

# CS7646 - Machine Learning For Trading

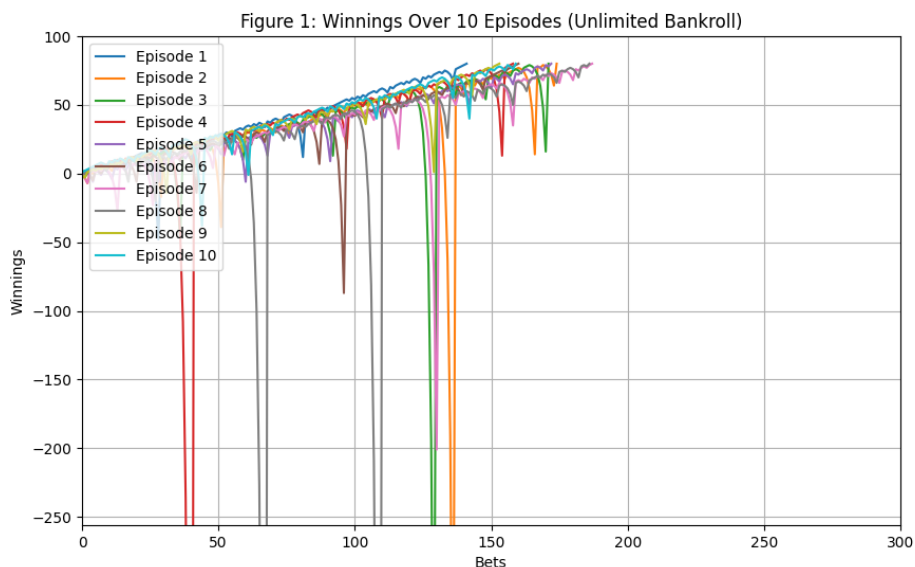
## Analyzing the Martingale Strategy

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### QUESTION 1

In the case of Experiment 1, we were not financially constrained and thus had a significant likelihood of winning \$80 within 1,000 sequential bets. As we can see from Figure 1, all ten betting episodes ultimately reached \$80 in winnings, with the last bet reaching \$80 at around the 175th spin. This is because our ability to tolerate loss was unlimited, and thus we could continue betting until we reached our desired goal of \$80. I confirmed this by creating an alternative script that simulated 1,000 unlimited loss episodes as in experiment one. One hundred percent of my simulated runs reached winnings of \$80 within 1,000 spins.

