Assignment 4

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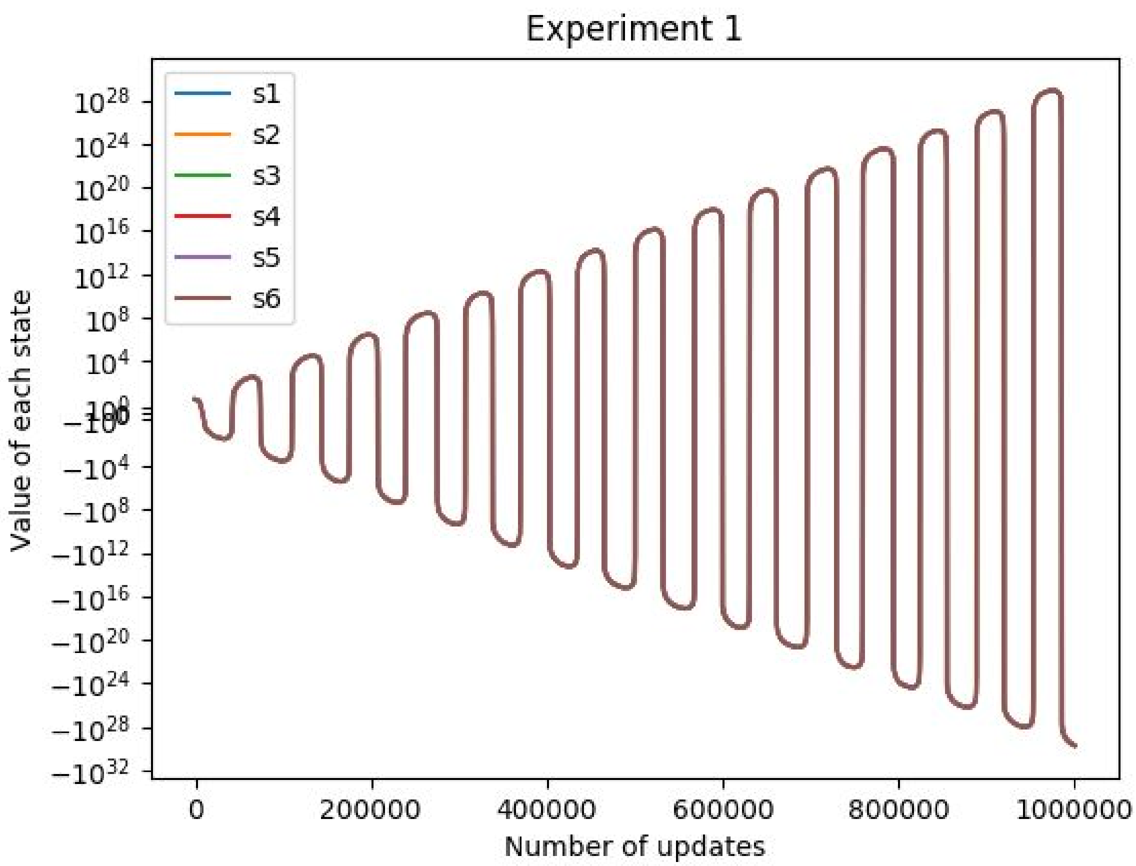
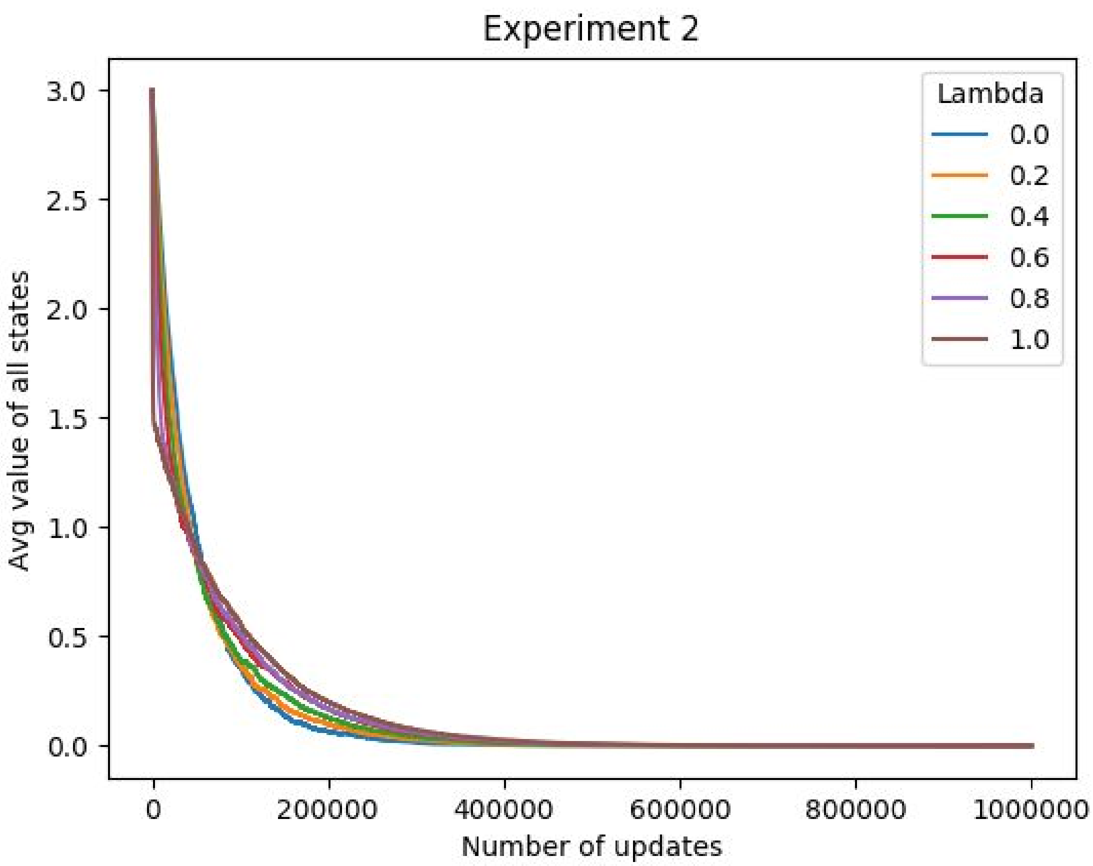
1. The figure below shows the results of experiment one. It can be seen that the value function does not converge at all.



