Assignment 3

(Last Update: 30 Oct)

Introduction

Download the code for this assignment here and then unzip the archive.

As in assignments 1 and 2, this assignment uses python 3. Do not use python 2. You can work on the assignment using your favorite python editor. We recommend VSCode.

Post any questions or issues with this assignment to our discussion forum. Alternatively you may also contact your TA directly.

This assignment uses autograding for Problem 1, Problem 2 and Problem 3. For the first question of this assignment we rely on the random number generator generating the same random sequence. Same as in Assignment 2. This time, we will be using the random.choices() function as follows.

```
import random
from collections import Counter
seed = 2
if seed!=-1:
       random.seed(seed, version=1)
n = 0.1 #noise
a = 'N' #intended action
d = {'N':['N', 'E', 'W'], 'E':['E', 'S', 'N'], 'S':['S', 'W', 'E'], 'W':['W', 'N', 'S']}
l = []
for _ in range(100000):
    l += random.choices(population=d[a], weights=[1 - n*2, n, n])[0]
print(Counter(l).keys()) # equals to list(set(words))
print(Counter(l).values()) # counts the elements' frequency
print(l[:5])
```

This will give the following output.

```
dict_keys(['W', 'N', 'E'])
dict_values([10025, 80059, 9916])
['W', 'W', 'N', 'N', 'E']
```

Note that we obtain ~80% intendent actions and 10% unintended actions here. Make sure that you understand the output and that you can reproduce it on your machine before proceeding. Note that we use anaconda python 3.9 to obtain the above result.

Problem 1: An MDP Episode

In this part of the assignment, we are going to play an episode in an MDP by following a given policy. Consider the first test case of problem 1 (available in the file `test_cases/p1/1.prob`).

```
seed: 2
noise: 0.1
livingReward: -0.05
grid:
    _    _    _    1
    _    #    _   -1
    S    _    _    _
policy:
    E    E    E exit
    N    #    N exit
    N    W    N    W
```

The first part of this file specifies an MDP. `S` is the start state with four available actions (`N`, `E`, `S`, `W`), `_` is an ordinary state with the same four available actions and `1`,`-1` are states where the only available action is `exit` and the reward are `1` and `-1` respectively. The reward for action in other states is `-0.05`. `#` is a wall.
Actions are not deterministic in this environment. In this case with `noise = 0.1`, we are successfully acting 80% of the time and 20% of the time we will act perpendicular to the intended direction with equal probability, i.e. 10%, for each unintended direction. If the agent attempts to move into a wall, the agent will stay in the same position. Note that this MDP is identical to the example that we covered extensively in our class.

The second part of this file specifies the policy to be executed.

As usual, your first task is to implement the parsing of this grid MDP in the function `read_grid_mdp_problem_p1(file_path)` of the file `parse.py`. You may use any appropriate data structure.

Next, you should implement running the episode in the function `play_episode(problem)` in the file `p1.py`.

