

Introduction to Reinforcement Learning

Syed Mustafa
Habib University
sm06554@st.habib.edu.pk
Submitted to Shahid Shaikh

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1 Planning

Topics tested in this assignment:

1. Optimal Policy and Optimal function.
2. Chapter 3, 4 and 5.

Explanation of GridWorld

This section is to explain the MDP for question 1 and 2.

This is a grid representation of a finite Markov Decision Process (MDP). Each cell is a state of the MDP. Four actions are possible at a given state, i.e. **north, south, east, west**. Actions that would cause the agent to get off the grid leave its location unchanged.

Question 1

The optimal value function v^* for the GridWorld is generated by the code GridWorld 3 5.py which is available on Canvas. Write a program which takes the value function generated by the above code as input and generates the corresponding optimal policy.

```
1. Initialization
    $V(s) \in \mathbb{R}$  and  $\pi(s) \in \mathcal{A}(s)$  arbitrarily for all  $s \in \mathcal{S}$ 

2. Policy Evaluation
   Repeat
      $\Delta \leftarrow 0$ 
     For each  $s \in \mathcal{S}$ :
        $v \leftarrow V(s)$ 
        $V(s) \leftarrow \sum_{s',r} p(s', r | s, \pi(s)) [r + \gamma V(s')]$ 
        $\Delta \leftarrow \max(\Delta, |v - V(s)|)$ 
   until  $\Delta < \theta$  (a small positive number)

3. Policy Improvement
   policy-stable  $\leftarrow$  true
   For each  $s \in \mathcal{S}$ :
      $a \leftarrow \pi(s)$ 
      $\pi(s) \leftarrow \operatorname{argmax}_a \sum_{s',r} p(s', r | s, a) [r + \gamma V(s')]$ 
     If  $a \neq \pi(s)$ , then policy-stable  $\leftarrow$  false
   If policy-stable, then stop and return  $V$  and  $\pi$ ; else go to 2
```

Figure 1: Policy Iteration Psuedocode

The given code has already implemented the policy evaluation. Now to obtain a optimal policy we must implement policy improvement.
The code for this code is provided below:

Code for Question 1

Listing 1: The above piece of code remained unchanged

```
import numpy as np
WORLD_SIZE = 5
A_POS = [0, 1]
A_PRIME_POS = [4, 1]
B_POS = [0, 3]
B_PRIME_POS = [2, 3]
DISCOUNT = 0.9
# left, up, right, down
ACTIONS = [np.array([0, -1]),
            np.array([-1, 0]),
            np.array([0, 1]),
            np.array([1, 0])]

def step(state, action):
    if state == A_POS:
        return A_PRIME_POS, 10
    if state == B_POS:
        return B_PRIME_POS, 5

    next_state = (np.array(state) + action).tolist()
    # print(f'The next_state = (np.array(state) + action).tolist() outputs= \n
    #       {next_state} ')
    x, y = next_state
    if x < 0 or x >= WORLD_SIZE or y < 0 or y >= WORLD_SIZE:
        reward = -1.0
        next_state = state
    else:
        reward = 0
    return next_state, reward
```

Listing 2: This was part of the policy improvement code. This function would return a new policy.

```
def optimal_policy(value):
    policy = np.zeros((WORLD_SIZE, WORLD_SIZE), dtype=object)
    for i in range(WORLD_SIZE):
        for j in range(WORLD_SIZE):
            values = []
            for action_idx, action in enumerate(ACTIONS):
                (next_i, next_j), reward = step([i, j], action)
                values.append(reward + DISCOUNT * value[next_i, next_j])

            best_actions = np.argwhere(values == np.max(values)).flatten().tolist()
            policy[i, j] = np.array(best_actions)
    return policy
```