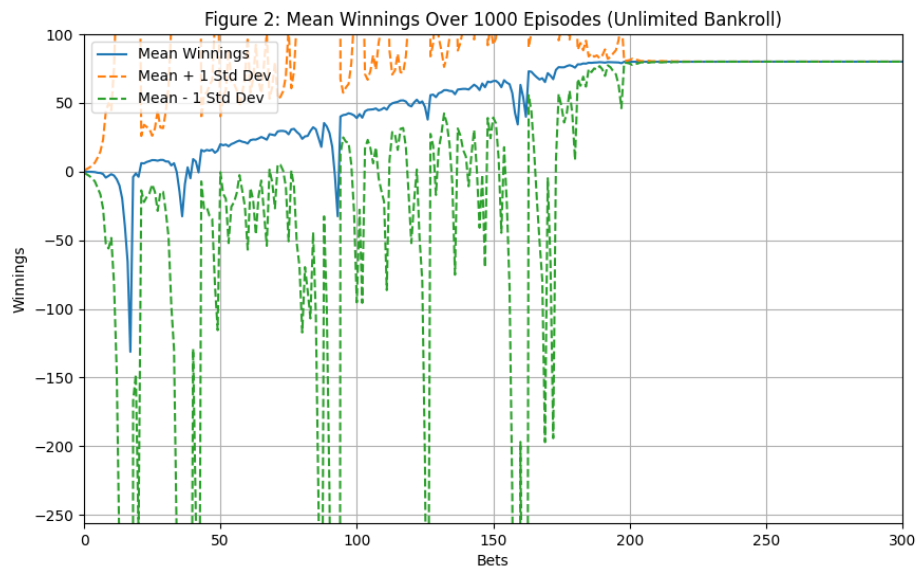


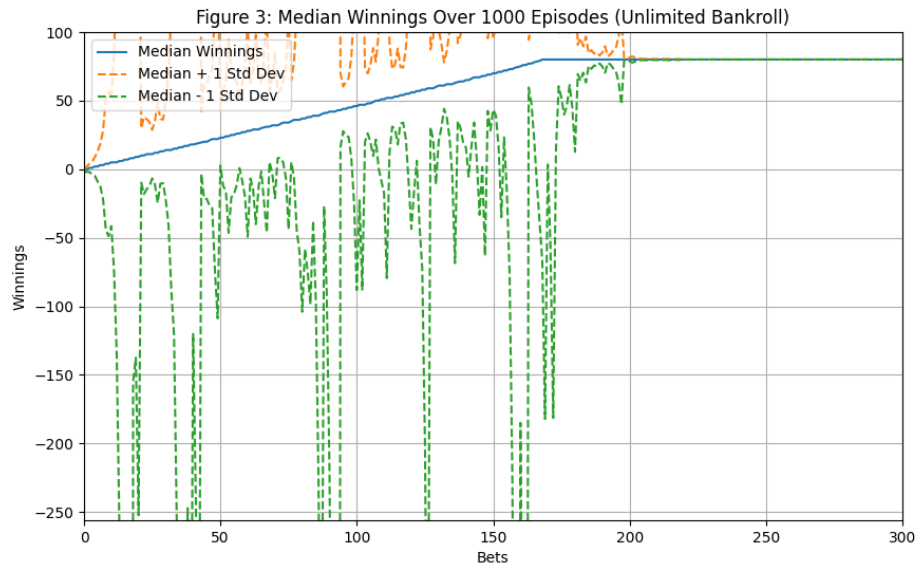
## Question 2

In order to compute the expected value in this case, I simulated the unlimited loss condition while removing the condition where we stopped playing once we reached \$80 in winnings. By removing the condition of a winning limit and by running the simulation a large amount of times we are able to get a fairly accurate estimate of what the theoretical expected value is. In this case, I ran the unlimited loss condition 1,000 times and the approximated expected value of the simulation was \$465.79.

## Question 3

As we can see demonstrated by Figure 2 below, the upper standard deviation line and lower standard deviation line converge as they approximately approach spin number 195. This is because the theoretically expected number of spins it takes to reach \$80 in winnings is around 195 spins. The figure was generated by averaging out the results of 1,000 episodes, and the data becomes less and less variable as it approaches the theoretical true value.





#### Question 4

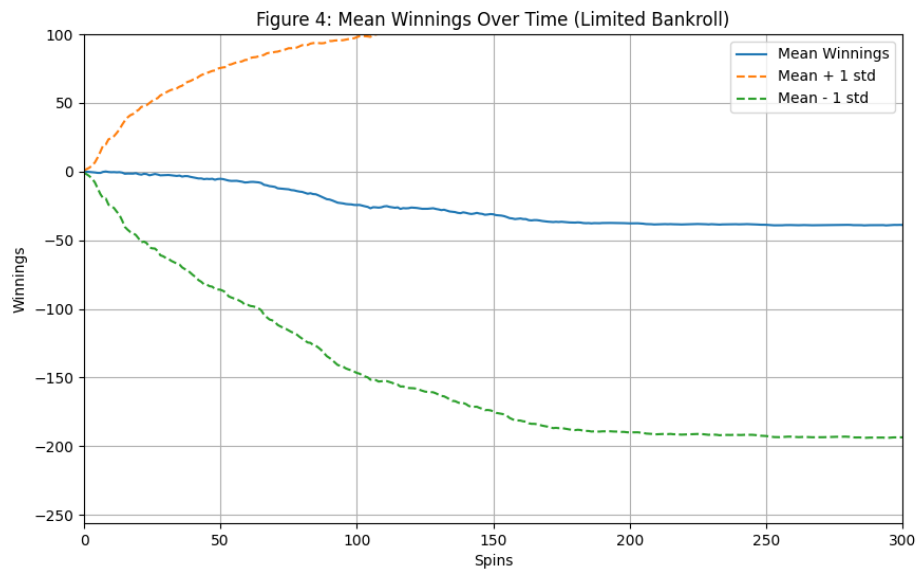
Taking a similar approach to how I answered question 1, I ran 1,000 episodes and recorded what percent of them reached an amount of \$80 in winnings. Ultimately, there is approximately a 64.48% chance that an episode will reach \$80 in winnings, given the limit of a \$256 bankroll.