This is because, in this experiment, updates are being done differently than what original MDP trajectory suggests [1]. The updates are off policy and each state is getting updated uniformly. In this experiment, states are not being backed up with same distribution as it would have been if the same experiment is repeated for more number of steps per episode. This difference between the estimation distribution and the distribution due to original policy to be evaluated along with the function approximation is leading to divergence. However, this divergence is only for some choices of initial weights (eg. all 1s). There may or may not be other choices of weights for which same approach converges [2].

2. The figure shows the result of experiment 2 . Since all the weights are initialized with all 1s, the initial value function for all states is 3. As lambda is varies from 0 to 1, the values start decreasing towards 0. Initially higher lambda leads to faster decrease in values. But, after a while trend reverses and the lowest lambda has highest rate of decrease.



This trend is observed because, each lambda from 0 to 1 gives longer lasting traces of previous values as the lambda increases. Effectively lambda 1 means all the values encountered from beginning have some contribution to the current update. So, initially lambda approaches true value of 0 quickly as every update encountered so far has a contribution to next update. But, lambda 0 update has contribution from only the previous update.

After sufficient number of updates, and when the estimates are fairly correct, the same longer lasting traces lead to slower decrease in the value function. Initially the value of each state is 3. So, it takes more number of updates for value to reach zero when lambda is 1 than if lambda is a lower value like 0.6 as lambda 0.6 means that initial value of 3 has less contribution to current update than lambda 1 case and hence quickly approaches zero.

3. The following table shows the results of trials with different initial weights.

A.

Initial Weights	1	1	1	1	1	1	1
Final Value	-0.000017	-0.000021	0.000017	0.000015	0.000010	-0.000001	
Final Weights	0.279992	0.279990	0.280008	0.280008	0.280005	1.119999	-0.560000

B.

Initial Weights	1	2	3	4	5	6	7
Final Value	-0.001138	-0.000868	-0.000158	0.001065	0.001693	-0.000006	
Final Weights	0.999420	0.999555	0.999910	1.000522	1.000835	3.999950	-1.999978

C.

Initial Weights	1	6	2	9	10	0	5
Final Value	-0.002300	0.000700	-0.002583	0.001684	0.002558	0.000058	
Final Weights	0.718839	0.720340	0.718698	0.720832	0.721268	2.880016	-1.439979

It can be seen that the process converges to same value function but different weights for each choice of initial weights.

Note: In the code, the numbering of states and weights starts from 0 to 6, (6 being terminal state) instead of 1 to 7, (7 being terminal state).

References

1. An Analysis of Temporal-Difference Learning with Function Approximation John N. Tsitsiklis, Member, IEEE, and Benjamin Van Roy http://web.mit.edu/jnt/www/Papers/J063-97-bvr-td.pdf
2. Section 8.5: Off Policy Bootstrapping - Sutton and Barto (1998) http://incompleteideas.net/sutton/book/ebook/node90.html