

Artificial Intelligence: Programming 3 (P3)

Reinforcement Learning

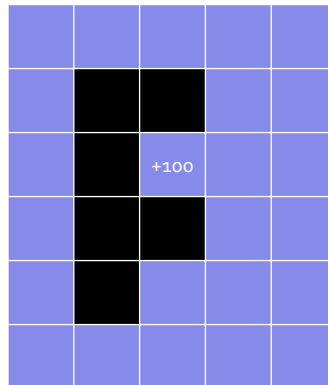
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Due Time: 10PM, 12/3/2020

In this project, we aim to implement one of Reinforcement Learning algorithms: the Q-Learning algorithm.

1 Instructions

We extend the windy maze defined in P1 with probabilistic outcome after an action and one terminal state (top left) with a reward +100. It becomes a MDP problem. The maze map is shown in the following figure. However, we assume that the agent doesn't know either the reward function or the



transition model. The agent aims to run many trials in order to obtain Q-value for each (state, action) pair and the optimal action at each state.

Environment In your implementation, you need to simulate the windy maze environment: We assume that the wind comes from the north and the cost of one step for the agent is defined as follows: 1 for moving southward; 2 for moving westward or eastward; 3 for moving northward. The reward will be the negation of the reward. The agent can drift to the left or the right from the perspective of moving direction with probability 0.15. If the drifting direction is an obstacle, it will be bounced back to the original position. If the agent falls into any terminal state, it can't move out.

Reinforcement Learning In your implementation, you will generate many trials, each of which will result in a trajectory of (state, action, reward) tuple. The agent will use the ϵ -Greedy algorithm to choose an action at each state along each trajectory, where $\epsilon = 0.05$: the agent chooses a latest optimal

action at each state with 95% and a random action with 5%. The initial state for each trial is chosen randomly and each trial will end at the goal state. Along each trajectory, the agent will use **Q-Learning** to update the Q-values. Since the reward function $R(s, a)$ here depends on both the state and the action taken at this state, the Q-value update equations should be revised accordingly.

$$N(s, a) \leftarrow N(s, a) + 1 \quad (1)$$

$$Q(s, a) \leftarrow Q(s, a) + \frac{1}{N_{s,a}} \left(R(s, a) + \gamma \max_{a'} Q(s', a') - Q(s, a) \right) \quad (2)$$

We choose $\gamma = 0.9$.

Testing and Outputs In your testing, generate 10,000 trials starting from a random open square. We initialize the Q-values at any state-action as 0 except for one terminal state with +100 respectively. If the number of steps of a trial is more than 100, you can abort this trial and continue with next trial to save time. After 10,000 trials (including the aborted trials), report the following three outcomes for each algorithm:

- the access frequency at each state-action $N_{s,a}$;
- the Q-value function at each state-action $Q(s, a)$;
- the optimal action at each state-action.

The expected outcome should look like as follows:

- **Table of $N(s, a)$:**

	28		72		689		85		38
36	2071	63	3596	128	8347	93	86	35	45
	285		406		175		6643		2711
	1584						309		139
150	53	####		####		335	328	1015	155
	1235						26916		11212
	38						428		167
44	37	####		+100		35796	474	13041	185
	2929						484		503
	68						25141		1836
70	69	####		####		312	342	16690	256
	4526						312		245
	107			83		10266		13045	
132	110	####		70	5767	871	163	162	179
	7730			115		154		223	
	260		149	172		8794		5131	
243	5352	157	9061	187	12647	128	147	88	78
	12459		1934		934		539		578

• Table of $Q(s, a)$:

-1.1		6.4		8.2		22.5		20.3	
-3.3	1.7	1.7	12.4	9.7	22.7	22.2	26.0	24.8	24.2
-4.7		-2.3		8.8		33.7		30.4	
-4.5						31.2		27.9	
-6.0	-6.5	####		####		40.6	39.5	33.5	33.9
-6.2						51.7		41.7	
-7.8						48.8		36.9	
-6.9	-7.1	####		+100		67.7	40.5	47.3	35.3
-6.7						54.4		39.8	
-8.4						46.7		33.6	
-7.5	-7.1	####		####		43.3	31.7	37.1	28.9
-6.8						30.0		28.2	
-8.5				10.8		28.1		25.5	
-7.4	-7.2	####		5.5	13.4	15.2	19.7	22.3	18.6
-6.3				4.5		9.1		13.9	
-7.6		-4.3		4.9		13.9		14.1	
-7.1	-4.9	-5.5	-0.5	-0.0	6.4	7.2	8.9	9.0	8.3
-5.9		-5.4		-3.9		-2.1		-2.3	

• Table of the optimal policy:

>>>>	>>>>	>>>>	vvvv	vvvv
^^^^	####	####	vvvv	vvvv
vvvv	####	+100	<<<<	<<<<
vvvv	####	####	^^^^	<<<<
vvvv	####	>>>>	^^^^	^^^^
>>>>	>>>>	>>>>	^^^^	^^^^

where <<<<: moving westward; ^^^^^: moving northward; >>>>: moving eastward; vvvv: moving southward; +100: the terminal reward.

For the first two tables, it is expected that the trend of your outputs should match the above while the exact values could be very different from the above due to the random operations. For the last table regarding the optimal policy, most actions of your output should match exactly with above.

2 Submission

Form a group on Canvas if you want to work with another student. You are going to report the following things:

- (a) Describe in details how you implemented the following modules in the report: `environment simulation`, `ϵ -greedy`, and `Q-learning update`.
- (b) Comment your code in details so that the grader can understand it well.
- (c) Include the screenshots of all above testing outcomes. Each screenshot should include your username and the current time, which show that you did it by yourself.
- (d) Specify the contribution made by each member if you work as a group.

The report should be written in a “.docx”, “.doc”, or “.pdf” format. Submit both the report and the source code to the assignment folder P3 on Canvas. Any compression file format such as .zip is not permitted.