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Machine Learning with Python-From Linear Models to Deep Learning

Course **Progress** Discussion Dates Resources

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5. Policy and Value Functions

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Exercises due May 3, 2023 08:59 -03 Completed

Policy and Value Functions



Video

♣ Download video file

Transcripts

- ♣ Download SubRip (.srt) file
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Definition of Optimal Policy

1/1 point (graded)

Given an MDP, and a utility function $U[s_0, s_1, \ldots, s_n]$, our goal is to find an optimal maximizes the expectation of the utility. Here, a **policy** is a function $\pi: S \to A$ that as any state s. We denote the optimal policy by π^* .

Which of the following option is correct about the optimal policy function?

- The optimal policy function would only depend on the state and action space bu reward structure.
- The optimal policy assigns an action at every state that maximizes the expected
- For any given state, the optimal policy function should always take an action that

	-1
	Agent's starting state

Recall the MDP example in the lecture. An Al agent navigates in the 3×3 grid depicted a square is not accessible (and hence is greyed out).

The MDP is defined as follows. As before, every state—is defined by the current positions of the actions are the 4 directions "up", "down", "left", "right".

Now, The transition probabilities from state via action to state is given by

Reward structure:

As before, the agent receives a reward of for arriving at the top right cell, and a revelled the cell immediately below it. It does not receive any non-zero reward at the other cells following figure.

However, this time, the agent also receives a reward (or penalty) of any action that leads the agent into the or cells.

Transition Probabilities:

For simplicity, assume that all the transitions are deterministic. That is, given any state actions are deterministic: The next state reached is completely predictable.

For intance, taking the action "left" from the bottom right cell will always take the agent to its left. Any action pointing off the grid would lead the agent to remain in its current of the grid would lead the agent to remain in its current of the grid would lead the agent to remain in its current of the grid would lead the agent to remain in its current of the grid would lead the agent to remain in its current of the grid would lead the agent to remain in its current of the grid would lead the agent to remain in its current of the grid would lead the agent to remain in its current of the grid would lead the agent to remain in its current of the grid would lead the agent to remain in its current of the grid would lead the agent to remain in its current of the grid would lead the agent to remain in its current of the grid would lead the agent to remain in its current of the grid would lead the agent to remain in its current of the grid would lead the agent to remain in its current of the grid would lead the agent to remain in its current of the grid would lead the agent to remain in its current of the grid would lead the agent to remain in its current of the grid would lead the grid woul

Initial State:

Also, assume that the agent always starts off from the bottom right corner of the grid. action until it reaches the top right corner, at which point it stops and does not act any

Optimal policy - Numerical Example

2/2 points (graded)

Recall that in this setup, the agent receives a reward (or penalty) of for every action of the and when it reached the corresponding cells. Since the agent always stated the outcome of each action is deterministic, the discounted reward depends only on the can be written as:

Maximum discounted reward:

-15.5



Submit

You have used 1 of 3 attempts

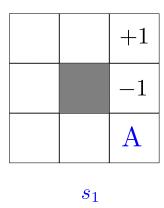
Value Function

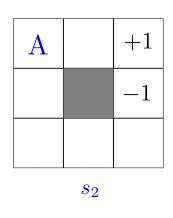
0/1 point (graded)

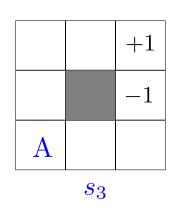
As above, we are working with the grid example with reward at the top right cell below it. The agent also gets a reward of for every action that it takes. The addeterministic. The agent continues to act until it reaches the cell, when it stops.

The following figures show states

in which the letter "A" marks the current lo







A **value function** of a given state is the expected reward (i.e the expectation of the agent acts optimally starting at state . In the given MDP, since the action outcome expected reward simply equals the utility function.

Which of the following should hold true for a good value function under the rewa

Note: You may want to watch the video on the next page before submitting this question









. - .

. . . .

I believe that the equation in the second part in not mathematically correct. Why does the left side depends

- Yalue Function is gamma assumed to be 1 in the last question?
 - * didn't see gamma in the answer for that question
- ? [STAFF] Optimal policy Numerical Example last step

This is a critical for my understanding. Why we do not count last step as gamma^2*R(s_2,a_3), a_3=0?????!

Better example needed

The study example needs to be refined or even better replaced with a more intuitive one. It is not a good one

? Formal definition of R for the numerical problem

How does one define R? The description doesn't really define it formally. Specifically, does the R(s(n),a(n+1))

- 🗪 <u>s_0</u>
- awful notation and word choice
- Optimal policy ambiguity in question
 The question clearly states: "For the cases (gamma=0) and (gamma=0.5), what is the maximum discounted in the property of the cases (gamma=0) and (gamma=0.5).
- ? Confusion about what step the +1/-1 rewards apply
 Based on the discounted rewards function, I am not clear at which term the destination rewards of +1 and -1
- ? Answer for gamma = 0.5 does not seem correct
 The answer for gamma = 0.5 does not seem correct, as it didn't factor in R(s_2, a_3).

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