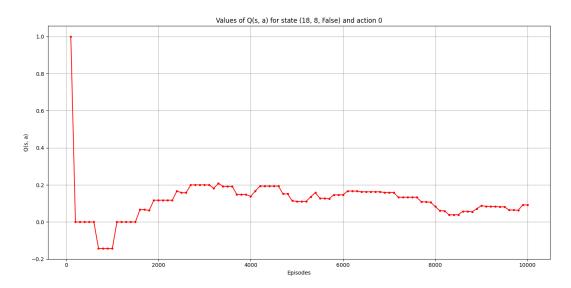
Assignment 2

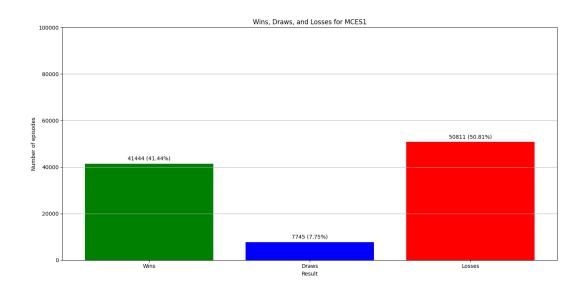
Question 1

Below is the plotting of Q(s,stick)

where s := (player total = 18, dealer showing = 8, no usable ace) in the first MCES version of the Blackjack game over 10,000 training epsiodes (where every 100th episode was recorded).



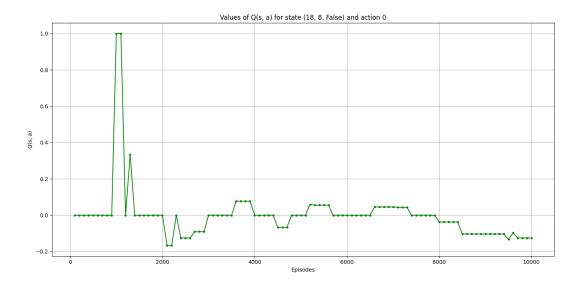
Moreover, here are the winning, drawing, and losing rates of the first MCES version of the Blackjack game after 10,000 training episodes and then 100,000 testing episodes.



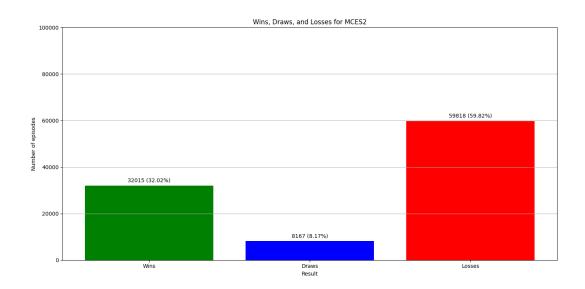
Question 2

Below is the plotting of Q(s,stick)

where s := (player total = 18, dealer showing = 8, no usable ace) in the second MCES version of the Blackjack game over 10,000 training epsiodes (where every 100th episode was recorded).



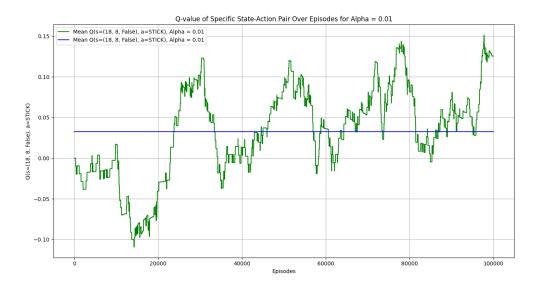
Moreover, here are the winning, drawing, and losing rates of the second MCES version of the Blackjack game after 10,000 training episodes and then 100,000 testing episodes.

