Martingale Roulette Strategy: Simulation and Expected Value

Author Name
sspickard3@gatech.edu

Abstract—Roulette is a common game in casinos. This paper evaluates the Martingale betting strategy through simulation and expected value, examining its performance under both ideal and realistic constraints.

1 INTRODUCTION

Roulette is a casino game commonly found in Las Vegas, Nevada. In the game, players may place bets on individual numbers, groups of numbers, the color (red or black), or the parity (odd/even) of the outcome [2]. A wheel is spun, a ball tossed, and the player wins if the ball lands on a result that matches their bet.

As with any gambling game, understanding the probability involved is crucial. A strategic approach can help maximize winnings or at least reduce losses. In this paper we are evaluating the Martingale strategy, which involves betting $1 on black and doubling the bet after each loss [1].

2 EXPERIMENTS

A Monte Carlo simulation was used to evaluate the Martingale strategy. Two scenarios were considered: one idealized case with no limit on the amount of money the player could lose and one more realistic scenario where the players bankroll was limited to $256.

2.1 Experiment 1

The first experiment simulated the strategy with an unlimited bankroll. In the initial run of 10 episodes (Figure 1), the player frequently experienced large losses, but ultimately ended each episode with positive cumulative winnings.

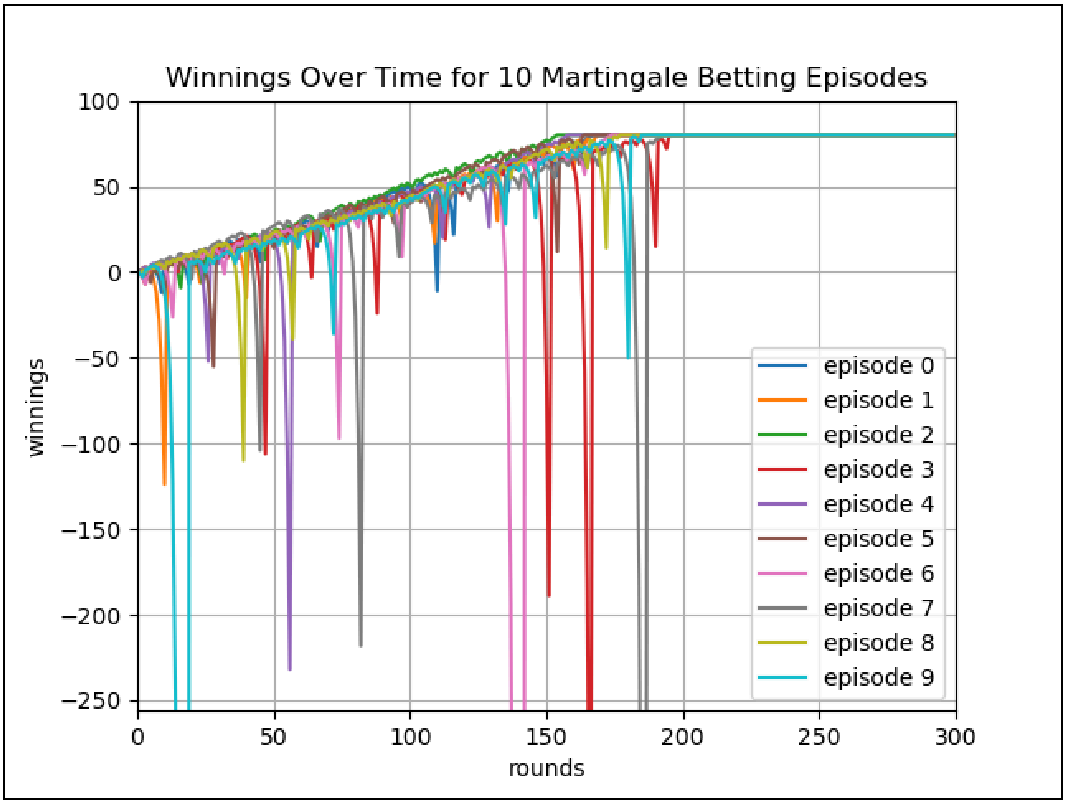

Figure 1—Winnings over rounds for 10 episodes.

When the experiment was repeated 1000 times (Figures 2 and 3), the mean and median winnings over time showed an upward trend and both stabilized near $80. Standard deviation bands remained wide, reflecting the high variability in individual rounds of the episode paths.

From the raw simulation results, the probability of reaching $80 in cumulative winnings within 1000 bets was observed to be 100%. This is consistent with the theoretical behavior of the strategy under the unlimited bankroll: because the player doubles their bet after each loss, a single win is sufficient to recover previous losses and generate a net gain. Given enough time and no capital constraint, the probability of eventually hitting a win and resetting the bet approaches 1. As such, it is not surprising that the strategy consistently reached the $80 threshold within 1000 rounds.

