Mixed-Integer Linear Parlays, An Optimized Sports Betting Approach

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I. Introduction

In May 2018, the Supreme Court of the United States struck down the Professional and Amateur Sports Protection Act [1] enabling casinos to offer wagers regarding the outcome of sporting matches. After the fact, the sports betting industry has grown massively with $426 billion legally wagered since the repeal [2]. With increased interest in the industry, there has been a demand for predictive mathematical models that can tip the odds in your favor.

II. Background and Related Work

The field of optimal gambling strategies is fairly new. However, there are several published articles referencing either predictive modeling of sporting outcomes or the optimal allocation of resources given a predictive model. Uhrín et al. [3] argue that given an accurate prediction model, the actual returns are still highly dependent on the allocation of wagers. They investigate both formal and informal methods to determine the criterion for when to place a wager given the same probability distribution. Whereas, Dmochowski [4] uses more standard optimal estimation strategies but applied to various wager types. These wagers include points spread, moneyline, and point totals. The goal is to identify specific types of wagers that are most suitable to this sort of optimization. On the other hand there is a larger volume of work regarding the predictive modeling side of the problem. This is largely due to its broader applications for both team and injury management. Horvat [5] provides a comprehensive review of machine learning algorithms with respect predicting outcomes of sporting matches. The majority of existing work is use chronological data sense in order to extract features. However, this can be very stiff of large data sets. This implies that more local feature sets may be required for dynamic prediction. As opposed to allocating wagers aligned with given sports book odds, Galekwa et al. [6] argue that predictive models can be used to identify misaligned odds on the sport book side. As odds change constantly, leveraging these temporal anomalies can help increase the expected return on given wagers. Lastly in a case study, Gifford et al. [7] use logistic regressions and decision trees to predict the outcome of NFL games. This work identifies specific features that have the largest contribution to the overall likelihood of observing the output.

III. Problem Formulation

A. Probability of Home-Team Winning

First consider predicting the probability of home team A winning game i, $\hat{p}_i \in \{0,1\}$. Let $\vec{x}_i \in \mathcal{R}^n$ be vector representing the set of features/statistics that can be used to predict the outcome of the given game. Let $\vec{\theta} \in \mathcal{R}^n$ be a weighting vector that is applied to the feature set indicating the importance of each statistic relative to the output. Then the model $f(\vec{x}_i,\vec{\theta}) = \hat{p}_i : \mathcal{R}^n \rightarrow \mathcal{R}$ uses the input features and weights to generate a probability of home team A winning. A probability of greater than 0.5 indicates that it is more probable that team A wins the game and less than 0.5 indicates that it is more probable that team A loses the game.

Specifically, let the likelihood of observing a win or loss, $y_i \in \{0,1\}$, take the form:

$$L(\vec{x}_i,\vec{\theta}) = P(y_i|\vec{x}_i,\vec{\theta}) \tag{1}$$

The goal is to find the weights the maximize the likelihood of observing either a win or loss given that a win or loss occurred. In simpler terms, if a team A is observed to win, the goal is to find the set of weights such that when they are multiplied by $\vec{x}$, it generates a large probability. If team A is observed to lose, the same weighting vector multiplied by $\vec{x}$ must generate a low probability of winning. While the set of features remains constant across all games, the values of the features can differ game to game. Since the value of features can be greater than 1, i.e. average scoring margin, the Sigmoid function is used to transform the input features and weights into a probability between {0,1}:

$$P(y_i|\vec{x}_i,\vec{\theta}) = \sigma(\vec{x}_i,\vec{\theta}) = \frac{1}{1+\exp(-\vec{x}_i^T\ \vec{\theta})} \tag{2}$$

Thus, the overarching goal is to find a set features and weights that maximize the likelihood of predicting a win given a win occurred or predicting loss considering a loss occurred for all games $i \in \{1,n\}$.

$$\max_{\theta}(L(\vec{x},\vec{\theta})) = \max_{\theta}(\sum_{i=1}^{n} P(y_i|\vec{x}_i,\vec{\theta})^{y_i} \cdot P(y_i|\vec{x}_i,\vec{\theta})^{1-y_i}) \tag{3}$$

For mathematical convenience, numerical stability, and differentiability within the optimizers for gradient based search, the logarithm of the likelihood function is used:

$$\max_{\theta}(\mathcal{L}(\vec{x},\vec{\theta})) = \max_{\theta}(\sum_{i=1}^{n} y_i \log \sigma(\vec{x}_i,\vec{\theta}) + (1-y_i)\log(1-\sigma(\vec{x}_i,\vec{\theta}))) \tag{4}$$