Listing 3: Changes to given code

```
def figure_3_5():
    value = np.zeros((WORLD_SIZE, WORLD_SIZE))
    policy = np.random.randint(0,4,(5,5,1))
```

```

epoch = 0
while True:
    it = 0
    # it = 0
    while True:
        # keep iteration until convergence
        new_value = np.zeros_like(value)
        for i in range(WORLD_SIZE): #nested loop to loop over each state
            for j in range(WORLD_SIZE):
                values = [] #values is different from value.
                for x in policy[i, j]:
                    action = ACTIONS[x]
                    # print('The Action = ', action)

                    (next_i, next_j), reward = step([i, j], action)
                    # value iteration
                    values.append(reward + DISCOUNT * value[next_i, next_j]) #V(s)
                        = Sum over all s', r: p(Rt+1 + DISCOUNT * value[next_i,
                            next_j])
                new_value[i, j] = np.max(values)

        if np.sum(np.abs(new_value - value)) < 1e-2:
            np.set_printoptions(precision=2)
            print(f'The value function at epoch {epoch} coonverged at iteration
                {it} is \n {value} \n With the policy: \n {policy}')
            print()
            break
        value = new_value
        it += 1

    stable = True
    new_policy = optimal_policy(value)
    for i in range(len(new_policy)):
        for j in range(len(new_policy[i])):
            if not (new_policy[i, j].tolist() == policy[i,j].tolist()):
                stable = False
    if stable == True:
        optimalPolicy = policy
        optimal_value = value
        break

    # print(f'And the new_policy is in epoct {epoch}= \n{new_policy}')

    epoch += 1

    policy = new_policy
    return optimalPolicy, optimal_value
    # print(f'And the optimal policy is = \n{policy}')

```

Listing 4: Code to make policy easier to view

```

policy, value = figure_3_5()
print(value)

```

```

left, up, right, down = 0,1,2,3
arrow_dic = dict([(0 , "left"), (1 , "up"), (2 , "right"), (3, "down")])

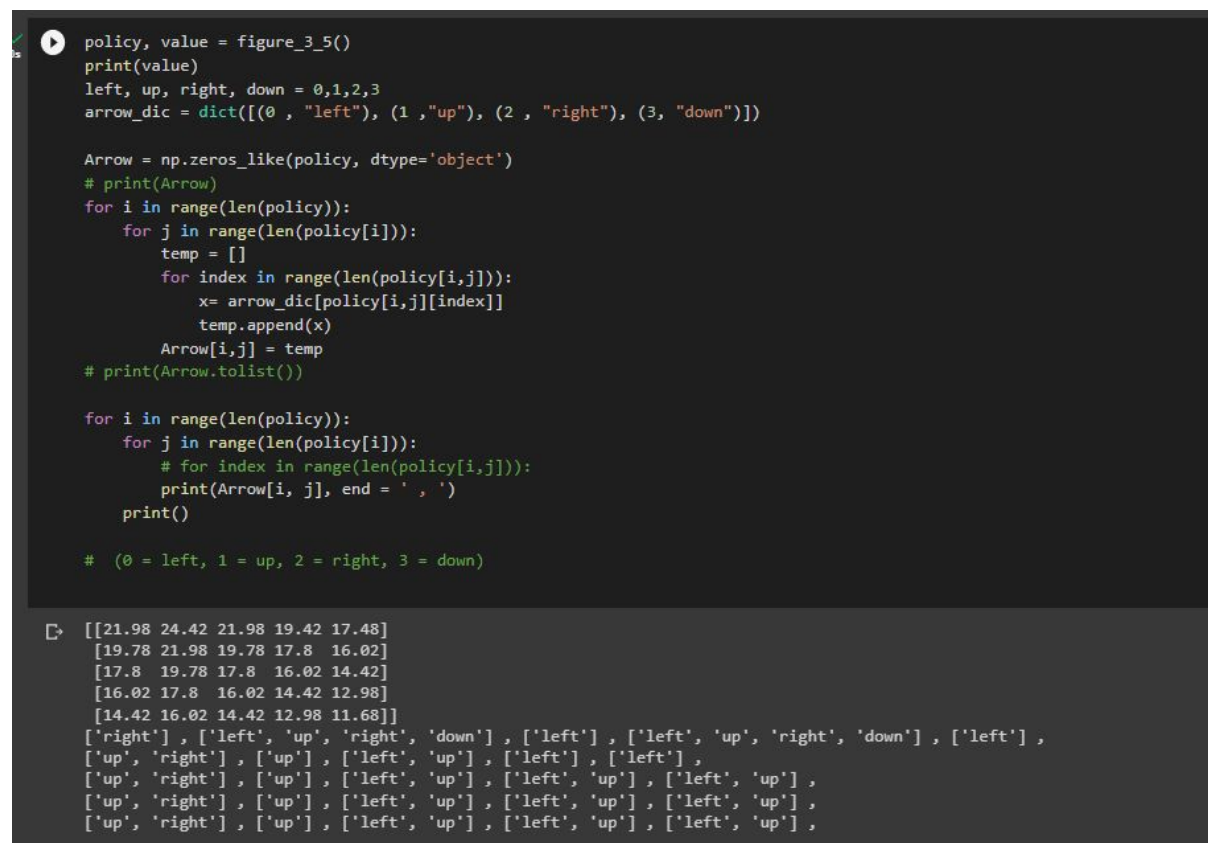
Arrow = np.zeros_like(policy, dtype='object')
# print(Arrow)
for i in range(len(policy)):
    for j in range(len(policy[i])):
        temp = []
        for index in range(len(policy[i,j])):
            x= arrow_dic[policy[i,j][index]]
            temp.append(x)
        Arrow[i,j] = temp
# print(Arrow.tolist())

for i in range(len(policy)):
    for j in range(len(policy[i])):
        # for index in range(len(policy[i,j])):
            print(Arrow[i, j], end = ' , ')
        print()

# (0 = left, 1 = up, 2 = right, 3 = down)

