

**RBE 595 — Reinforcement Learning**  
**Week #3 Assignment**

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## Problem 1

Suppose  $\gamma = 0.8$  and we get the following sequence of rewards

$$R_1 = -2, R_2 = 1, R_3 = 3, R_4 = 4, R_5 = 1.0$$

Calculate the value of  $G_0$  by using the equation 3.8 (work forward) and 3.9 (work backward) and show they yield the same results.

### Answer

#### Work Forward

From the the book, the *discounted return* (equation 3.8),  $G_t$ , is defined as,

$$G_t \doteq R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \dots = \sum_{k=0}^{\infty} \gamma^k R_{t+k+1} \quad (3.8)$$

Plugging in the values from this problem, we get,

$$\begin{aligned} G_0 &= R_1 + \gamma R_2 + \gamma^2 R_3 + \gamma^3 R_4 + \gamma^4 R_5 \\ &= -2 + 0.8 \cdot 1 + 0.8^2 \cdot 3 + 0.8^3 \cdot 4 + 0.8^4 \cdot 1 \\ &= -2 + 0.8 + 0.64 \cdot 3 + 0.512 \cdot 4 + 0.4096 \\ &= 3.1776 \end{aligned}$$

#### Work Backward

From the book, the “recursive” representation of *discounted return* (equation 3.9),  $G_t$ , is defined as,

$$G_t \doteq R_{t+1} + \gamma G_{t+1} \quad (3.9)$$

Plugging in the values from this problem, we get,

$$\begin{aligned} G_0 &= R_1 + \gamma G_1 \\ &= -2 + 0.8 \cdot G_1 \end{aligned}$$

Where we apply 3.8 to  $G_1$ ,

$$\begin{aligned} G_1 &= R_2 + \gamma R_3 + \gamma^2 R_4 + \gamma^3 R_5 \\ &= 1 + 0.8 \cdot 3 + 0.8^2 \cdot 4 + 0.8^3 \cdot 1 \\ &= 6.472 \end{aligned}$$

Therefore,

$$\begin{aligned} G_0 &= -2 + 0.8 \cdot G_1 \\ &= -2 + 0.8 \cdot 6.472 \\ &= 3.1776 \end{aligned}$$

### Conclusion

We see that both methods yield the same result,  $G_0 = 3.1776$ .

## Problem 2

Explain how a room temperature control system can be modeled as an MDP? What are the states, actions, rewards, and transitions.

### Answer

A room temperature control system can be modeled as an MDP as follows.

### Scope

Let us make some assumptions to define the scope of the solution.

- The temperatures are being measured in Fahrenheit.
- The temperature resolution of the temperature sensor in the room is  $1^\circ\text{F}$ .
- Given the climate of the area, the room naturally stays between the range of  $40^\circ\text{F}$  and  $90^\circ\text{F}$ .
- The humans in the room are comfortable with temperatures between  $68^\circ\text{F}$  and  $72^\circ\text{F}$ .

### States

Therefore, the states of the system are the temperatures in the room,  $S = \{s \in \mathbb{Z} \mid 40 \leq s \leq 90\}$ .

### Actions

The actions of the system are the temperature changes in the room. Assume that the control system can change the temperature by up to  $5^\circ\text{F}$  in either direction. Therefore, in general, the set of all actions are  $A = \{a \in \mathbb{Z} \mid -5 \leq a \leq 5\}$ . However, the action at each state is limited by the state itself. For example, if the current temperature is below  $68^\circ\text{F}$ , then the action cannot be to decrease the temperature further. Therefore, the set of actions can take on three possible sub-sets of  $A$  depending on the state, as follows,

- $A_{\text{low}} = \{a \in A \mid a \geq 0\}$ , if  $s \leq 68$
- $A_{\text{mid}} = \{a \in A \mid -1 \leq a \leq 1\}$ , if  $68 < s < 72$
- $A_{\text{high}} = \{a \in A \mid a \leq 0\}$ , if  $s \geq 72$

### Rewards

The reward for the system is defined as the difference between the current temperature and the desired temperature. Therefore, the reward function is defined as,

$$r(s, a, s') = \begin{cases} |70 - s|, & \text{if } 68 \leq s \leq 72 \\ 68 - s, & \text{if } s < 68 \\ s - 72, & \text{if } s > 72 \end{cases}$$

Notice that the reward is always non-negative. If the temperature does not change, then the reward is zero. If the temperature changes (the direction of which is enforced by the action set), then the reward is positive.

