# Reinforcement Learning Tutorial Exercises

### Exercise 1

Consider the  $\epsilon$ -greedy action selection in reinforcement learning problems, in the case of two actions and  $\epsilon = 0.5$ . What is the probability that the greedy action is selected?

- a) 0.5
- b) 0.25
- c) 0.75
- d) 0
- e) 1.0

### Exercise 2

Consider the gridworld problem shown in Figure 1. An agent needs to move to the target goal position G starting from any cell (arbitrary position) by following the optimum policy which gathers the largest reward.

The immediate rewards r(s, a) for the transition from one state to another for this problem are also shown in Figure 1. For example, the reward received by moving from state  $s_1$  to  $s_2$  by taking the *right* action is 0. The reward for moving from state  $s_5$  to state G (i.e. taking the *north* action) is 100.

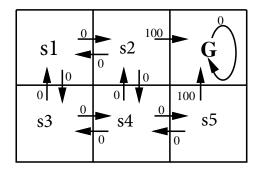


Figure 1: r(s, a) (immediate reward) values.

Now, consider the application of the Q learning algorithm in the above reinforcement learning gridworld problem. Reminder: the Q values are calculated using the following formula:

$$\hat{Q}(s, a) \leftarrow r + \gamma \max_{a'} \hat{Q}(s', a')$$

The current values of  $\hat{Q}$  (i.e. in the current iteration) are shown in Figure 2. For example,  $\hat{Q}(s_1, a_{right}) = 72$ ,  $Q(s_2, a_{left}) = 63$ ,  $\hat{Q}(s_3, a_{north}) = 63$ .

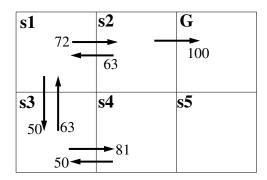


Figure 2: Current values of  $\hat{Q}(s, a)$  for all state-action pairs.

What will be the new value for  $\hat{Q}(s_1, a_{down})$  after applying the above Q-learning formula for one iteration, if  $\gamma = 0.9$ ?

- a) 63
- b) 81
- c)  $0.9 \times 72 = 64.8$
- d)  $0.9 \times 63 = 56.7$
- e)  $0.9 \times 81 = 72.9$
- f) 90

### Exercise 3

Implement in a programming language of your choice (Python or Java) the Q-learning applied to the problem of the previous Exercise 2, until the Q values converge and they do not change any more.

Hint: You need to consider multiple episodes, i.e. after the terminal (final, goal state) is reached, a new episode is started. The initial values of the Q values for the new episode will be the ones that the previous episode had calculated.

Check your derived Q values with the Figure 4 in the lecture slide 14.

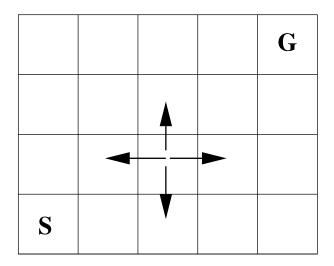


Figure 3: The grid world example for the application of reinforcement learning techniques.

# Exercise 4

Consider the grid in Figure 3. An agent can move in either of the four directions starting from S and finishing in the goal state G.

- 1. If the reward on reaching the goal is 100, and all other rewards between state transitions are 0, write a program in a programming language of your choice (e.g. Java, Python, C++) which uses Q learning to learn the optimal policy. Assume that  $\gamma = 0.9$ .
- 2. What are the actions of the optimal policy?

# Exercise 5

In Exercise 4, how does the optimal policy change if another goal state is added to the lower right corner with reward -100.

Hint: To see this, rerun your implementation with the additional goal.