

Evaluating profitability in sports betting using probabilistic models and betting strategies*

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Abstract. Sports betting has evolved into a multibillion-dollar global industry, raising the question of whether consumers can achieve sustainable long-term profit. This study explores whether combining probabilistic prediction models with various betting strategies can yield statistically significant profit in football betting. We examine six prediction models – including Poisson, logistic regression, Elo, Monte Carlo simulation, and two novel heuristics (Veto and Balance) – alongside five popular betting strategies: Flat Betting, Martingale, Fibonacci, Value Betting, and the Kelly criterion. A custom Python-based simulation system was developed using real match data from 539 unique football games played between March and May 2025. A total of 10,000 match groups were generated, each containing 25 unique matches, yielding *300,000 model-strategy runs* ($6 \times 5 \times 10,000$). Simulations preserved chronological order and modeled realistic stake adjustments. Our results highlight the complex relationship between predictive accuracy and profitability, and the limitations of exploiting statistical advantages in an efficient market. While some combinations showed short-term gains, consistent long-term profit remained elusive under most conditions. The findings provide insight into model performance, risk management, and the practical challenges of algorithmic sports betting. *This study is intended solely for academic purposes; the results should not be interpreted as practical betting advice.*

Keywords: sports betting, probabilistic models, Veto model, Balance model, Kelly criterion, value betting, simulation

AMS Subject Classification: 62P05, 91B84

*This research was supported by the Eköp-24 University Research Fellowship Program of the Ministry for Culture and Innovation from the Source of the National Research, Development and Innovation Fund.

1. Introduction

Sports betting, particularly football prediction, has become a global-scale phenomenon with both economic and social implications. The global betting market exceeded USD 240 billion in 2023 and is projected to reach nearly USD 350 billion by 2030 [7]. In the United States alone, the legal sector generated a record USD 13.7 billion in 2024 [6], while sportsbooks maintain stable profit margins of 9–10% [19].

Alongside its financial significance, sports betting also carries social risks, including problem gambling and addiction, particularly among young men [1, 13, 18]. These contrasting aspects – strong financial incentives versus societal challenges – make academic investigation into betting efficiency both timely and relevant. This paper addresses a central question: can probabilistic forecasting combined with structured betting strategies achieve sustainable long-term profit?

To explore this, we evaluate six prediction models: Poisson regression [14], Elo ratings [5, 10], Monte Carlo simulation [15, 16], logistic regression [9], and two novel heuristics developed for this study, the *Veto* and *Balance* models. These are tested with five betting strategies: flat betting, Martingale, Fibonacci progression, value betting, and the Kelly criterion [12].

The contribution of this work lies in identifying model–strategy combinations capable of outperforming bookmaker odds, while highlighting the roles of probability calibration, risk management, and market dynamics. Special emphasis is placed on the interpretability and performance of the proposed *Veto* and *Balance* models.

2. Related work

Research on sports betting has focused mainly on two areas: (1) probabilistic modeling of match outcomes and (2) betting market efficiency.

Early approaches were Poisson-based, starting with Maher [14] and later refinements such as Dixon–Coles [4] and Karlis–Ntzoufras [11]. The Elo rating system, originally for chess [5], has been adapted for football [10], while logistic regression models use team-level features to estimate outcome probabilities [8]. Monte Carlo simulations have been applied to account for uncertainty in match and season forecasts [16]. More recently, machine learning techniques have also been tested, though often limited by data sparsity and overfitting risks [2].

Market efficiency studies examined biases such as the favorite–longshot effect [17], expected value modeling [3], and the use of staking systems like the Kelly criterion [12]. However, relatively few works combined probabilistic modeling with automated betting simulations using real historical odds, and even fewer assessed actual profitability under multiple strategies.

To the best of our knowledge, no prior study has proposed the *Veto* or *Balance* models. These heuristic approaches aim to translate team form and balance into full 1X2 probability distributions with high interpretability and low computational cost.

Our work builds on the above foundations while specifically addressing whether custom-built models can achieve sustainable profit in realistic betting conditions.

3. Prediction models

We evaluate six probabilistic models for football prediction. Four are standard in the literature:

- **Poisson:** assumes independent Poisson goal distributions, with expected goals aggregated into 1X2 probabilities [14].
- **Monte Carlo:** simulates thousands of matches using Poisson sampling, deriving outcome frequencies [16].
- **Elo:** updates league-based ratings after each match and converts rating differences to probabilities using logistic functions [10].
- **Logistic Regression:** multinomial model trained on team-level features (e.g., shots, possession) with softmax normalization [8].