If $y = 1$, the function is penalized for probabilities that are less than one. If $y = 0$, the function is penalized for probabilities greater than zero. This maximization problem is reformulated into minimization problem using the negative of the log-likelihood. Synonymously this problem seeks to minimize the cross entropy loss:

$$\theta^* \leftarrow \arg\min_{\theta}(-\sum_{i=1}^{n} y_i \log \sigma(\vec{x}_i,\vec{\theta}) + (1-y_i)\log(1-\sigma(\vec{x}_i,\vec{\theta}))) \tag{5}$$

Then for any given game with features $\vec{x}_i$ and weights θ^*, the predicted probability of winning is

$$\hat{p}_i \leftarrow \sigma(\vec{x}_i,\vec{\theta}^*) \tag{6}$$

B. Decision Problem

The sports book provides two money lines for any game i: home team A, M_i^A and away team B, M_i^B. For each moneyline, $M_i \in [\{-\infty,-100\},\{100,\infty\}]$, the wager multiplier takes following piecewise form:

$$R_i(M_i) = \begin{cases} \frac{M_i}{100}, & \textbf{if } M_i > 0 \\ \frac{100}{|M_i|}, & \textbf{if } M_i < 0 \end{cases} \tag{7}$$

Therefore, assuming a win, the profit of a wager, $b_i \in \mathcal{R}'$, on moneyline, M_i, is computed using:

$$P_i(b_i, M_i) = b_i \cdot R_i(M_i) \tag{8}$$

This implies that a positive moneyline returns a profit more than the initial wager, and a negative money returns a profit less than the initial wager.

Then the weighted expected value of the profit given wager b_i and probability of winning $\hat{p}_i$:

$$\mathrm{E}[b_i] = \hat{p}_i \cdot P_i(b_i, M_i) - (1-\hat{p}_i)\cdot b_i \tag{9}$$

After considering the expected profits for a single game, the problem is expanded to all available games and their respective odds. The decisions are which games to wager upon and how much to wager per game. A mixed-integer linear program (MILP) is an optimal and efficient way to solve for the set of wagers, $W(b_i, k_i)$, that generate the greatest expected profit.

Generally, let the optimziation problem take the form:

$$\begin{aligned} W = \arg\max_{b_i,k_i} \quad & (\mathrm{E}[\vec{b}]^T\vec{k}) \\ \text{subject to} \quad & \sum_{i=1}^{n} k_i = 5 \\ & \sum_{i=1}^{n} b_i k_i \le B \\ & b_i \ge 0, \quad \forall i = 1,\ldots,n \\ & k_i \in \{0,1\}, \quad \forall i = 1,\ldots,n \end{aligned} \tag{10}$$

where k_i is a binary decision variable indicating a wager of b_i on game i. The problem is constrained to wager on exactly 5 games with a maximum budget B. However, this general formulation is actually a non-linear program since the decision variables are being multiplied within the objective function and the constraints. Therefore let a new slack variable $z_i = b_i \cdot k_i$ be introduced in order to linearized the problem:

$$\begin{aligned} W = \arg\max_{z_i,b_i,k_i} \quad & \sum_{i=1}^{n} \mathrm{E}[\vec{z}]\ \vec{1}^T \\ \text{subject to} \quad & \sum_{i=1}^{n} k_i = 5 \\ & \sum_{i=1}^{n} z_i \le B \\ & z_i \le b_i, \quad \forall i = 1,\ldots,n \\ & z_i \le B \cdot k_i, \quad \forall i = 1,\ldots,n \\ & z_i \ge 0, \quad \forall i = 1,\ldots,n \\ & b_i \ge 0, \quad \forall i = 1,\ldots,n \\ & k_i \in \{0,1\}, \forall i = 1,\ldots,n \end{aligned} \tag{11}$$

This formulation is now linear in the objective and the constraints. The problem is still constrained to pick exactly five games and spend less than the total budget. The new constraints ensure that z_i does not exceed b_i if $k = 1$, z_i never exceeds B, and $z_i = 0$ if $k = 0$.