Below is the expected output. Note that we always use exactly 5 characters for the output of a single grid and that the last line does not contain a new line.

```
Start state:
    _    _    _    1
    _    #    _   -1
    P    _    _    _
Cumulative reward sum: 0.0
--------------------------------------------
Taking action: W (intended: N)
Reward received: -0.05
New state:
    _    _    _    1
    _    #    _   -1
    P    _    _    _
Cumulative reward sum: -0.05
```

```
--------------------------------------------
Taking action: W (intended: N)
Reward received: -0.05
New state:
    _    _    _    1
    _    #    _   -1
    P    _    _    _
Cumulative reward sum: -0.1
--------------------------------------------
Taking action: N (intended: N)
Reward received: -0.05
New state:
    _    _    _    1
    P    #    _   -1
    S    _    _    _
Cumulative reward sum: -0.15
--------------------------------------------
Taking action: N (intended: N)
Reward received: -0.05
New state:
    P    _    _    1
    _    #    _   -1
    S    _    _    _
Cumulative reward sum: -0.2
--------------------------------------------
Taking action: S (intended: E)
Reward received: -0.05
New state:
    _    _    _    1
    P    #    _   -1
    S    _    _    _
Cumulative reward sum: -0.25
--------------------------------------------
Taking action: N (intended: N)
Reward received: -0.05
New state:
    P    _    _    1
    _    #    _   -1
    S    _    _    _
Cumulative reward sum: -0.3
--------------------------------------------
Taking action: E (intended: E)
Reward received: -0.05
New state:
    _    P    _    1
    _    #    _   -1
    S    _    _    _
Cumulative reward sum: -0.35
--------------------------------------------
Taking action: E (intended: E)
Reward received: -0.05
New state:
    _    _    P    1
    _    #    _   -1
    S    _    _    _
Cumulative reward sum: -0.4
--------------------------------------------
Taking action: E (intended: E)
Reward received: -0.05
New state:
    _    _    _    P
    _    #    _   -1
    S    _    _    _
Cumulative reward sum: -0.45
--------------------------------------------
```

```
Taking action: exit (intended: exit)
Reward received: 1.0
New state:
    _    _    _    1
    _    #    _   -1
    S    _    _    _
Cumulative reward sum: 0.55
```

As you can see, in this question we don't use any discount factor. We will introduce that in the next question. You can also try some of the other test cases such as `test_cases/p1/8.prob`.

```
seed: 42
noise: 0.2
livingReward: -1
grid:
    #   10    #
 -100    _ -100
 -100    _ -100
 -100    _ -100
 -100    _ -100
 -100    S -100
    #    1    #
policy:
    # exit    #
 exit    N exit
 exit    N exit
 exit    N exit
 exit    N exit
 exit    N exit
    #    1    #
```

With a correct implementation, you should be able to pass all test cases.

```
(base) scdirk@Dirks-Air a3 % python p1.py -8
Grading Problem 1 :
----------> Test case 1 PASSED <----------
----------> Test case 2 PASSED <----------
----------> Test case 3 PASSED <----------
----------> Test case 4 PASSED <----------
----------> Test case 5 PASSED <----------
----------> Test case 6 PASSED <----------
----------> Test case 7 PASSED <----------
----------> Test case 8 PASSED <----------
```

Problem 2: Policy Evaluation

In problem 2 you will implement policy evaluation as follows

$$V^{\pi}(s) = \sum_{s'} T(s, \pi(s), s')[R(s, \pi(s), s') + \gamma V^{\pi}(s')]$$

This time we have discounting and we also introduce a new variable for the number of iterations. Here is the first test case.

```
discount: 0.9
noise: 0.1
livingReward: 0
iterations: 10
grid:
  -10  100  -10
  -10    _  -10
  -10    _  -10
  -10    S  -10
policy:
  exit exit exit
  exit    N exit
  exit    N exit
  exit    N exit
```

Note that there is no randomness involved this time and that we use discounting.
As usual, your first task is to implement the parsing of this grid MDP in the function `read_grid_mdp_problem_p2(file_path)` of the file `parse.py`. You may use any appropriate data structure.