In addition, two novel form-based heuristics were developed for this study: the *Veto* and *Balance* models. Unlike the statistical or machine learning approaches above, these focus on recent team form and opponent strength to produce interpretable and computationally efficient forecasts.

Model Design and Naming Logic

- The **Veto model** is based on an asymmetric logic: the chance of a team winning is diminished by the strength of the opponent – hence, the opponent may “veto” the win.
- The **Balance model** represents a symmetric design: it averages a team’s performance with the weakness of the opposing team in equal proportion.

Definition 3.1 (Veto Model). Let n denote the number of recent matches considered for each team, and let `decay_factor` $\in (0, 1]$ be the exponential decay parameter. Define:

$$w_i = \text{decay_factor}^{n-i} \quad (\text{weight assigned to the } i\text{-th most recent match})$$

For a team T , define the exponentially weighted outcome probabilities:

$$P_T(\text{win}) = \frac{\sum_{i=1}^n w_i \cdot \mathbb{I}_{\text{win}}(i)}{\sum_{i=1}^n w_i},$$

$$P_T(\text{draw}) = \frac{\sum_{i=1}^n w_i \cdot \mathbb{I}_{\text{draw}}(i)}{\sum_{i=1}^n w_i},$$

$$P_T(\text{loss}) = \frac{\sum_{i=1}^n w_i \cdot \mathbb{I}_{\text{loss}}(i)}{\sum_{i=1}^n w_i}$$

where $\mathbb{I}_{\text{result}}(i)$ is the indicator function for result type.

Let H and A denote the home and away teams respectively. The raw match outcome probabilities are computed as:

$$\begin{aligned} P(1) &= P_H(\text{win}) \cdot (1 - P_A(\text{win})) \\ P(2) &= P_A(\text{win}) \cdot (1 - P_H(\text{win})) \\ P(X) &= \frac{P_H(\text{draw}) \cdot n_H + P_A(\text{draw}) \cdot n_A}{n_H + n_A} \end{aligned}$$

These values are then normalized:

$$P'(r) = \frac{P(r)}{P(1) + P(X) + P(2)} \cdot 100 \quad \text{for } r \in \{1, X, 2\}$$

Definition 3.2 (Balance Model). This model computes probabilities using symmetric averaging. For the same notation as above:

$$\begin{aligned} P(1) &= \left(\frac{P_H(\text{win}) + (1 - P_A(\text{win}))}{2} \right) \cdot 100 \\ P(2) &= \left(\frac{P_A(\text{win}) + (1 - P_H(\text{win}))}{2} \right) \cdot 100 \\ P(X) &= \left(\frac{P_H(\text{draw}) + P_A(\text{draw})}{2} \right) \cdot 100 \end{aligned}$$

Final normalization is applied:

$$P'(r) = \frac{P(r)}{P(1) + P(X) + P(2)} \cdot 100 \quad \text{for } r \in \{1, X, 2\}$$

Key Distinction Between the Two Models

- The **Veto model** is *asymmetric*: it suppresses a team's win probability if the opponent is also strong.
- The **Balance model** is *symmetric*: it applies equal weight to both teams' performance metrics in a balanced averaging approach.

Author's note These models were independently developed and offer novel heuristic approaches based on form-weighted probabilities. No similar implementation was found in existing literature.

4. Betting strategies

Five common strategies were tested for managing stake allocation:

- **Flat Betting:** Fixed stake per bet, regardless of confidence or odds. Serves as a baseline.
- **Martingale:** Doubles the stake after each loss to recover losses. High bankruptcy risk due to exponential growth.
- **Fibonacci:** Stake increases by the Fibonacci sequence after each loss. Slower than Martingale but still risky.
- **Value Betting:** Bet only when:

$$P \cdot \text{odds} > 1$$

indicating positive expected value. Uses a fixed stake.

- **Kelly criterion:** Stake fraction:

$$f = \frac{b \cdot P - (1 - P)}{b}, \quad \text{where } b = \text{odds} - 1$$

Maximizes long-term growth while avoiding overbetting.

Each strategy was applied consistently per model. Key metrics included total profit, bankroll evolution, and bankruptcy rate.

5. Simulation setup

A custom Python-based framework was developed to evaluate the combined performance of prediction models and betting strategies. It integrates a GUI, database storage, and API-Football data access, enabling interactive match selection, model execution, and result visualization.