### Transitions

The transitions are defined as follows,

$$p(s' | s, a) = \begin{cases} \alpha_{\text{low}}, & \text{if } s \leq 68 \text{ and } s' = s + a \\ \alpha_{\text{mid}}, & \text{if } 68 < s < 72 \text{ and } s' = s + a \\ \alpha_{\text{high}}, & \text{if } s \geq 72 \text{ and } s' = s + a \\ 1 - \alpha_{\text{low}}, & \text{if } s \leq 68 \text{ and } s' = s \\ 1 - \alpha_{\text{mid}}, & \text{if } 68 < s < 72 \text{ and } s' = s \\ 1 - \alpha_{\text{high}}, & \text{if } s \geq 72 \text{ and } s' = s \\ 0, & \text{otherwise} \end{cases}$$

where  $\alpha_{\text{low}}$ ,  $\alpha_{\text{mid}}$ , and  $\alpha_{\text{high}}$  are the probabilities of the actions being taken when the state is low, mid, and high respectively. The value of these  $\alpha$ 's would vary depending on how effective the cooling and heating systems are. For example, if the cooling system is very effective, then  $\alpha_{\text{low}}$  would be high. Similarly, if the heating system is very effective, then  $\alpha_{\text{high}}$  would be high.

### Tabular Summary

The tabular summary of the MDP is as follows,

$s$	$a$	$s'$	$p(s'   s, a)$	$r(s, a, s')$
$40 \leq s \leq 68$	$a \geq 0$	$s + a$	$\alpha_{\text{low}}$	$68 - s$
$40 \leq s \leq 68$	$a \geq 0$	$s$	$1 - \alpha_{\text{low}}$	$68 - s = 0$
$68 < s < 72$	$-1 \leq a \leq 1$	$s + a$	$\alpha_{\text{mid}}$	$ 70 - s $
$68 < s < 72$	$-1 \leq a \leq 1$	$s$	$1 - \alpha_{\text{mid}}$	$ 70 - s  = 0$
$72 \leq s \leq 90$	$a \leq 0$	$s + a$	$\alpha_{\text{high}}$	$s - 72$
$72 \leq s \leq 90$	$a \leq 0$	$s$	$1 - \alpha_{\text{high}}$	$s - 72 = 0$

## Problem 3

What is the reward hypothesis in RL?

### Answer

The textbook states the *reward hypothesis* as follows,

“That all of what we mean by goals and purposes can be well thought of as the maximization of the expected value of the cumulative sum of a received scalar signal (called reward).”

Here is a simplified break-down of what the reward hypothesis means:

- In RL, we talk about goals and purposes, which is to find best way to solve a problem.
- Any solution to a complex problem can be broken down into a series of steps, and each step can have a value associated with it.
- We design this ‘value’ associated with each step as a scalar signal which is received from the environment. This scalar signal is called the *reward*.
- Therefore, **we hypothesize that** our all goals can be achieved by the maximization of the expected cumulative reward.
- A paper from 2021 titled “Reward is enough” by David Silver, Satinder Singh, Doina Precup, and Richard S. Sutton discusses this hypothesis in detail.

## Problem 4

We have an agent in maze-like world. We want the agent to find the goal as soon as possible. We set the reward for reaching the goal equal to +1 with  $\gamma = 1$ . But we notice that the agent does not always reach the goal as soon as possible. How can we fix this?

### Answer

As stated in the textbook, the *discounted return* (equation 3.8),  $G_t$ , is defined as,

$$G_t \doteq R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \dots = \sum_{k=0}^{\infty} \gamma^k R_{t+k+1} \quad (3.8)$$

Here, as  $\gamma$  approaches 1, the discounted return takes far-sighted rewards into account. Therefore, if the agent is not reaching the goal as soon as possible, then the agent is likely too far-sighted. Therefore, we can reduce the value of  $\gamma$  to make the agent more near-sighted and reach the goal sooner.

## Problem 5

What is the difference between policy and action?

### Answer

An *action* is a choice made by the agent at a given state. It is an attempted modification of the environment which leads to a new state or the same state. We give an agent an associated reward for each action.

In contrast, a policy determines how good it is for the agent to perform an action in a given state. Formally, a *policy* is a mapping from states to probabilities of selecting each possible action. It defines a probability distribution over actions for each state.

## Problem 6

(Exercise 3.14) Write prompt

**Answer**

TODO



## Problem 7

(Exercise 3.17) Write prompt

**Answer**

TODO

## Problem 8

(Exercise 3.22) Write prompt

**Answer**

TODO