CS 580 Reinforcement Learning HW3 Yang Zhang 11529139

Part I. Implementation of Temporal Difference Learning (Q-learning)

Result:

The policy from Q-learning is the optimal policy (e=0.3, a=0.01)

Part II. Implement eligibility traces and show how different value of lambda change the speed of learning (Sarsa with eligibility trace)

Iterations to converge (average of 6 runs)	Lambda
330211	0.9
159017	0.8
45040	0.7
148748	0.6
1518	0.5
535	0.4

From the table, we can see that in general, with smaller lambda comes to faster learning.

Part III. Compare on-policy vs. off-policy (Sarsa vs. Q-learning)

Method	Iterations to converge (average of 6 runs)	
Sarsa	37974	
Q-learning	1730	

Off-policy (Q-learning) works better in this domain. The reason is that this domain is quite sample, so that it is easy to pass value of terminal states to non-terminal states. Therefore, off-policy update is faster to converge than on-policy update.

Part IV. How different values of alpha and epsilon affects learning

Alpha	Epsilon	Iterations to converge
0.1	0.1	75483
0.2	0.2	17878
0.3	0.3	8103
0.4	0.4	4770
0.5	0.5	119
0.6	0.6	1964
0.7	0.7	1355
0.8	0.8	435
0.9	0.9	636

From the table, we can see that in general, with bigger alpha and bigger epsilon come with faster learning.