IV. Solution Approach

A. Feature Extraction

In order to gather data for the predictive model, the NBA API [8] provides historical game by game data. This approach uses data from 2020-24. Starting at the first game of 2020 season, the API returns a data frame containing but not limited to:

Team Details:

- CITY
- NICKNAME, TEAM_ID

Performance Stats:

- W, L
- W_HOME, L_HOME
- W_ROAD, L_ROAD

Shooting Stats:

- FG, FGA, FG_PCT
- FG3, FG3A, FG3_PCT
- FT, FTA, FT_PCT

Rebounds, Assists, Defense, and Points:

- OFF_REB, DEF_REB, TOT_REB
- AST, TOTAL_TURNOVERS
- PF, STL, BLK
- PTS

Then using this data frame, the specific features used in this approach are tabulated below:

TABLE I: Data Features

$\vec{x}$	Feature
x_1	Home Game Win Percentage
x_2	Away Game Win Percentage
x_3	Total Win Percentage
x_4	Offensive Efficiency
x_5	Rolling Offensive Efficiency
x_6	Rolling Scoring Margin
x_7	Number of Rest Days

The first three features are relatively straightforward to compute using the schedule and results. The offensive efficiency is a single statistic reflecting a teams offensive ability. It is calculated using:

$$OE = \text{FG\_PCT} + \frac{\text{AST}}{\text{FGA}} - \text{OFF\_REB} + \text{AST} - \text{TOTAL\_TURNOVERS} \quad (12)$$

The fifth and sixth features are rolling statistics take the 3 game moving average. This rolling averages can help indicate how hot a team is. These rolling averages help alleviate the stiffness of the data set as the season progress. The number of rest days is defined as the difference between current game and the last a last game played. More rested teams typically perform better as opposed to exhausted teams. While infinite features can be chosen, these were chosen for simplicity and herritage.

B. Model Evaluation

There are several statistics that reflect a models ability to generate accurate predictions. This paper will consider six statistics: accuracy, precision, recall, F1 score, cross-entropy loss, and the area under the receiver operating characteristic curve (AUC-ROC).

There are four cases that can occur in this classification model. A true positive (TP) indicates the model correctly predicted a team to win. A false positive (FP) indicates that the model incorrectly predicted the team to win. A true negative (TN) indicates that the model correct predicted the team to lose. A false negative (FN) indicates that the model incorrectly predicted the team to lose.

The accuracy refers represents the proportion of total predictions (both wins and losses) that were correct.

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Number of Predictions}} \quad (13)$$

The precision reflects the proportion of predicted wins that were correct. If there are false positives, predicting a team to win and they lose, then the precision value decreases. The same applies to predicting losses.

$$\text{Precision} = \frac{TP}{TP + FP} \quad (14)$$

The recall indicates the models ability to identify wins compared the total number of actual wins. If there are false negatives, incorrectly predicting a team to lose, then the recall value decreases. This logic is similairly applied to identifying losses.

$$\text{Recall} = \frac{TP}{TP + FN} \quad (15)$$

The F1 score is the harmonic mean between the precision and recall. It provides a balance between false positives and false negatives

$$\text{F1-Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (16)$$

The cross-entropy loss, mentioned in the formulation, indicates the confidence in either a win or loss. A lower value indicates that the model is more confident in its prediction.

$$\text{Cross-Entropy Loss} = -\frac{1}{n}\sum_{i=1}^{n}[y_i \log(\hat{p}_i) + (1-y_i)\log(1-\hat{p}_i)] \quad (17)$$

The ROC plots the true positive rate against the false positive rate. The area under this curve represents the models ability to differentiate between the positive and zero classes. A value of 1 indicates it can perfectly differentiate between the two classes as their would be no false positives and only true positives.

$$\text{ROC-AUC} = \int_0^1 \text{TPR(FPR)}\, d(\text{FPR}) \quad (18)$$

V. Results

A. Modeling

For each of the models, the feature set is obtained for the 2020-21, 2021-22, 2022-23, 2024-25 seasons. An concatenated example of the feature set is shown in Figure 1

Each model then receives a $\frac{3}{4}$ to $\frac{1}{4}$ randomized split of training to testing data. This allows each model to evaluate its current candidate feature weights against a random assortment of game outputs. Before passing the data to each model, the input features are transformed using the Sigmoid function into value between 0 and 1. This helps each model not obtain better relative weights between features such that any element of the feature set with a large magnitude does not dominate the optimizer. Afterwards, the unit scaled data is passed into each model to generate the optimal feature weights. These