Next you implement value iteration for policy evaluation as discussed in class. Your `policy_evaluation(problem)` function in `p2.py` should return the evolution of values as follows.

```
V^pi_k=0
|    0.00||    0.00||    0.00|
|    0.00||    0.00||    0.00|
|    0.00||    0.00||    0.00|
|    0.00||    0.00||    0.00|
V^pi_k=1
|  -10.00||  100.00||  -10.00|
|  -10.00||    0.00||  -10.00|
|  -10.00||    0.00||  -10.00|
|  -10.00||    0.00||  -10.00|
V^pi_k=2
|  -10.00||  100.00||  -10.00|
|  -10.00||   70.20||  -10.00|
|  -10.00||   -1.80||  -10.00|
|  -10.00||   -1.80||  -10.00|
V^pi_k=3
|  -10.00||  100.00||  -10.00|
|  -10.00||   70.20||  -10.00|
|  -10.00||   48.74||  -10.00|
|  -10.00||   -3.10||  -10.00|
V^pi_k=4
|  -10.00||  100.00||  -10.00|
|  -10.00||   70.20||  -10.00|
```

```
| -10.00||  48.74|| -10.00|
| -10.00||  33.30|| -10.00|
V^pi_k=5
| -10.00|| 100.00|| -10.00|
| -10.00||  70.20|| -10.00|
| -10.00||  48.74|| -10.00|
| -10.00||  33.30|| -10.00|
V^pi_k=6
| -10.00|| 100.00|| -10.00|
| -10.00||  70.20|| -10.00|
| -10.00||  48.74|| -10.00|
| -10.00||  33.30|| -10.00|
V^pi_k=7
| -10.00|| 100.00|| -10.00|
| -10.00||  70.20|| -10.00|
| -10.00||  48.74|| -10.00|
| -10.00||  33.30|| -10.00|
V^pi_k=8
| -10.00|| 100.00|| -10.00|
| -10.00||  70.20|| -10.00|
| -10.00||  48.74|| -10.00|
| -10.00||  33.30|| -10.00|
V^pi_k=9
| -10.00|| 100.00|| -10.00|
| -10.00||  70.20|| -10.00|
| -10.00||  48.74|| -10.00|
| -10.00||  33.30|| -10.00|
```

This example should look familiar. We have covered it in chapter 2 of our lecture slides.

Hint: The output of an individual floating point value `v` was done as follows

```
return_value += '|{:7.2f}|'.format(v)
```

Finally, check the correctness of your implementation via

```
(base) scdirk@Dirks-Air a3 % python p2.py -7
Grading Problem 2 :
----------> Test case 1 PASSED <----------
----------> Test case 2 PASSED <----------
----------> Test case 3 PASSED <----------
----------> Test case 4 PASSED <----------
----------> Test case 5 PASSED <----------
----------> Test case 6 PASSED <----------
----------> Test case 7 PASSED <----------
```

Problem 3: Value Iteration

Now it is time to complement value iteration.

$$V_{k+1}(s) \leftarrow \max_a \sum_{s'} T(s,a,s')[R(s,a,s') + \gamma V_k(s')]$$

This time, the provided problems do not include policies:

```
discount: 1
noise: 0.1
livingReward: -0.1
iterations: 10
grid:
    _    _    _    1
    _    #    _   -1
    S    _    _    _
```

As usual, load the problem definition in the function `read_grid_mdp_problem_p3(file_path)` of the file `parse.py`.