Data. The dataset contained 539 unique matches played between March and May 2025. Teams were required to have sufficient historical statistics and valid 1X2 odds; matches with incomplete data were excluded.

Simulation Design. We generated *10,000 synthetic match groups* (25 matches each), yielding *300,000 model-strategy runs* ($6 \times 5 \times 10,000$) across six prediction models (Veto, Balance, Monte Carlo, Poisson, Logistic Regression, Elo) and five betting strategies (Flat, Martingale, Fibonacci, Value, Kelly criterion). Each run started with a bankroll of 10,000 units; fixed-stake betting used 1,000 units, while Kelly applied dynamic stake sizing. Value bets were placed only when $P \cdot \text{odds} > 1$.

Odds and Output. For each outcome, the best available bookmaker odds were used to approximate optimal odds shopping, providing an upper bound on theoretical returns. Simulation results included bankroll trajectories and detailed tables. Core components were unit-tested, and the full code is available at: https://github.com/JocmanHUN/Szakdolgozat-Pal_Jozsef_Gergo_NZ5MI3

Note. Optimal odds shopping is idealized and likely overestimates achievable ROI; in practice, account limits, taxes, and latency reduce effective profitability.

6. Results and discussion

The extensive simulation experiments presented insightful results on the intricate relationship between probabilistic model accuracy and betting strategy efficiency. While general profitability across all strategies remained challenging, significant variations emerged depending on specific model-strategy combinations. The key findings are detailed below.

Overall Predictive Performance. Table 1 presents a statistical summary of each model’s performance across 539 unique matches. While the Elo model achieved the highest accuracy, its lower average odds limited profitability. The Veto model produced competitive accuracy with higher win-odds, supporting its success under the Kelly criterion. In contrast, the Logistic Regression model, though less accurate, frequently selected high-return opportunities, contributing to its volatile performance.

Table 1. General model performance statistics based on 539 unique matches. The last two columns report the mean odds conditional on wins and losses, respectively.

Model	Avg. Odds	Correct Pred.	Accuracy (%)	Win. Odds	Loss Odds
Logistic Regression	2.91	218	40.45	2.34	3.29
Veto	2.80	225	41.74	2.34	3.12
Balance	2.58	238	44.16	2.13	2.94
Monte Carlo	2.48	254	47.13	2.12	2.80
Poisson	2.45	248	46.01	2.08	2.77
Elo	2.25	262	48.61	1.97	2.51

Detailed Analysis of Model Performances. Figure 1 illustrates all 10,000 bankroll trajectories produced by the Balance model under the Value Betting strategy. Despite the theoretical potential of the Balance model, the performance proved consistently weak across the simulations. Although some individual bankrolls showed moderate growth, the aggregate average was negative, demonstrating poor value identification. A plausible explanation for this behavior is the model’s inability to consistently select truly value-rich matches, leading to a frequent selection of marginal or negative expected-value bets.

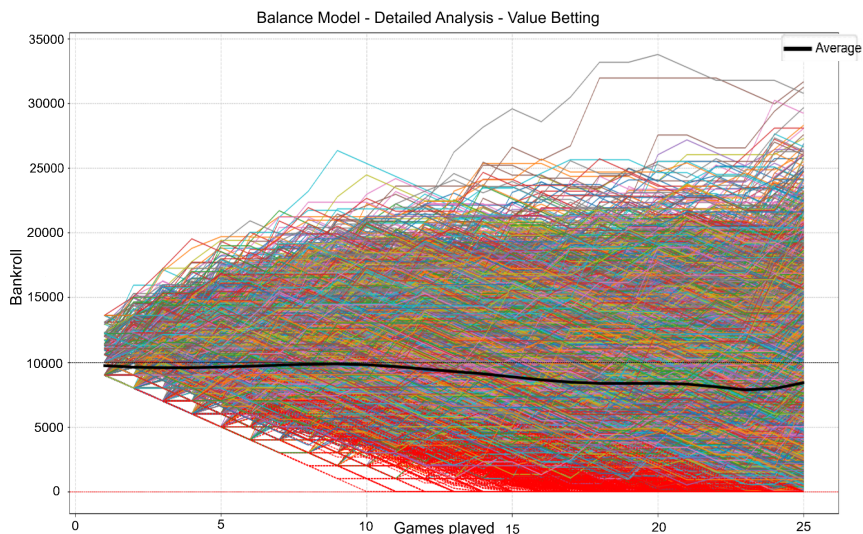


Figure 1. Detailed bankroll curves for the Balance model using Value Betting. All 10,000 simulations are shown; the black curve is the average bankroll.