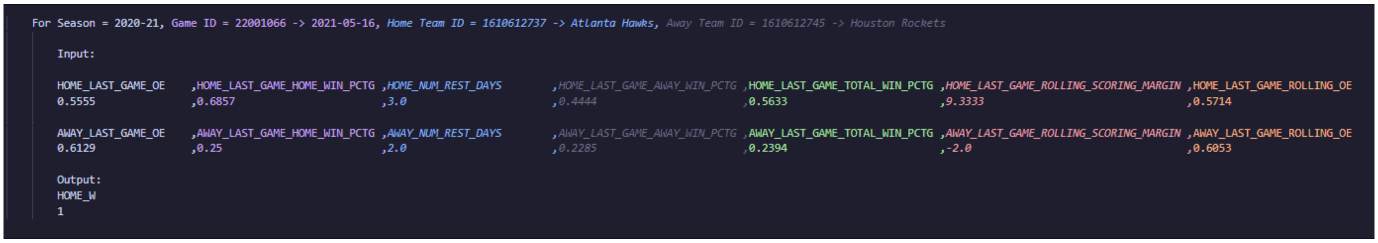


Fig. 1: Example Data for Model

feature weights and corresponding feature values are then used generate predictions to compare against a validation data set from the current 2024-25 NBA season.

1) Logistic Regression: The ROC curve and temporal correct predictions for the training and validation data shown in Figure 2. Additionally, the classification report and relevant statistics are tabulated in II and III for both the training and validation data.

TABLE II: Training Data: Logistic Regression Report

Class	Precision	Recall	F1-Score	Support
0	0.63	0.48	0.54	511
1	0.65	0.77	0.70	636
Weighted Average	0.64	0.64	0.63	1147
Additional Metrics:				
Accuracy	0.64			
Cross-Entropy Loss	0.64			
AUC-ROC	0.66			

TABLE III: Validation Data: Logistic Regression Report

Class	Precision	Recall	F1-Score	Support
0	0.61	0.49	0.54	130
1	0.68	0.77	0.72	181
Weighted Average	0.65	0.66	0.65	311
Additional Metrics:				
Accuracy	0.66			
Cross-Entropy Loss	0.64			
AUC-ROC	0.66			

Looking at these results, it is clear from the classification reports the training and validation data sets have similar performance. Both report an accuracy of about 66% with a cross-entropy loss of 64%. The similarity between the two data sets indicates a consistent model. Interestingly, while both models are able have a high precision for the positive class demonstrating the ability to correctly predict a home win, they struggle to identify the times when a home team loses with lower recall values for the zero class. Nevertheless, the area under the ROC curve is large enough to argue that the model does a decent job of differentiating between the two classes. These statistics match up well with the results from Figure 2.

2) Neural Network: The multi-layer perceptron neural network performance is demonstrated for both the training and validation data sets shown in Figures 3. Similar to before, the classification report and relevant statistics are tabulated in IV and V.

TABLE IV: Training Data: Neural Network Report

Class	Precision	Recall	F1-Score	Support
0	0.53	0.54	0.49	533
1	0.60	0.58	0.59	614
Weighted Average	0.57	0.56	0.57	1147
Additional Metrics:				
Accuracy	0.56			
Cross-Entropy Loss	2.84			
AUC-ROC	0.55			

TABLE V: Validation Data: Neural Network Report

Class	Precision	Recall	F1-Score	Support
0	0.45	0.52	0.48	130
1	0.61	0.55	0.58	181
Weighted Average	0.55	0.54	0.54	311
Additional Metrics:				
Accuracy	0.54			
Cross-Entropy Loss	3.12			
AUC-ROC	0.55			

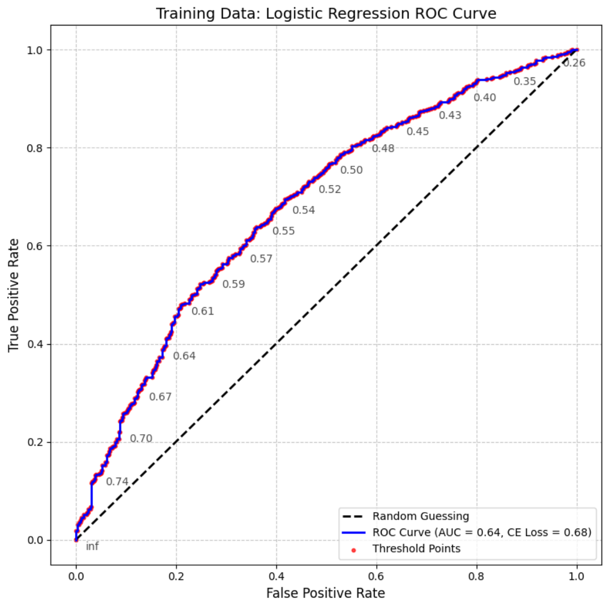
Compared to the logistic regression, the neural network has worse accuracy. Most visually apparent in Figure 3, this method generates either very large or very small probabilities. There are few data points that fall in between. As a result, this model is much less confident in its predictions shown by the larger cross-entropy value. Furthermore, while this model has a larger recall value for the zero class, and is subsequently able to identify home losses at a better rate. This is likely due to the model predicting more losses in general, and it not necessarily reflective of a better model for those cases.