Next implement value_iteration(problem) in p3.py such that it returns the following string for the first test case. Note that this is still a non-deterministic environment as before with the same stochastic motion.

```
V_k=0
|    0.00||    0.00||    0.00||    0.00|
|    0.00|| ##### ||    0.00||    0.00|
|    0.00||    0.00||    0.00||    0.00|
V_k=1
|   -0.10||   -0.10||   -0.10||    1.00|
|   -0.10|| ##### ||   -0.10||   -1.00|
|   -0.10||   -0.10||   -0.10||   -0.10|
pi_k=1
| N || N || N || x |
| N || # || N || x |
| N || N || N || N |
V_k=2
|   -0.20||   -0.20||    0.68||    1.00|
|   -0.20|| ##### ||   -0.20||   -1.00|
|   -0.20||   -0.20||   -0.20||   -0.20|
pi_k=2
| N || N || E || x |
| N || # || W || x |
| N || N || N || S |
V_k=3
|   -0.30||    0.40||    0.75||    1.00|
|   -0.30|| ##### ||    0.32||   -1.00|
|   -0.30||   -0.30||   -0.30||   -0.30|
pi_k=3
| N || E || E || x |
| N || # || N || x |
| N || N || N || S |
V_k=4
|    0.16||    0.58||    0.81||    1.00|
|   -0.40|| ##### ||    0.43||   -1.00|
|   -0.40||   -0.40||    0.10||   -0.40|
pi_k=4
| E || E || E || x |
```

```
| N || # || N || x |
| N || N || N || S |
V_k=5
|   0.34||   0.66||   0.82||   1.00|
|  -0.05|| ##### ||   0.49||  -1.00|
|  -0.50||  -0.10||   0.16||  -0.16|
pi_k=5
| E || E || E || x |
| N || # || N || x |
| N || E || N || W |
V_k=6
|   0.46||   0.69||   0.83||   1.00|
|   0.16|| ##### ||   0.51||  -1.00|
|  -0.20||   0.01||   0.26||  -0.08|
pi_k=6
| E || E || E || x |
| N || # || N || x |
| N || E || N || W |
V_k=7
|   0.52||   0.70||   0.83||   1.00|
|   0.30|| ##### ||   0.52||  -1.00|
|   0.01||   0.11||   0.30||   0.00|
pi_k=7
| E || E || E || x |
| N || # || N || x |
| N || E || N || W |
V_k=8
|   0.54||   0.71||   0.83||   1.00|
|   0.37|| ##### ||   0.52||  -1.00|
|   0.15||   0.16||   0.32||   0.04|
pi_k=8
| E || E || E || x |
| N || # || N || x |
| N || E || N || W |
V_k=9
|   0.56||   0.71||   0.84||   1.00|
|   0.41|| ##### ||   0.52||  -1.00|
|   0.23||   0.19||   0.34||   0.06|
pi_k=9
| E || E || E || x |
| N || # || N || x |
| N || E || N || W |
```

Once you are done. Check if you can pass all test cases as follows.

```
(base) scdirk@Dirks-Air a3 % python p3.py -4
Grading Problem 3 :
----------> Test case 1 PASSED <----------
----------> Test case 2 PASSED <----------
----------> Test case 3 PASSED <----------
----------> Test case 4 PASSED <----------
```

Problem 4: Q-Value TD Learning

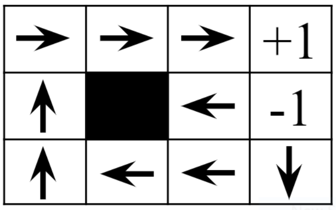
In the final problem of this assignment you will implement temporal difference learning of Q values.

$$sample = R(s, a, s') + \gamma \max_{a'} Q(s', a')$$
$$Q(s, a) \leftarrow (1 - \alpha)Q(s, a) + (\alpha)\, [sample]$$

Your task is to apply temporal difference learning of Q values to the test case 2 of problem 3 and see if you can get an optimal policy. Discount, noise and living reward should be the same as specified in the test case. In your solution, you should …

- start from initial Q values = 0
- use epsilon greedy (with decay) or exploration functions to force exploration
- implement an appropriate learning rate decay to reach an optimal policy
- stop your iteration when the a solution is found (don't compare against optimal policy to decide when to stop)
- run your learning algorithm multiple times (don't set a fixed seed) and output how often the optimal policy can be found e.g., 9/10

Note that the optimal policy for this example can be found on slide 15 of chapter 2 (same as test case 2 of problem 3) shown below.



R(s) = -0.01

Write your findings with short analysis as comments in the beginning of the file `p4.py`.

There are no autograder and no test cases provided for this question. You should provide all parameters and the problem definition itself in the file `p4.py`. Also tell us how to run your code.

To submit your assignment to Moodle, `*.zip` the following files ONLY:

- `p1.py`
- `p2.py`
- `p3.py`
- `p4.py`
- `parse.py`

Do not zip any other files. Use the `*.zip` file format. Make sure that you have submitted the correct files.