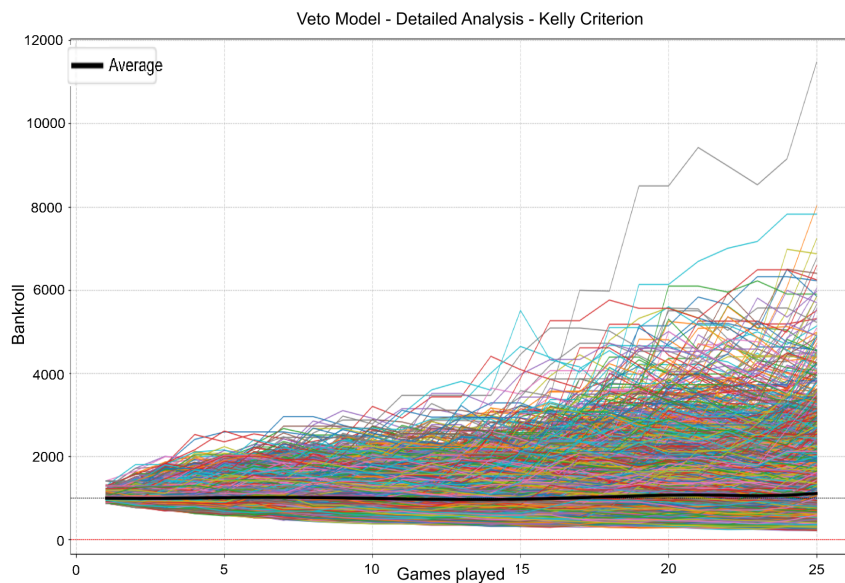


Figure 2. Detailed bankroll trajectories for the Veto model under the Kelly criterion. All 10,000 simulations are shown; the black curve is the average bankroll.

Contrastingly, the Veto model delivered remarkable results when combined with the Kelly criterion (Figure 2), which plots all 10,000 simulated bankroll paths alongside their average (black curve). This pairing stood out as the only consistently profitable combination across extensive testing. The exceptional outcome can be attributed to the model’s strong probability calibration, particularly within odds ranges most advantageous to Kelly-style proportional staking. Importantly, no bankruptcies occurred over 10,000 simulations, indicating both a stable risk profile and robust profitability potential. The success of the Veto model underscores the strength of heuristic-based approaches that incorporate recent team form and opponent quality into their calculations. Additionally, an important practical advantage of the Veto model is its extremely low computational resource requirements, allowing it to operate efficiently even on modest hardware.

ROI Analysis by Odds Range. To further investigate the Veto model’s success under the Kelly strategy, Table 2 breaks down the return on investment (ROI) by odds intervals. While the hit rate naturally declines with increasing odds, the highest ROI (+30.43%) was achieved in the 2.21–3.50 range – confirming that the model is particularly well-calibrated for identifying underpriced moderate-to-high odds. Surprisingly, very low odds (1.01–1.30) yielded perfect accuracy but only moderate ROI, while high odds consistently outperformed the others in profitability.

Table 2. ROI of the Veto model under Kelly strategy by odds range. Match Count counts only placed wagers (rounds where the Kelly fraction was zero are excluded). Bins were chosen to align with the model’s preferred odds corridor; alternative nearby binning yielded the same qualitative result.

Odds Range	Hit Rate	Match Count	ROI
Very Low (1.01–1.30)	100.00%	1,725	+23.74%
Low (1.31–1.60)	71.77%	4,602	-4.81%
Medium (1.61–2.20)	38.13%	33,641	-24.54%
High (2.21–3.50)	38.40%	76,017	+30.43%
Very High (3.51–10.00)	22.72%	73,144	-0.90%

The Logistic Regression model showed distinct characteristics under the Value Betting strategy, depicted in Figure 3. Its performance was marked by high volatility, frequent bankroll swings, and a considerable bankruptcy rate. All 10,000 simulated bankroll paths are plotted, with the black curve marking the mean trajectory. Nevertheless, the Logistic Regression was consistently able to detect matches where odds implied higher-than-actual risks, capitalizing on high-odds betting opportunities. The volatility is likely due to occasional overestimation of event probabilities, suggesting that while the model excels at identifying valuable bets, improved calibration or additional filtering mechanisms could stabilize its performance.

