

Reinforcement Learning Tutorial Exercises Solutions

Exercise 1

Consider the ϵ -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

Correct answer: 0.75. There is a 0.5 chance of selecting the greedy action directly, plus a 0.25 chance of selecting it as one of the 2 actions when a random action is selected.

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.

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, $\hat{Q}(s_1, a_{right}) = 72$, $\hat{Q}(s_2, a_{left}) = 63$, $\hat{Q}(s_3, a_{north}) = 63$.

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

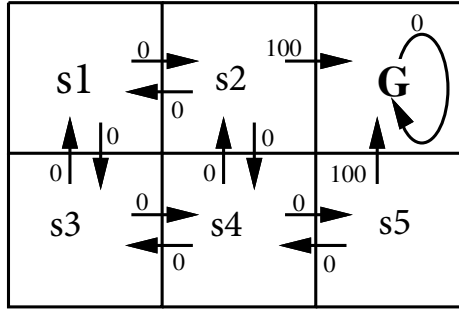


Figure 1: $r(s, a)$ (immediate reward) values.

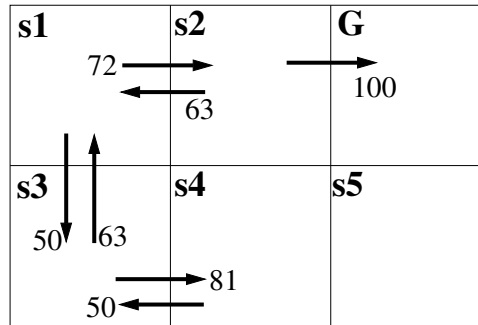


Figure 2: Current values of $\hat{Q}(s, a)$ for all state-action pairs.

- 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

Correct Answer: $0.9 \times 81 = 72.9$

$$\begin{aligned}
 \hat{Q}(s_1, a_{down}) &\leftarrow r + \gamma \max_{a'} \hat{Q}(s_3, a') \\
 &\leftarrow 0 + 0.9 \max\{63, 81\} \\
 &\leftarrow 72.9
 \end{aligned}$$

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.

Solution

```
import random

#####
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#####

# delta (see lecture slides formulas) is a dictionary containing
# the states of the dynamic system and mapping them to a dictionary
# {a: s'} where s' is the new state that we arrive when we apply
# action a when in state s

# We assume that states, s_1, s_2 to s_6 are assigned by row traversing:
# -----
# |s1 |s2 |s3|
# |s4 |s5 |s6|
# -----

delta = {}
Q = {}

# 'N' is go North action
# 'E' is go East action
# 'S' is go South action
# 'W' is go West action

delta['s1'] = {'N':'s1', 'E':'s2', 'S':'s4', 'W':'s1'}
delta['s2'] = {'N':'s2', 'E':'s3', 'S':'s5', 'W':'s1'}
delta['s3'] = {'N':'s3', 'E':'s3', 'S':'s6', 'W':'s2'}
delta['s4'] = {'N':'s1', 'E':'s5', 'S':'s4', 'W':'s4' }
delta['s5'] = {'N':'s2', 'E':'s6', 'S':'s5', 'W':'s4'}
delta['s6'] = {'N':'s3', 'E':'s6', 'S':'s6', 'W':'s5'}

# all rewards are zero, except those leading to state s3

# initialise all Q with 0
Q['s1'] = {'N':0, 'E':0, 'S':0, 'W':0}
```

```

Q['s2'] = {'N':0, 'E':0, 'S':0, 'W':0}
Q['s3'] = {'N':0, 'E':0, 'S':0, 'W':0}
Q['s4'] = {'N':0, 'E':0, 'S':0, 'W':0}
Q['s5'] = {'N':0, 'E':0, 'S':0, 'W':0}
Q['s6'] = {'N':0, 'E':0, 'S':0, 'W':0}

# action 1 is North
# action 2 is East
# action 3 is South
# action 4 is West
def num2Action(action):
    if action == 1:
        a = 'N'
    elif action == 2:
        a = 'E'
    elif action == 3:
        a = 'S'
    else:
        a = 'W'

    return a

# find and return the action which will lead to the
# maximum Q, given the current state s
def findMaxAction(s):
    max_so_far = Q[s]['N']
    max_action = 'N'

    if Q[s]['E'] > max_so_far:
        max_so_far = Q[s]['E']
        max_action = 'E'

    if Q[s]['S'] > max_so_far:
        max_so_far = Q[s]['S']
        max_action = 'S'

    if Q[s]['W'] > max_so_far:
        max_so_far = Q[s]['W']
        max_action = 'W'

    return max_action

# display Q values
def displayQ():
    print('s1: -> ', Q['s1'])
    print('s2: -> ', Q['s2'])