```

Output



The screenshot shows a Jupyter Notebook interface. The top part contains the same Python code as in the previous block. Below the code, the output of the execution is displayed. It starts with a list of five numerical arrays, each containing five elements. These are followed by a grid of directional strings ('left', 'up', 'right', 'down') that correspond to the values in the arrays above, based on the mapping defined in the code (0=left, 1=up, 2=right, 3=down).

```

policy, value = figure_3_5()
print(value)
left, up, right, down = 0,1,2,3
arrow_dic = dict([(0 , "left"), (1 , "up"), (2 , "right"), (3, "down")])

Arrow = np.zeros_like(policy, dtype='object')
# print(Arrow)
for i in range(len(policy)):
    for j in range(len(policy[i])):
        temp = []
        for index in range(len(policy[i,j])):
            x= arrow_dic[policy[i,j][index]]
            temp.append(x)
        Arrow[i,j] = temp
# print(Arrow.tolist())

for i in range(len(policy)):
    for j in range(len(policy[i])):
        # for index in range(len(policy[i,j])):
            print(Arrow[i, j], end = ' , ')
        print()

# (0 = left, 1 = up, 2 = right, 3 = down)

```

```

[[21.98 24.42 21.98 19.42 17.48]
 [19.78 21.98 19.78 17.8 16.02]
 [17.8 19.78 17.8 16.02 14.42]
 [16.02 17.8 16.02 14.42 12.98]
 [14.42 16.02 14.42 12.98 11.68]]
['right' , ['left', 'up', 'right', 'down'] , ['left'] , ['left', 'up', 'right', 'down'] , ['left'] ,
['up', 'right'] , ['up'] , ['left', 'up'] , ['left'] , ['left'] ,
['up', 'right'] , ['up'] , ['left', 'up'] , ['left', 'up'] , ['left', 'up'] ,
['up', 'right'] , ['up'] , ['left', 'up'] , ['left', 'up'] , ['left', 'up'] ,
['up', 'right'] , ['up'] , ['left', 'up'] , ['left', 'up'] , ['left', 'up'] ,

```

Figure 2: Output of question 1

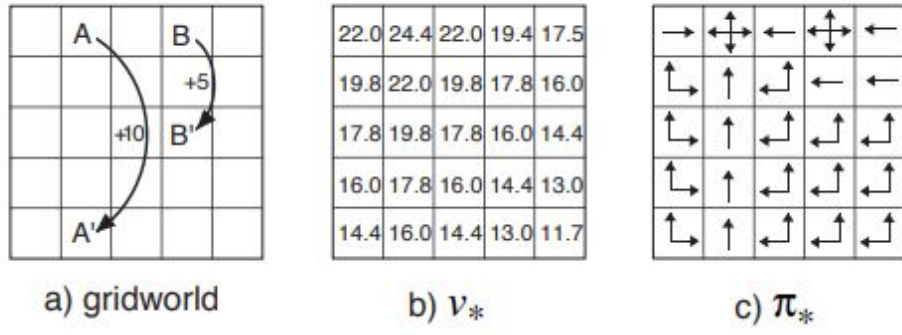


Figure 3: The output matches the given answer in book

Question 2

Starting from the code GridWorld 3 2.py, which is available on Canvas, implement the complete value iteration algorithm to generate the optimal value function v^* and an optimal policy π^* .

```
Initialize array  $V$  arbitrarily (e.g.,  $V(s) = 0$  for all  $s \in \mathcal{S}^+$ )

Repeat
   $\Delta \leftarrow 0$ 
  For each  $s \in \mathcal{S}$ :
     $v \leftarrow V(s)$ 
     $V(s) \leftarrow \max_a \sum_{s',r} p(s', r|s, a)[r + \gamma V(s')]$ 
     $\Delta \leftarrow \max(\Delta, |v - V(s)|)$ 
until  $\Delta < \theta$  (a small positive number)

Output a deterministic policy,  $\pi$ , such that
 $\pi(s) = \operatorname{argmax}_a \sum_{s',r} p(s', r|s, a)[r + \gamma V(s')]$ 
```

Figure 4.5: Value iteration.