An overarching comparison of all models under the Kelly criterion (Figure 4)

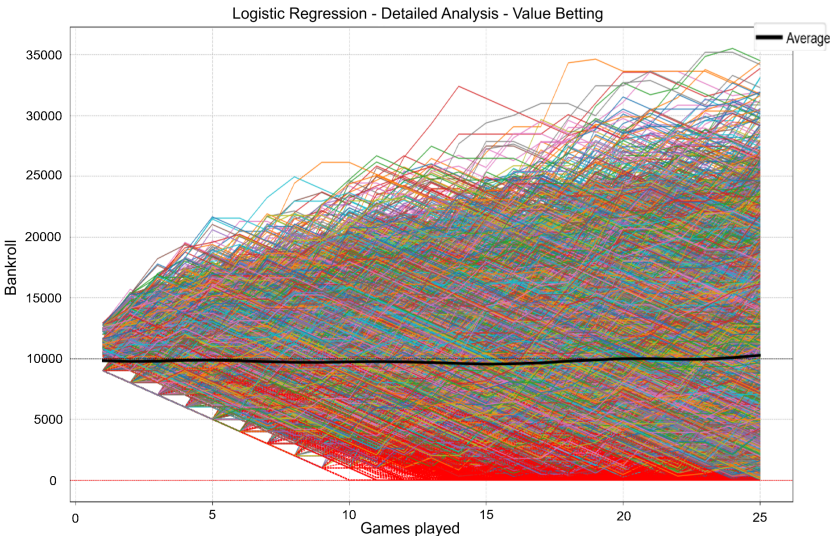


Figure 3. Detailed bankroll trajectories for the Logistic Regression model under Value Betting. All 10,000 simulations are shown; the black curve is the average bankroll.

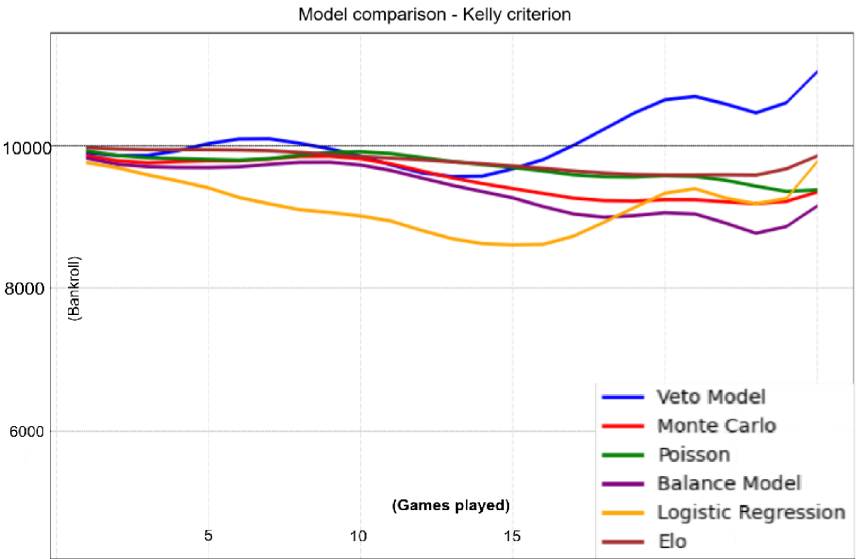


Figure 4. Comparative average bankroll performance of all models under the Kelly Criterion strategy.

plots the mean bankroll trajectory for each model; the Veto curve therefore coincides with the average line already shown in Figure 2, whereas the other curves depict the corresponding averages for their models. Unlike other models, which showed declining bankroll trends, the Veto model demonstrated a consistent upward trajectory, highlighting its superior long-term stability. The Elo model, despite having high prediction accuracy, suffered minor losses due to overly conservative odds selection, limiting its profitability potential. Models like Monte Carlo and Poisson showed moderate losses, indicating reasonable calibration but insufficient precision for consistently profitable outcomes.

It is essential to consider several practical limitations inherent to this research. The study's timeframe (March–May) was strategically chosen due to the density of competitive matches, yet following this period, notably fewer matches are available during the summer months, potentially altering model performance due to seasonal effects. Furthermore, many matches had to be excluded entirely due to missing or incomplete statistical data, limiting the total predictive coverage achievable in real-world scenarios.