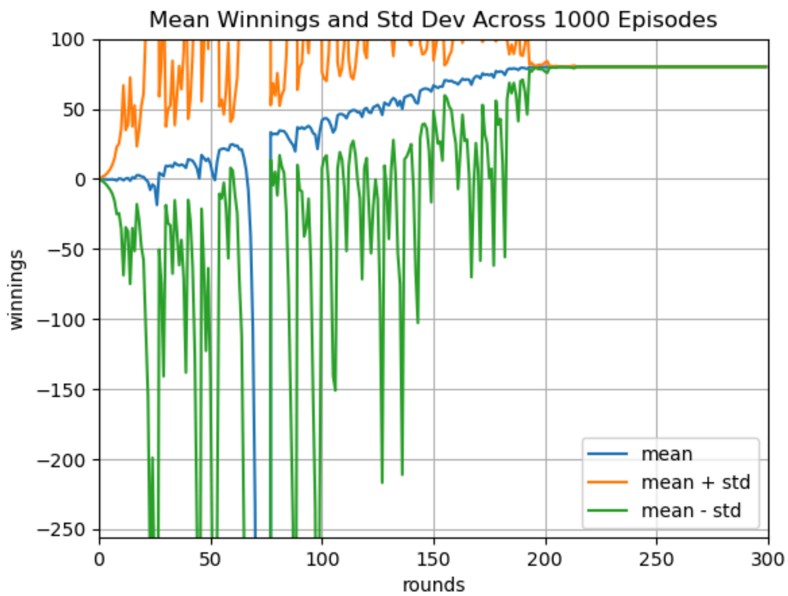

Figure 2—Mean and Population Standard Deviation across 1000 episodes of the unconstrained experiment.

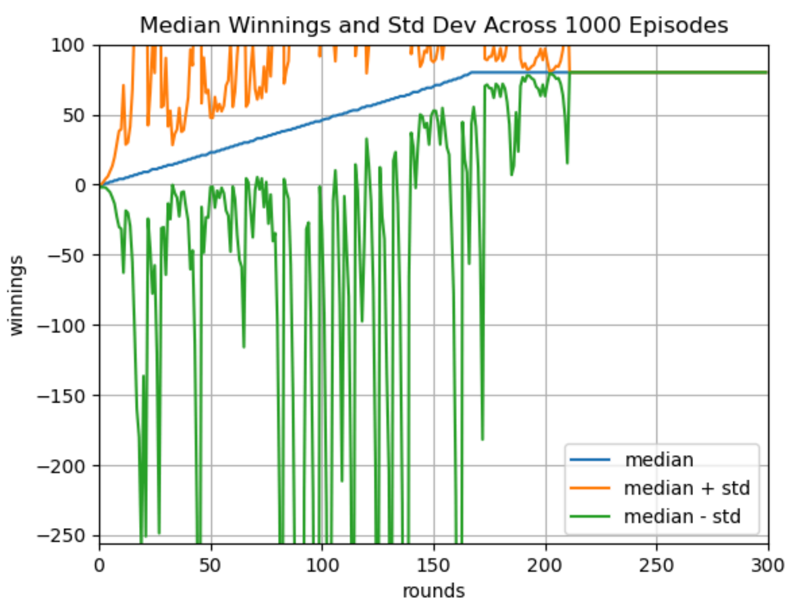

Figure 3—Median and Population Standard Deviation across 1000 episodes of the unconstrained experiment.

Each round is a Bernoulli trial, with P(win) = 0.47. The number of trials until the first win follows a Geometric distribution, which has an expected value of E[X] =

$1/p \approx 2.13$ [3]. Furthermore, to achieve 80 total wins, the expected number of spins is approximately 80 * 2.13 ≈ 170 spins. This value is far below 1000 spins, showing that the expected value of winnings after 1000 rounds is $80.

In experiment 1, the upper and lower standard deviation lines do not converge until the exit threshold of $80 is hit, and then it goes to 0. This is because as the player loses their bets become larger and larger without any limitation from their bankroll.

2.2 Experiment 2

The second experiment adds an additional constraint to the simulation by limiting the bankroll of the player. In this experiment, there were only 650 out of 1000 successes where the player exited with $80 rather than exiting due to depleting their bankroll. This experimental result makes sense because the player cannot come back from losses in the same way by doubling their bet. Instead, they hit a maximum amount where they simply must walk away.

