Assignment 3

(Last Update: 10 Oct)

Introduction

Download the code for this assignment 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 auto-grading for Problem 1, Problem 2, and Problem 3. For this assignment's first question, 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% intended 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 will 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 is `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 we covered extensively in 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
    # exit    #
```

With 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.

$$sample = R(s,a,s') + \gamma \max_{a'} Q(s',a')$$

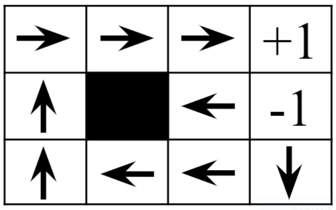
$$Q(s,a) \leftarrow (1-\alpha)Q(s,a) + (\alpha)\,[sample]$$

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

你的任务是将Q值的时间差异学习应用于问题3的测试用例2，并查看是否可以得到最优策略。折扣、噪音和存活奖励应与测试案例中指定的相同。你应该……
-从初始Q值= 0开始
-使用epsilon贪婪（带衰减）或探索函数来强制探索
-实现适当的学习率衰减以达到最优策略
-找到解决方案时停止迭代（不要与最优策略进行比较以决定何时停止）
-多次运行你的学习算法（不要设置固定的种子）并输出找到最优策略的频率，例如9/10
请注意，此示例的最佳策略之一可以在第2章的幻灯片15中找到（与下面所示的问题3的测试用例2相同）



R(s) = -0.01

Note that there could be multiple optimal policies for this particular example, or for the examples provided in the test cases. Write your findings with a short analysis as comments at the beginning of the file `p4.py`.

There are no auto-graders 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:

注意，对于这个特定的例子，或者对于测试用例中提供的例子，可能有多个最佳策略。将你的发现以注释的形式写在文件p4. py的开头。
这个问题没有自动评分，也没有测试用例。你应该在文件p4. py中提供所有参数和问题定义本身。另外，告诉我们如何运行你的代码。

- `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.