Overall, the logistic regression provides more accurate results, better differentiates between the two classes, and is more confident in its predictions. Therefore it will be used as the primary model for the MILP.

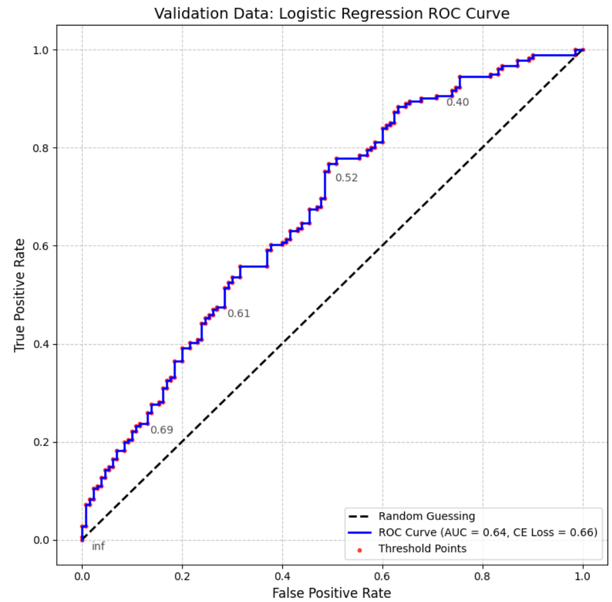
B. Mixed Integer Linear Parlay

Using the logistic regression, the mixed integer linear program was given four sets, one set per day, of moneyline odds shown Figure 4 that were directly generated by from DraftKings.

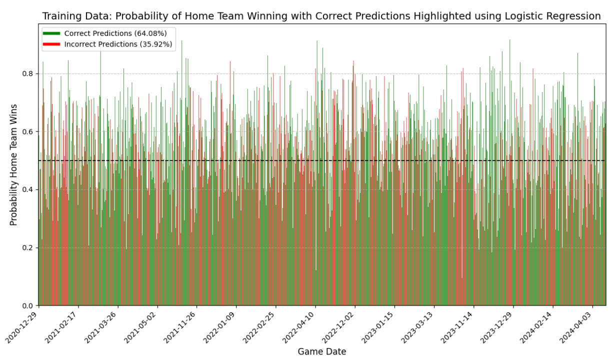
The program is constrained to bet a maximum of $1000 per day and choose at least half of the available games to wager upon. The results are shown in Figures 5, 6, 7, 8. Overall, the method ended up losing $353.33. This is largely due to the optimizer spending all of its money on one, moderately



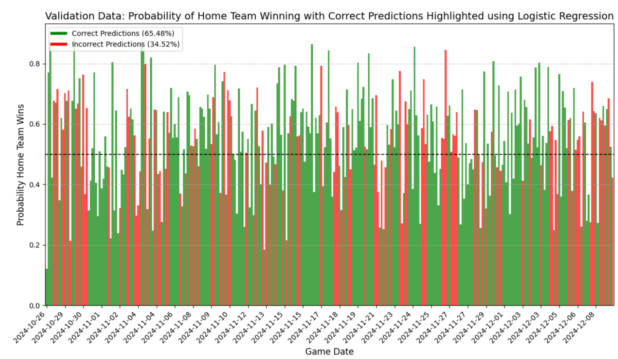
(a) Logistic Regression on Training Data



(b) Logistic Regression on Validation Data



(c) Logistic Regression on Training Data



(d) Logistic Regression on Validation Data

Fig. 2: Logistic Regression Model Evaluation

probable, but extremely profitable wager. As a result, the risk is not very well spread across the number of bets and the success of the algorithm is entirely based upon the success of the one large wager. While this worked on December 5th, Figure 8, it failed on November 27th, Figure 5.

It is important to note that there was a very small data set of sports book odds evaluate the MILP. Additionally, there are weak constraints on the allocation of resources. As a result, the algorithm typically wagers the majority of its money on a single bet and the minimum wager on more probable, but less profitable, money lines. The constraint to wager on exactly half of the available games was an initial attempt to distribute the risk among multiple wagers but proved unsuccessful.