The expected value of the limited bankroll differs because the player can only survive eight consecutive losses before running out of money ($\sum_{i=0}^{7} 2^{i} = 255$). As a result, there is a non-zero probability of losing all available funds in a single sequence of losses. Now the expected value of winnings = ($80 * p_winning) + (p_bust *-$255). From the experimental data, the probability of success was p_win = 0.65, implying a bust rate of p_bust = 0.35. Using this, the expected value becomes E[X] = (0.65 * 80) + (0.35 * -255) = -$37.60. The average number of spins to win is still roughly the same, but now there is a risk that the more rounds, the higher the chance to bust.

This can be seen in Figure 4 and Figure 5 where the standard deviation increases consistently as the rounds increase rather than being random. The standard deviation appears to converge around $160 in the experimental data. This makes some sense because the distribution settles as it gets enough data to either a win or a loss for each episode.

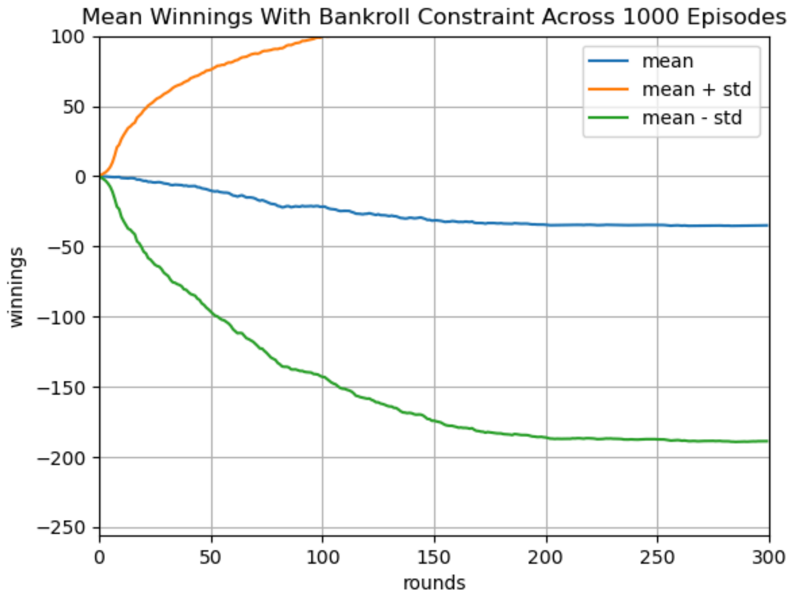

Figure 4—Mean and Population Standard Deviation across 1000 episodes of the constrained experiment.

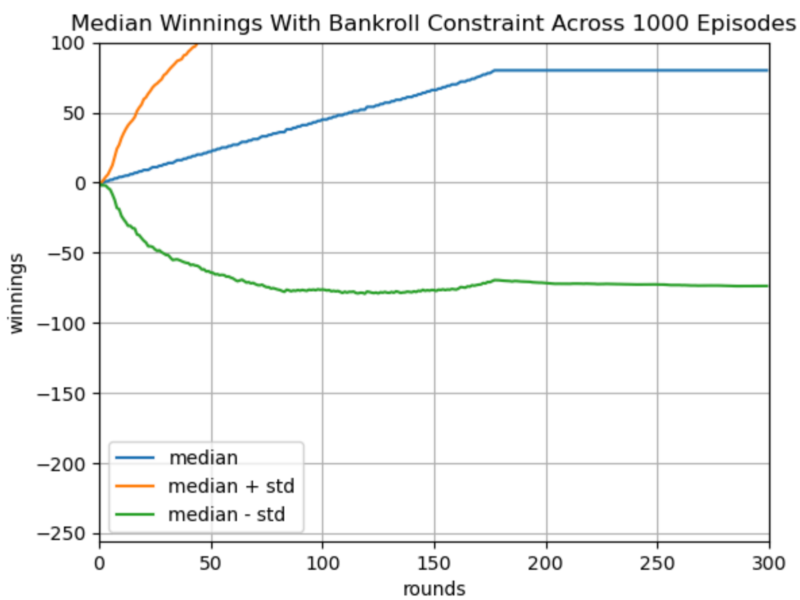

Figure 5—Median and Population Standard Deviation across 1000 episodes of the constrained experiment.

3 CONCLUSIONS

Simulation is a powerful tool to understand complicated scenarios in an explainable way. Looking at the two simulations helps us understand how the strategy behaves under ideal and constrained settings, as well as allowing us to relax or add constraints and measure their impact. Further, using expected value to estimate the winnings that the strategy has also allows us to understand what the outcome is in a more statistical way rather than relying on small numbers of data, such as would have been collected by an individual player in a casino.

4 REFERENCES

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