```

```

print('s3: -> ', Q['s3'])
print('s4: -> ', Q['s4'])
print('s5: -> ', Q['s5'])
print('s6: -> ', Q['s6'])

# apply Q-learning
def Q_learning():
    gamma = 0.9

    # Run many episodes
    for e in range(10000):
        # Run 1 episode of the problem (i.e. until state 'G' is reached)

        # Start with from random state s
        s = random.randint(1, 6)
        s = 's' + str(s) # current state

        while s != 's3':
            # 1. Select an action and execute it
            a = random.randint(1, 4)

            a = num2Action(a)

            # 3. Observe the new state s'
            s_new = delta[s][a]

            if __debug__:
                print(s, '(', a, ')', '->', s_new)

            # 3. Receive immediate reward r
            # if next state is the goal state G then the reward is 100,
            # otherwise it is 0
            if s_new == 's3':
                r = 100
            else:
                r = 0

            # 4. Update the table entry for  $\hat{Q}(s,a)$  as follows:
            #  $\hat{Q}(s,a) \rightarrow r + \gamma \max_{a'} [\hat{Q}(s',a')]$ 
            # where s' is the next state after applying action a in state s
            if s_new != s:
                a_next = findMaxAction(s_new)
                Q[s][a] = r + gamma*Q[s_new][a_next]

            # 5. s <- s'
            # The new state becomes the next current state
            s = s_new

```

```

displayQ()

# the starting point of program execution
def main():
    Q_learning()

if __name__ == "__main__":
    main()

```

The same code can be found as a Python notebook format in:

https://dracopd.users.ecs.westminster.ac.uk/DOCUM/courses/applied_ai/gridworld.ipynb

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*.

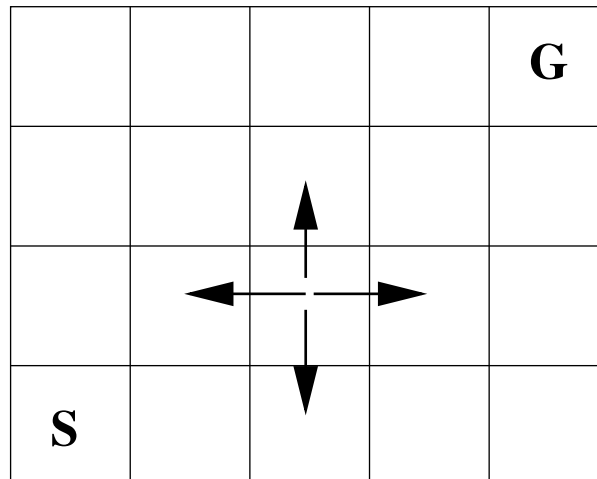


Figure 3: The grid world example for the application of reinforcement learning techniques.

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?

Solution

This should be based on the previous Exercise code, the only changes is in the initialisation of the dictionaries for the different states. The number of states is larger here, but the *Q*-learning code is the same.

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.

Solution

Just a modification of the calculation of the reward (step 3 of the Q -learning portion of the code).