RL - Assignment - 3

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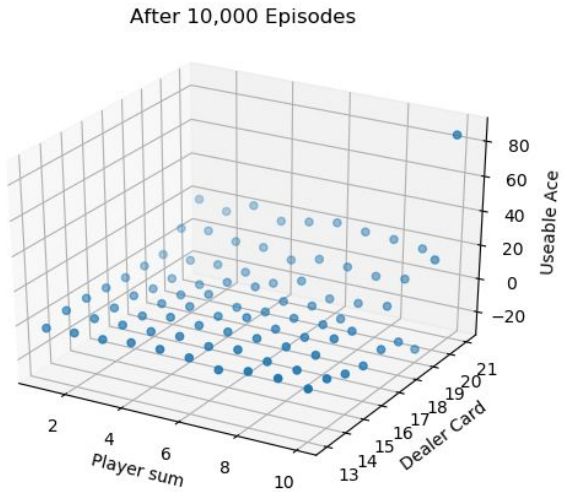
Question - 4 (Blackjack)

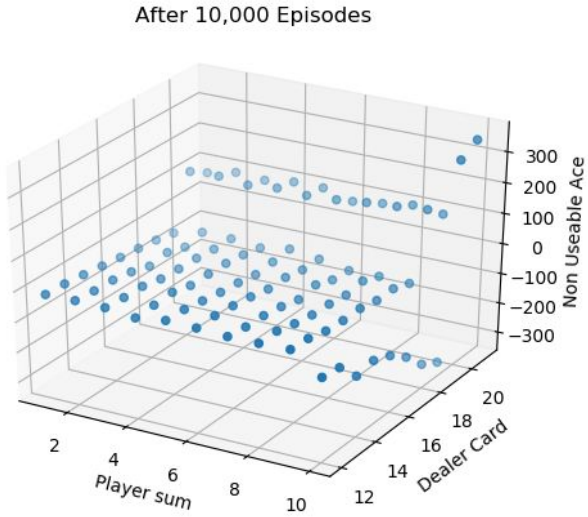
Figure - 5.1

For 10,000 Episodes

Useable Ace

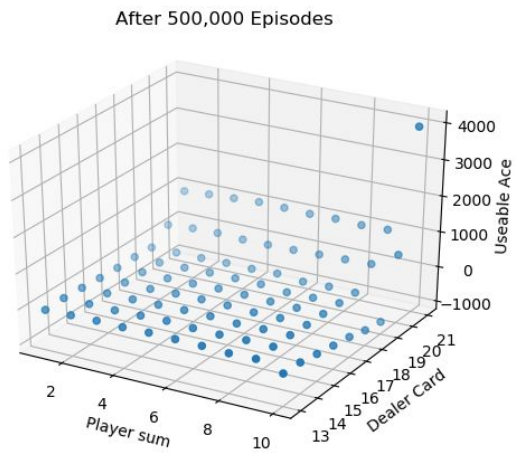


Non-Useable Ace

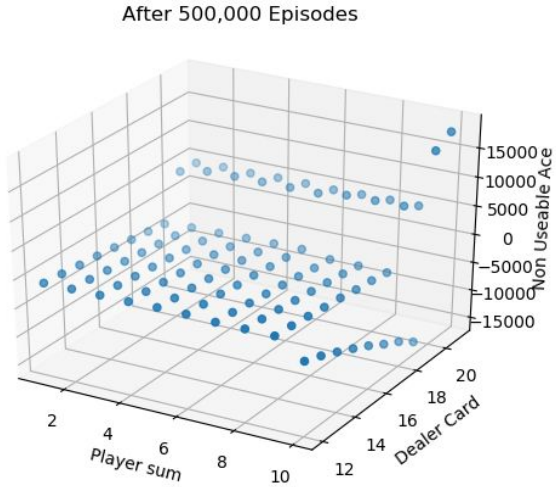


For 500,000 Episodes

Useable Ace

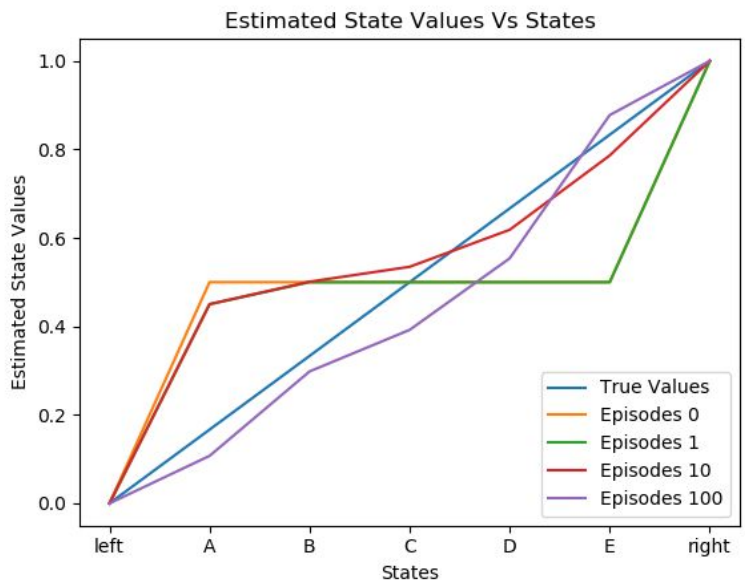


Non-Useable Ace

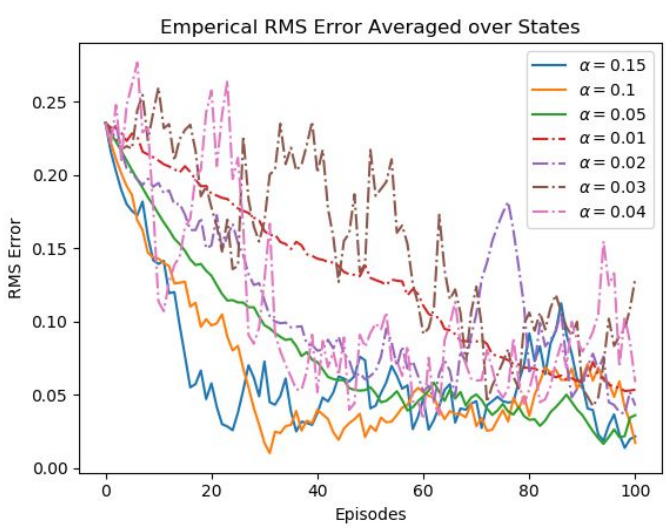


Question - 6 (Random Walk)

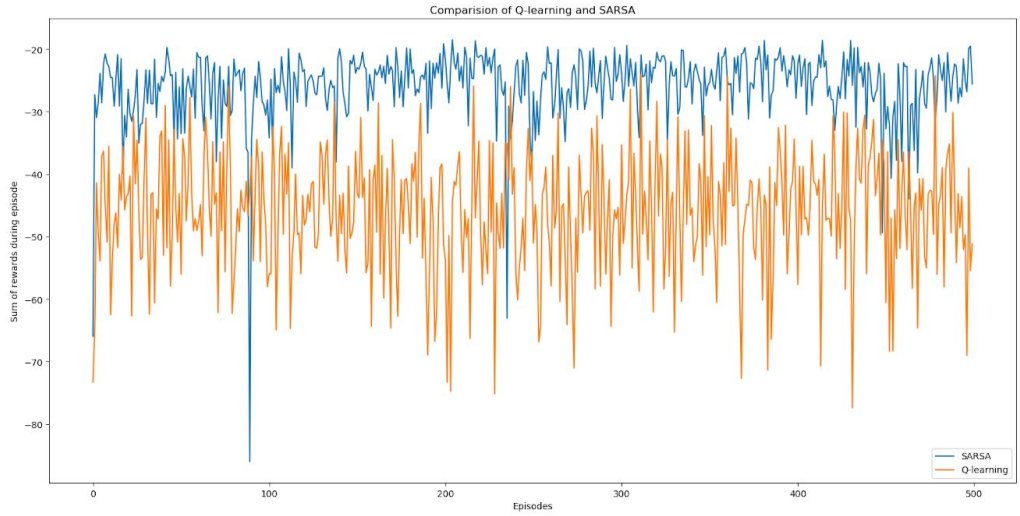
Estimated State Values



Empirical RMS error, averaged over states



Question - 7 (Q-Learning and SARSA)



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Q1. Ex - 5.4.

Intialize :

$\pi(s) \in A(s)$, for all $s \in S$.
$Q(s,a) \in \mathbb{R}$ for $s \in S$, $a \in A(s)$
returns $(s,a) \leftarrow$ empty list $s \in S$, $a \in A(s)$.

Loop forever (for each episode).

Choose $S_0 \in S$, $A_0 \in A(S_0)$ randomly such that all pairs probability > 0.

Generate an episode from S_0, A_0, following π: $S_0, A_0, R_1, \ldots, S_{T-1}, A_{T-1}, R_T$.

