration of Value Iteration at which the value function converges for some x for a particular state (i.e. $V_k(s) = V^*(s)$). For each state A, B, C and D, list all possible values of k. In the case a value function for a particular state never converges, set $k = \infty$ for that state.

Now for questions 13.2) and 13.3) consider the following deterministic MDP with four states A, B, C and D:



The edges designate actions between states, the weights on those edges are the rewards, and the discount factor is again $\gamma = 1$.

Furthermore assume that $x, y \geq 0$.

13.2) (5 pts) Let k be the first iteration of Value Iteration for some nonnegative x and y at which the value function converges for a particular state ($V_k(s) = V^*(s)$). For each state A, B, C and D list all possible values of k. In case a value for a particular state never converges set $k = \infty$ for that state.

13.3) (6 pts) Now consider that we perform Policy Iteration and that k is the first iteration for which the policy is optimal for a particular state (i.e. $\pi_k(s) = \pi^*(s)$). On top of $x, y \geq 0$ also assume that $x + y < 1$ and that tie-breaking during policy improvement is alphabetical. For each state A, B, C and D, find k; if the policy never converges set $k = \infty$ for that state. The
initial policy is given in the table below.

State s	**Policy** $\pi_0(s)$
A	C
B	C
C	D
D	D

The following two questions are conceptual.

13.4) (2 pts) Which of the following statements are guaranteed to be correct for any MDP? Select all that apply.
A. For all states s and for all policies π, $V_\pi(s) \leq V^*(s)$.
B. For no state s and for all policies π, $V_\pi(s) \leq V^*(s)$.
C. For some state s and some policy π, $V_\pi(s) \leq V^*(s)$.
D. None of the above.

13.5) (2 pts) Which of the following statements are guaranteed to be correct for Value Iteration? Select all that apply.
A. At each iteration, the value functions are at least as high as the values at the previous iteration for all states.

B. At each iteration, the value functions are higher than the values at the previous iteration for all states.
C. At each iteration, the value function can be lower than the earlier values for some state.
D. Once its converged, value iteration does not change the value function for any state.
E. None of the above.

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