Another critical assumption within the simulation was the use of optimal odds shopping, wherein the best available odds were always selected. However, in a practical environment, odds shopping is significantly more complex, as bettors must continuously monitor multiple bookmakers, navigate various platforms, and handle differing national regulations and taxes, all of which may substantially reduce realized profitability. Moreover, executing a successful betting strategy – especially strategies relying on dynamically adjusting stakes such as Kelly – requires constant attention and rapid decision-making. This implies a significant time and logistical commitment from bettors, which might not be feasible for every participant in real-world settings.

Key Insights on Strategy Efficiency. The simulations reaffirmed the critical importance of choosing betting strategies compatible with the predictive model's inherent risk profile and calibration characteristics. Aggressive strategies like Martingale and Fibonacci exhibited high bankruptcy rates across all models, indicating their unsuitability for sustainable long-term use. Conversely, the Kelly criterion and Value Betting strategies demonstrated clear potential, but only when aligned with appropriately calibrated models. Specifically, the Veto model's compatibility with Kelly criterion betting points towards a best-practice combination for maximizing returns while minimizing financial risk, albeit with the previously mentioned practical limitations considered.

7. Conclusion

This research sought to rigorously evaluate the profitability potential of combining probabilistic sports betting models with well-known betting strategies. Through extensive computational experiments involving 10,000 simulations per strategy-model combination, several critical conclusions emerged:

Predictive Accuracy and Odds Calibration. All models demonstrated statistically significant predictive skill compared to random guessing (33.33%). Elo ratings produced the highest accuracy (48.61%), closely followed by Monte Carlo, Poisson, and Balance models. Despite slightly lower accuracy rates, the Veto and Logistic Regression models effectively targeted higher odds, crucial for profit generation under specific strategies.

Sustainable Profitability. Achieving long-term profitability proved challenging for most model-strategy pairs. The notable exception was the Veto model combined with the Kelly criterion strategy, consistently generating positive average returns (+10.17%) without bankruptcy occurrences. This underscores the paramount importance of probability calibration and disciplined stake sizing in betting scenarios. The Logistic Regression model showed profitability potential through Value Betting but required improved volatility management.

Influential Factors. Several factors emerged as essential to successful betting systems:

- **Probability Calibration:** Precise probability estimation was critical. Poor calibration quickly eroded bankrolls, especially under strategies like Kelly, which heavily penalize inaccuracies.
- **Risk Management:** Strategies incorporating dynamic stake adjustment (e.g., Kelly) demonstrated significant resilience against bankroll depletion, highlighting the importance of adaptive risk management.
- **Selective Odds Range Betting:** Models excelling within particular odds ranges, such as Veto in moderate-odds markets and Logistic Regression in high-odds markets, significantly benefited from tailored betting strategies.

Significance of the Proposed Models. The study introduced two original heuristic-based models: Veto and Balance. While Balance underperformed, primarily due to insufficient value detection and overly concentrated betting suggestions, the Veto model exhibited outstanding performance. Its combination of exponentially weighted recent form and asymmetric opponent strength assessments provided exceptional calibration and robust predictive reliability. This highlights that even relatively simple heuristics can compete effectively with more sophisticated statistical models when carefully calibrated and appropriately applied.

Future Research Directions. Future extensions could significantly enhance model accuracy and practical usability:

- Integration of advanced machine learning algorithms (e.g., ensemble methods, neural networks, XGBoost).

- Incorporation of additional predictive factors such as player injuries, lineup changes, weather conditions, or betting market dynamics.
- Expanding historical datasets to strengthen statistical reliability.
- Enhancing computational resources via parallel computing or cloud-based systems.
- Development of a public-facing web-based betting advisory platform based on refined versions of these models.

These extensions could further validate whether the identified Veto–Kelly combination maintains profitability in broader and more realistic contexts.

Final Remarks. This work clearly demonstrates the challenges inherent in generating consistent profits from sports betting but also highlights viable pathways towards sustainable profitability through rigorous model calibration, strategic betting approaches, and disciplined risk management. The exceptional performance of the Veto model within the Kelly criterion framework serves as a compelling proof-of-concept, emphasizing that carefully designed probabilistic models, even heuristic-based, can yield meaningful advantages in competitive betting environments.

Ethical note. This work is for academic analysis only. Sports betting carries risks, including gambling addiction; results here should not be construed as betting advice, and real-world frictions (limits, taxes, latency) further reduce practical applicability.

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