$G \leftarrow 0$
Loop for each step of episode $t = T-1, T-2, \ldots, 0$
$G \leftarrow \gamma G + R_{t+1}$

Unless the pair S_t, A_t appears in $S_0, A_0, S_1, A_1, \ldots, S_{t-1}, A_{t-1}$

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$$mean_t \quad count_t = Returns(S_t, A_t)$$

$$\text{New mean} = \frac{mean_t \times Count_t + G}{Count_t}$$

$$Mean_t = \text{New mean}$$
$$count_t ++$$

$$\pi(S_t) \leftarrow \arg\max_a Q(S_t, a)$$

In the proposed code we are just maintaing the mean and count of total no. of terms which we have visited till it some as maintaing the whole list and calculating Average time we visit the state again. ~~so~~ but the proposed code requires less memory as compared to the original one.

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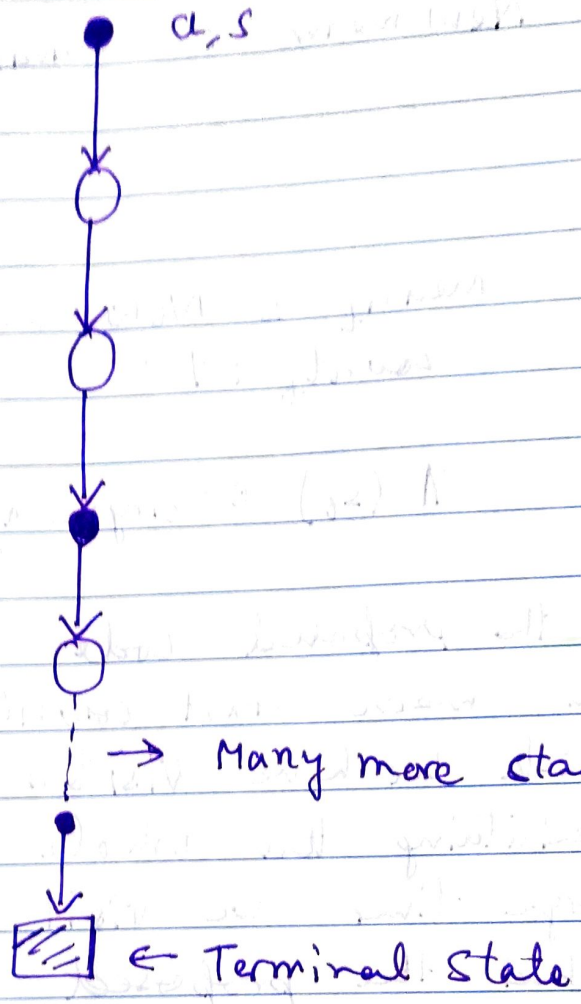
Q 2 Exercise 5.3



Q 3 Exercise 5.6

$$q(s,a) = \frac{\sum_{t \in \tau(s,a)} \rho_{t:T(t)-1} G_t}{\sum_{t \in \tau(s,a)} \rho_{t:T(t)-1}}$$

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Q5 Ex - 6.2

Considring the hint which is mentioned in the question if we have lot of driving experience and suddenly we shift to new building and new parking lot.

In this scenrio TD will perform better than the Monte carlo estimation because of the following reasons.

1. TD method exploits the markove property ie future rewards rely on upon the current state and therefore it generally more efficient to use TD in markov environment because in our case starting and ending location has change but intermediate states are still the same so TD method will able to converge easily and will faste adapt to the environment as compared to the MC.

As for as MC methods are concern they are not based on the markov property as it is based on the rewards of the entire learning process, so in our case intially MC method will suffer to converge but later it will converge to optimal value.

Q8

Exercise 6.12

Yes Q-learning will behave exactly same as the SARSA if action selection is greedy because in this case Targeted policy will be same as the behaviour policy and in SARSA we also have the same scenerio.

Q6

Exercise-6.3

The problem is discounted ($\lambda = 1$) and taking $\gamma = 0.1$ for TD(0) update we obtain

$$V(S_t) \leftarrow V(S_t) + 0.1\left(r_{t+1} + V(S_{t+1}) - V(S_t)\right)$$

for transition among states that do not end in one of the terminal states we receive a zero reward. and since intially our value function begins as the constant

if we take step left

$$V(A) \leftarrow V(A) + 0.1\left(0 + 0 - V(A)\right)$$

$$= 0.9\,V(A) = 0.45.$$

which agrees with plotted value of V(A) for the first iteration

Exercise - 6.4

MC methods are susceptible to wide values of α which we can see the graph itself. In TD if we used values α > 0.5 it will converge more faster than the shown in the graph.

Exercise - 6.5 -

Large value of α imply more V(s) in update in each step. This will make TD(0) algorithm depend more heavily on specific returns recerived at each step of the specific. value.
~~rand~~
And smaller values of α learning takes longer to do but is much less sensitive to random step.