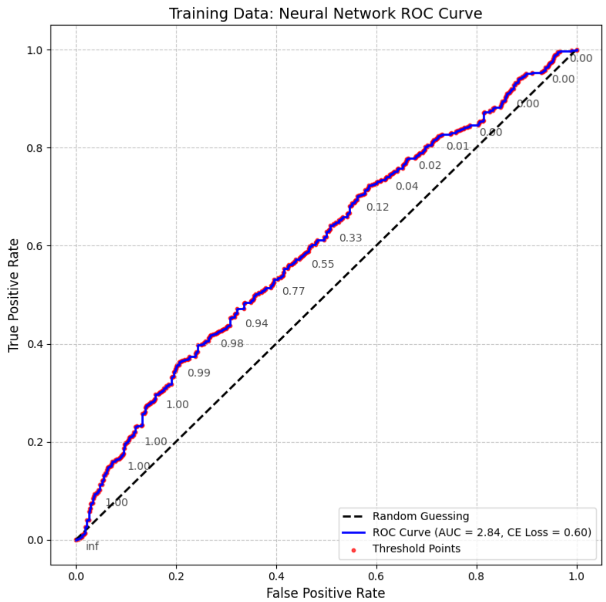
VI. Conclusions

Overall, both methods were able to have an accuracy greater than 50% which is good for modeling purposes. However this is not novel and several off-the-shelf algorithms are capable of generating these results. Compare the two models, the logistic regression was able to generate probabilities that aided the MILP in balancing the expected value of the profit. However, the neural network struggled in that regard and was not able to generate moderate probabilities that would have helped balanced risk and reward. Nevertheless, the sample size for the money lines was small and more samples are required to argue more tangible conclusions about the profitability of these methods.

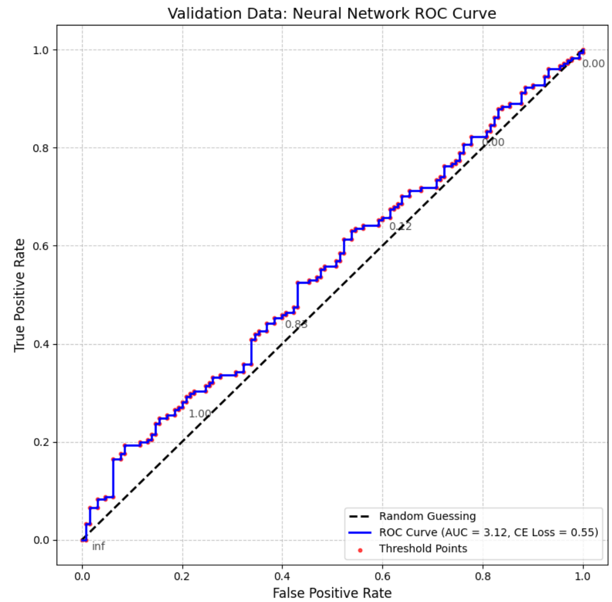
VII. Contributions,Future Work, and Release

This project was independently completed with the help of a tutorial provided by the NBA API documentation to generate a model for logistic regression using the same features presented in this paper.

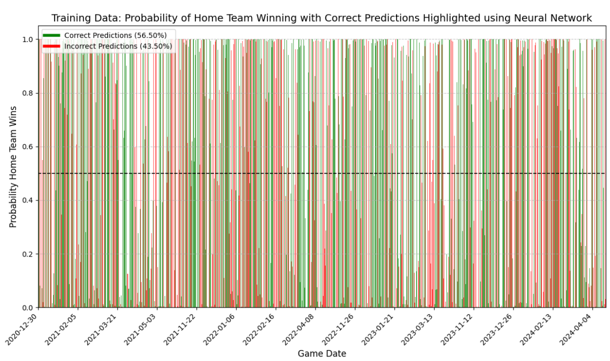
Future work involves adding new features to the data set specifically considering injuries and a historical frequency analysis of matchups. Furthermore, a more thorough investiga-



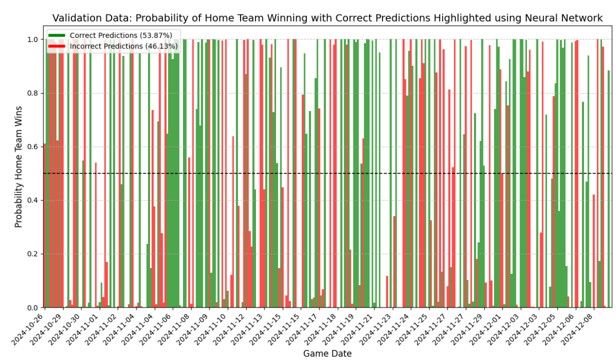
(a) Neural Network on Training Data



(b) Neural Network on Validation Data



(c) Neural Network on Training Data



(d) Neural Network on Validation Data

Fig. 3: Neural Network Model Evaluation

tion into the model parameters and the specific neural network classifier should be conducted to better explore the design space. Lastly, a more risk aware MILP can be constructed to better balance risk among the set of wagers as opposed to going big on a single money line.