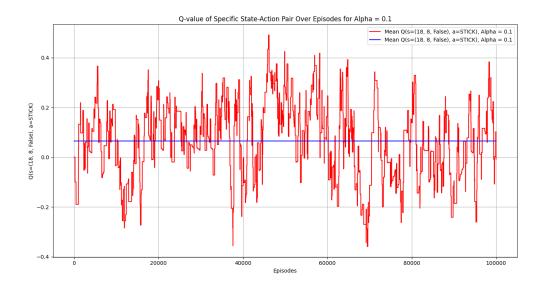


Question 3

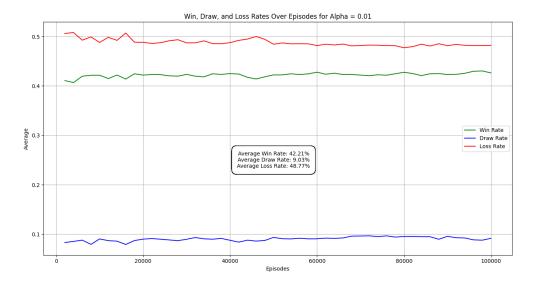
Below is the plotting of Q(s,stick)

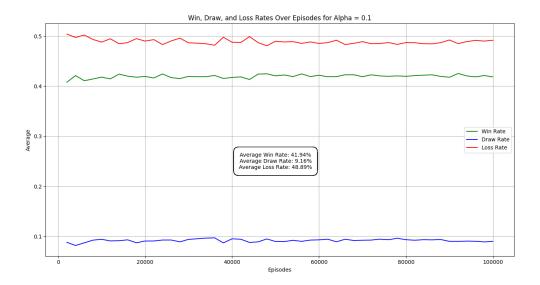
where $s := (player total = 18, dealer showing = 8, no usable ace) in the Q-learning version of the Blackjack game with <math>\alpha = 0.01$ and $\alpha = 0.1$ over all 100,000 training epsiodes.





Moreover, here are the winning, drawing, and losing rates of the Q-learning version of the Blackjack game with $\alpha = 0.01$ and $\alpha = 0.1$ after 100,000 testing episodes with each 2000th training episode (total of 50 averages).





Differences Between Algorithms

The MCES1 plot indicates a win rate of about 41.44% and a loss rate of 50.81%. The MCES2 plot shows a lower win rate of 32.02% and a higher loss rate of 59.82%. The Q-learning plots for both alpha values (0.1 and 0.01) seem to show an average win rate of approximately 42%, with a loss rate hovering around 49%. This suggests that Q-learning maintains a more consistent win/loss ratio across different learning rates compared to MCES.

MCES1 has a draw rate of 7.75%, and MCES2 has a slightly higher draw rate of 8.17%. Q-learning has slightly higher draw rates, with 9.16% for alpha 0.1 and 9.03% for alpha 0.01. This could indicate that the Q-learning policy is slightly more conservative, leading to more ties. It may also reflect a better balanced strategy that avoids losses by not taking unnecessary risks, resulting in slightly more draws.

For Q-learning, changing the alpha value from 0.1 to 0.01 does not seem to significantly affect the win and loss rates. However, it may influence the stability of learning. Typically, a smaller alpha would result in smoother learning curves as it integrates new information more conservatively. This can be slightly observed in the Q-learning plots, where the win and loss rates for alpha 0.01 are slightly more stable than those for alpha 0.1.

The Q-values plots show the value of a specific state-action pair over episodes. For alpha 0.1, the plot exhibits more variance, indicating less stability in the action-value estimates. This is expected as a higher alpha means that new information has a greater impact on the value updates. For alpha 0.01, the Q-values plot is smoother, suggesting more stability in the learning process due to the smaller alpha value, which integrates new information more slowly.

MCES exhibits a varying win/loss ratio between the two plots, suggesting that the results can differ significantly depending on the specifics of the MCES implementation or the conditions of the simulation. Q-learning appears to produce more consistent results across different alpha values, with a slight tendency towards more draws, which might suggest a more cautious approach. The alpha value in Q-learning does not seem to drastically alter the win/draw/loss rates but does affect the stability of the Q-value estimates, with a lower alpha leading to smoother updates. The slight increase in draw rates for Q-learning could imply a policy that is more risk-averse and better balanced, leading to more ties.