Figure 4: Policy Iteration Psuedocode

Code for Question 2

Listing 5: Preliminary

```
#####
# Copyright (C)                                     #
# 2016-2018 Shangtong Zhang(zhangshangtong.cpp@gmail.com) #
# 2016 Kenta Shimada(hyperkentakun@gmail.com)           #
# Permission given to modify the code as long as you keep this #
# declaration at the top                                     #
#####

import numpy as np

WORLD_SIZE = 5
A_POS = [0, 1]
A_PRIME_POS = [4, 1]
B_POS = [0, 3]
B_PRIME_POS = [2, 3]
DISCOUNT = 0.9

# left, up, right, down
ACTIONS = [np.array([0, -1]),
            np.array([-1, 0]),
            np.array([0, 1]),
            np.array([1, 0])]
ACTION_PROB = 0.25

def step(state, action):
    if state == A_POS:
```

```

        return A_PRIME_POS, 10
    if state == B_POS:
        return B_PRIME_POS, 5

    next_state = (np.array(state) + action).tolist()
    x, y = next_state
    if x < 0 or x >= WORLD_SIZE or y < 0 or y >= WORLD_SIZE:
        reward = -1.0
        next_state = state
    else:
        reward = 0
    return next_state, reward

```

Listing 6: Updated GridWorld3_2() code

```

def figure_3_2():
    value = np.zeros((WORLD_SIZE, WORLD_SIZE))
    it = 0
    while True:
        # keep iteration until convergence
        new_value = np.zeros_like(value)
        for i in range(WORLD_SIZE):
            for j in range(WORLD_SIZE):
                temp = []
                for action in ACTIONS:
                    (next_i, next_j), reward = step([i, j], action)
                    temp.append(ACTION_PROB * (reward + DISCOUNT * value[next_i,
                        next_j]))
                # bellman equation
                new_value[i, j] = max(temp)
        if np.sum(np.abs(value - new_value)) < 1e-2:
            break
        value = new_value
        it += 1
        # input("Press Enter to continue...")
        np.set_printoptions(precision=2)
        print(value)
        print()
    print("Converges in {} iterations".format(it))

    ## Greedy Policy ##

    policy = greedy_policy(value)
    print("The Policy is", policy, sep = ' = n')

    return policy, value
if __name__ == '__main__':
    policy, value = figure_3_2()
    print(value)
    left, up, right, down = 0,1,2,3
    arrow_dic = dict([(0, "left"), (1, "up"), (2, "right"), (3, "down")])

    Arrow = np.zeros_like(policy, dtype='object')
    # print(Arrow)
    for i in range(len(policy)):

```



```

    for j in range(len(policy[i])):
        temp = []
        for index in range(len(policy[i,j])):
            x= arrow_dic[policy[i,j][index]]
            temp.append(x)
        Arrow[i,j] = temp
    # print(Arrow.tolist())

    for i in range(len(policy)):
        for j in range(len(policy[i])):
            # for index in range(len(policy[i,j])):
            print(Arrow[i, j], end = ' , ')
        print()

# (0 = left, 1 = up, 2 = right, 3 = down)

```

Listing 7: Greedy Policy

```

def greedy_policy(value):
    policy = np.zeros((WORLD_SIZE, WORLD_SIZE), dtype=object)
    for i in range(WORLD_SIZE):
        for j in range(WORLD_SIZE):
            values = []
            for action_idx, action in enumerate(ACTIONS):
                (next_i, next_j), reward = step([i, j], action)
                values.append(reward + DISCOUNT * value[next_i, next_j])

            best_actions = np.argwhere(values == np.max(values)).flatten().tolist()
            policy[i, j] = np.array(best_actions)
    return policy

```

Google Colab Notebook

Please find the link to the google colab notebook:

<https://colab.research.google.com/drive/1SUZGc8QwLwSf7NQFFGH8O0Q4ZLBHoh-6?usp=sharing>

References

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