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The NBA API provided all data and a tutorial for how to create a logistic regression using the described feature set. The SciKit python library was used for logistic regression and neural network modeling and evaluation. The PULP library was used to create and solve the mixed integer linear program. No optimization algorithms were implemented from scratch.

DATE	AWAY	HOME	AWAY_MONEYLINE	HOME_MONEYLINE
2024-11-27	Hawks	Cavaliers	350	-455
2024-11-27	Bulls	Magic	320	-410
2024-11-27	Trail Blazers	Pacers	360	-470
2024-11-27	Clippers	Wizards	-470	360
2024-11-27	Rockets	76ers	-218	180
2024-11-27	Heat	Hornets	-175	145
2024-11-27	Knicks	Mavericks	-170	142
2024-11-27	Kings	Timberwolves	130	-155
2024-11-27	Pistons	Grizzlies	275	-345
2024-11-27	Raptors	Pelicans	130	-155
2024-11-27	Lakers	Spurs	-125	105
2024-11-27	Nuggets	Jazz	-535	400
2024-11-27	Nets	Suns	320	-410
2024-11-27	Thunder	Warriors	-180	150
2024-12-02	Heat	Celtics	575	-950
2024-12-02	Pelicans	Hawks	325	-540
2024-12-02	Lakers	Timberwolves	230	-285
2024-12-02	Nets	Bulls	250	-310
2024-12-02	Bucks	Pistons	-162	126
2024-12-02	76ers	Hornets	-205	170
2024-12-02	Wizards	Cavaliers	950	-1650
2024-12-02	Magic	Knicks	190	-230
2024-12-02	Pacers	Raptors	-130	110
2024-12-02	Jazz	Thunder	750	-1200
2024-12-02	Grizzlies	Mavericks	150	-180
2024-12-02	Spurs	Suns	205	-250
2024-12-02	Warriors	Nuggets	170	-205
2024-12-02	Rockets	Kings	-130	110
2024-12-02	Trail Blazers	Clippers	310	-395
2024-12-05	Mavericks	Wizards	-750	525
2024-12-05	Nuggets	Cavaliers	140	-166
2024-12-05	Hornets	Knicks	850	-1450
2024-12-05	Thunder	Raptors	-410	320
2024-12-05	Bulls	Spurs	110	-130
2024-12-05	Suns	Pelicans	-115	-105
2024-12-05	Kings	Grizzlies	150	-180
2024-12-05	Rockets	Warriors	-170	142
2024-12-05	Magic	Bucks	170	-205
2024-12-05	Mavericks	Thunder	170	-205

Fig. 4: Betting Odds

DATE	AWAY	HOME	Away ML	Home ML	Predicted Home Win	Probability Home Win	Wager	Optimal Wager	Potential Return	Actual Return
11/27/2024	Hawks	Cavaliers	350	-455	TRUE	0.845	Yes	$ 17.86	$ 3.92	$ (17.86)
11/27/2024	Bulls	Magic	320	-410	TRUE	0.714	No	$ -	$ -	$ -
11/27/2024	Trail Blazers	Pacers	360	-470	TRUE	0.627	No	$ -	$ -	$ -
11/27/2024	Clippers	Wizards	-470	360	FALSE	0.267	No	$ -	$ -	$ -
11/27/2024	Rockets	76ers	-218	180	FALSE	0.4	No	$ -	$ -	$ -
11/27/2024	Heat	Hornets	-175	145	TRUE	0.56	Yes	$ 892.86	$1,294.64	$ (892.86)
11/27/2024	Knicks	Mavericks	-170	142	TRUE	0.537	Yes	$ 17.86	$ 25.36	$ 25.36
11/27/2024	Kings	Timberwolves	130	-155	TRUE	0.551	Yes	$ 17.86	$ 11.52	$ (17.86)
11/27/2024	Pistons	Grizzlies	275	-345	TRUE	0.661	No	$ -	$ -	$ -
11/27/2024	Raptors	Pelicans	130	-155	FALSE	0.49	Yes	$ 17.86	$ 23.21	$ 23.21
11/27/2024	Lakers	Spurs	-125	105	TRUE	0.639	Yes	$ 17.86	$ 18.75	$ (17.86)
11/27/2024	Nuggets	Jazz	-535	400	FALSE	0.353	No	$ -	$ -	$ -
11/27/2024	Nets	Suns	320	-410	TRUE	0.566	No	$ -	$ -	$ -
11/27/2024	Thunder	Warriors	-180	150	TRUE	0.508	Yes	$ 17.86	$ 26.79	$ (17.86)
						Total	6	$1,000.00	$1,404.20	$ (915.71)

