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Assignment-3

Monte Carlo and TD:

Q1 Rather than calculating the mean of return repeatedly, we could follow an iterative update approach. Here we wish to update the state value or action-value function in each episode depending upon the state, action and type of visit approach.

The updated pseudo-code is as follows:

Loop for each step of episode, $t = T-1, T-2 \cdots 0$:

updated step.

$G \leftarrow \gamma G + R_{t+1}$ (updated → G, old → G)

$Q_\pi(S_t, A_t) \leftarrow (1-\alpha) Q_\pi(S_t, A_t) + \alpha G$

$\pi(S_t) \leftarrow \underset{a \in A(S_t)}{\operatorname{argmax}} Q_\pi(S_t, a)$

Note: Here $(1-\alpha)$ and α weights are used in case of Exponentially weighted average.

For Sample mean average, we can replace α by $\frac{1}{n}$ where n = the n^{th} instance for state S_t, action A_t among all episodes.

The intuition behind this is that:

$Q_\pi(S_t, A_t) = Q_\pi(S_t, A_t) + \alpha(G - Q_\pi(S_t, A_t))$

for the error

So 'α' is the weighing factor to improve the current action-state value function by.

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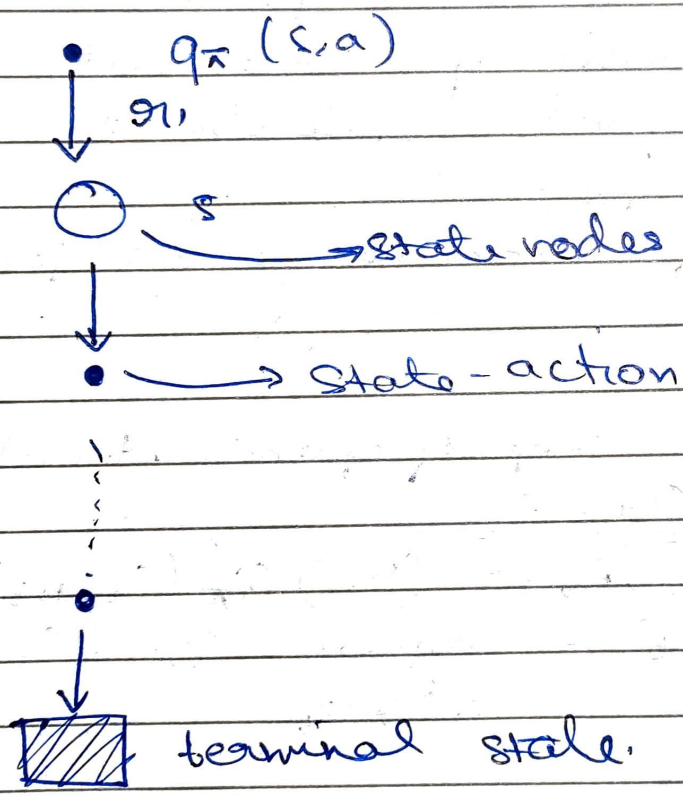
Q2. We initially choose a random state action pair which is then followed by reward and proceeding towards the next state.

Root node is the top most node which is a state action - value pairs.



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Q3. Equation analogous for action-values $Q(s,a)$ would be:

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

Here $Q(s,a)$ is the state-action pair and $\mathcal{T}(s,a)$ is the set of all time steps when $S_t = s$ and $A_t = a$.

Q5 TD learning would be very efficient in the case mentioned because:

→ Since only a small part of the route has changed, thus keeping most of the states similar in the new as well as old problem.

→ Since the device has prior experience on the initial route thus state-value func. of TD for old problem would have already converged to optimal values. Also TD bootstraps thus original state values are retained

→ We can update the new values for other / prev. states during the episode unlike monte carlo, wherein we need to wait for the episode to end.

Even if the initial state values are close to the true values, the same could be seen and they would converge faster.

Q6 (a) Left graph: Estimated values Graph
Right graph: Empirical RMS error, avg over all states

6.3

We have the following hyperparameters:
- $\alpha = 0.1$
- episodes = 100
- Reward for transition to each state except terminating right state = 0.
- Reward for transition to terminating right = 1

→ Updates in state-value func are as follows.

$$V(S_t) = V(S_t) + \alpha\left[R_{t+1} + \gamma V(S_{t+1}) - V(S_t)\right]$$

→ Initially, $V = [0, 0.5, 0.5, 0.5, 0.5, 0.5, 0]$
→ we start at state: C
Thus

$$V(C) = 0.5 + 0.1\,(0 + 0.5 - 0.5)$$

(both right and left action.)

$$= 0.5$$

Here V(C) is unchanged

Now we can either go left or go right
~~V(C) is also unchanged.~~
In the 1st ep, when we go to A, i.e. left terminal state, reward is 0.

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Also Also as value function for left terminal state is 0 thus,

~~V(A) = 0.5 + 0.0~~

$$V(A) = V(A) + 0.1(0 + 0 - V(A))$$

$$V(A) = 0.5 + 0.1(-0.5)$$

$$\Rightarrow 0.45$$

Thus, we can conclude that only only state value of A gets changed 0

The decrease is 0.05 i.e there is a 10 % deduction in the state value of A.

6.4

The conclusions about the performance of each algorithm are dependent on the range of α that we look to observe in.

TD(0) would perform poorly for larger values of α as then larger jumps/ oscillations would start to occur and it would be hard to get a better result as convergence would become difficult in this case.

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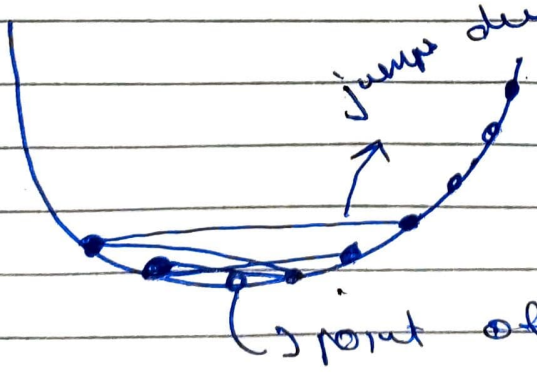
Whereas TD(0) would always perform better for smaller learning rate (α) relative to Monte-Carlo algorithm.

Also a specific alpha could be found where these algos might perform relatively well.

6.5

As 'α' increases, oscillation might start to occur in the case of TD learning algo. These oscillations or jumps would prevent the algorithm from converging.

This phenomena is true for all larger values of α and is not a function of how the value function is initialized.



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Q2. Even if the action selection is greedy, Q-learning and SARSA would be different as. In Q-learning, Q(s,a) is updated using greedy approach i.e by finding the best action for which target is max. ($\max_{a'}(R + Q(s',a'))$). here first Q values are updated and then the next action is picked whereas In SARSA, we pick the next action from the Q-values according to the next state. Further, the Q-values can now be updated according to the next-action.
Thus, due to these reasons Q-learning is different from TD learning