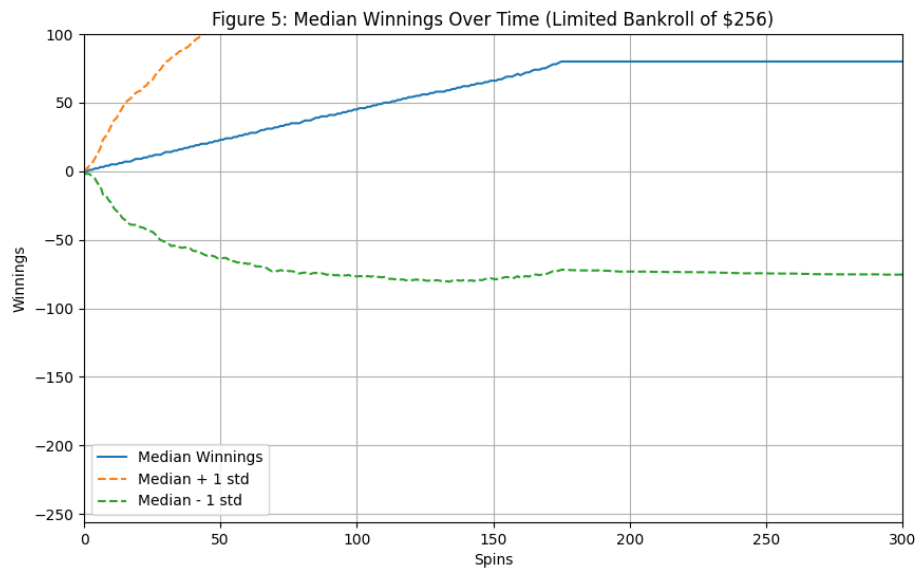
#### Question 5

Taking a similar approach to how I answered question 2, I ran 1,000 simulations except this time I limited the maximum loss to \$256. The approximate theoretical expected value of experiment 2 is -\$179.94. I found it really interesting that the fact that we had a limited bankroll created such a profound difference in the expected value, as compared to the theoretically expected value of experiment 1 (unlimited loss) of \$465.79. The constraint of \$256 ultimately creates a discrepancy of \$645.73 in the theoretical expected value.

## Question 6

When looking at Figure 4 which shows the standard deviations in relation to the mean of experiment 2 (limited bankroll of \$256) the standard deviations converge away from the mean. This is caused by a variety of factors. The first factor is the obvious new lower bound of (-\$256). This causes greater variability because the gambler can now win up to \$80 or go completely broke. In the first condition, there is no ability to “fully go broke” and thus this condition has greater variability. Further, this is a situation of asymmetric risk wherein the total possible loss and total possible gain are not equivalent, this causes the standard deviation to diverge from the mean. Lastly, the first experiment was affected by survivorship. Virtually every episode in the first condition reached \$80 and thus the standard deviations in the first condition converge towards the mean, but in the second condition, many episodes ended in a total loss, leading to divergence from the mean.





### Question 7

Expected values are calculated by averaging the outcomes of many different simulations, rather than just one random sample. A random sample can be very misleading as it is not necessarily representative of the true distribution of a possible set of outcomes. Thus expected values are a better way of understanding data.