Fig. 5: Betting Results November 27th, 2024

DATE	AWAY	HOME	Away ML	Home ML	Predicted Home Win	Probability Home Win	Wager	Optimal Wager	Potential Return	Actual Return
12/2/2024	Heat	Celtics	575	-950	TRUE	0.714	No	$ -	$ -	$ -
12/2/2024	Pelicans	Hawks	325	-540	TRUE	0.757	Yes	$ 937.50	$ 173.61	$ 173.61
12/2/2024	Lakers	Timberwolves	230	-285	TRUE	0.594	Yes	$ 62.50	$ 21.93	$ 21.93
12/2/2024	Nets	Bulls	250	-310	TRUE	0.601	No	$ -	$ -	$ -
						Total	2	$1,000.00	$ 195.54	$ 195.54

Fig. 6: Betting Results December 2nd, 2024

DATE	AWAY	HOME	Away ML	Home ML	Predicted Home Win	Probability Home Win	Wager	Optimal Wager	Potential Return	Actual Return
12/3/2024	Bucks	Pistons	-162	126	FALSE	0.488	No	$ -	$ -	$ -
12/3/2024	76ers	Hornets	-205	170	TRUE	0.615	Yes	$ 909.09	$1,545.45	$ (909.09)
12/3/2024	Wizards	Cavaliers	950	-1650	TRUE	0.803	No	$ -	$ -	$ -
12/3/2024	Magic	Knicks	190	-230	TRUE	0.535	No	$ -	$ -	$ -
12/3/2024	Pacers	Raptors	-130	110	TRUE	0.523	Yes	$ 22.73	$ 17.48	$ 17.48
12/3/2024	Jazz	Thunder	750	-1200	TRUE	0.788	No	$ -	$ -	$ -
12/3/2024	Grizzlies	Mavericks	150	-180	TRUE	0.556	No	$ -	$ -	$ -
12/3/2024	Spurs	Suns	205	-250	TRUE	0.656	Yes	$ 22.73	$ 9.09	$ 9.09
12/3/2024	Warriors	Nuggets	170	-205	FALSE	0.463	Yes	$ 22.73	$ 11.09	$ (22.73)
12/3/2024	Rockets	Kings	-130	110	FALSE	0.412	Yes	$ 22.73	$ 17.48	$ (22.73)
12/3/2024	Trail Blazers	Clippers	310	-395	TRUE	0.68	No	$ -	$ -	$ -
						Total	5	$1,000.00	$1,600.60	$ (927.97)

Fig. 7: Betting Results December 3rd, 2024

DATE	AWAY	HOME	Away ML	Home ML	Predicted Home Win	Probability Home Win	Wager	Optimal Wager	Potential Return	Actual Return
12/5/2024	Mavericks	Wizards	-750	525	FALSE	0.249	No	$ -	$ -	$ -
12/5/2024	Nuggets	Cavaliers	140	-166	TRUE	0.709	Yes	$ 31.25	$ 18.83	$ 18.83
12/5/2024	Hornets	Knicks	850	-1450	TRUE	0.765	No	$ -	$ -	$ -
12/5/2024	Thunder	Raptors	-410	320	FALSE	0.36	No	$ -	$ -	$ -
12/5/2024	Bulls	Spurs	110	-130	TRUE	0.547	No	$ -	$ -	$ -
12/5/2024	Suns	Pelicans	-115	-105	FALSE	0.369	Yes	$ 31.25	$ 29.76	$ (31.25)
12/5/2024	Kings	Grizzlies	150	-180	TRUE	0.654	Yes	$ 31.25	$ 17.36	$ 17.36
12/5/2024	Rockets	Warriors	-170	142	TRUE	0.52	Yes	$ 906.25	$1,286.88	$ 1,286.88
						Total	4	$1,000.00	$1,352.82	$ 1,291.81

Fig. 8: Betting Results December 5th, 2024

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