NBA Outcome Modeling

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Abstract

We investigate machine learning methods for predicting the combined points total for NBA game sports betting (the "Over–Under" betting category). Leveraging fully-connected neural networks, recurrent sequence models (LSTMs), and the collaborative filtering method, we train on historical box-score and betting-odds data to predict the outcomes of NBA games accurately in respect to time and different team match-ups.

1 Introduction

Sports betting is one of the fastest growing betting industries in the country, with an estimated 30% year-to-year growth [1]. As sports betting grows, so does the importance of being able to make accurate sports predictions and establish reliable betting lines. To that end, we investigate novel data-driven wagering decisions and employ several machine learning models that predict the total points scored in a game, also known as the Over-Under betting line, of NBA games. Our models include random forests, neural networks, collaborative filtering, and LSTMs.

2 Background & Related Work

Past efforts to predict sports betting outcomes have used traditional statistical approaches. Many utilize linear regression-based methods such as those proposed by Massey [2], which assign ratings to teams by solving a system of equations based on past game performance outcomes but is limited in its ability to capture non linear interactions. Recently, machine learning methods, particularly neural networks, have also risen in popularity for predicting sports betting outcomes due to their capacity to model complex relationships in data. Bunker and Susnjak [3] offer an overview of different machine learning applications in sports betting, concluding that deep learning methods or a combination of different machine learning methods frequently outperform simpler models.

Several works have attempted to address NBA-specific outcome modeling. Loeffelholz et al. [4] developed a neural network model to predict NBA game winners, achieving 74% accuracy on historical outcomes, demonstrating the relative success of using feedforward architectures. Meanwhile, Zimmermann et al. [5] examined various machine learning approaches for predicting player-specific performances, showing that metadata such as individual player metrics could be used to support team-level inferences.

This paper is a recreation and extension of The Bank is Open: AI in Sports Gambling [6].

2.1 Data

We scraped our NBA data from online sports websites. This data includes odds or betting data and game statistics such as points scored, rebounds, assists, steals, and more. In total, 3 websites were used.

- Sportsbook reviews [7]: This website contains betting and point data for every game in an NBA season. It includes the money line for each game, which is the odds to win the game, in addition to the point score at the end of each quarter.
- Basketball reference [8]: This website hosts a wide variety of NBA statistics, but we focus on using the box score data for each game. The box score includes information about each team and player after the game, such as the point scores, 3-pointers, rebounds, free throws, field goals, and more.
- Team rankings [9]: This website also stores information about every NBA matchup, but we specifically scraped each NBA team's average scoring margin per day. Scoring margin is the difference between how many points a team scores and how many points the other team scored in a single game.

This data is scraped in either excel or csv file format. The data processing system works as follows:

1. Clean odds and game DataFrames and map varying team names to 3-letter abbreviations for name standardization, and merge odds with game stats.
2. Compute chi-square tests comparing Over/Under vs. Moneyline.
3. Compute rolling averages of box-score stats over recent games for each team.
4. For each home game, collect 1) One-hot encodings of home and away teams, 2) Recent game stats for both teams, accounting for travel distances, and 3) Season-to-date average stats of opponents.
5. Stack these into an $(\text{games}, \#\text{ of recent games}, \text{features})$ array and save (X, y) as pickled NumPy arrays for modeling.

3 Methods

3.1 Baseline Model (Random Forest)

Overview To first create a baseline model, we create decision trees to perform regression. Each tree is trained on a bootstrap sample of the data and makes a prediction by averaging its leaf outputs. The forest's final prediction is the mean of all individual tree predictions:

$$\hat{y}(x) = \frac{1}{T} \sum_{t=1}^{T} h_t(x),$$

where T is the number of trees and h_t is the t-th tree's prediction.

3.2 Fully Connected Neural Networks

Our neural network implementation leverages PyTorch to create a deep fully-connected architecture for predicting the total points scored in NBA games. The model processes 1524 features representing each team's statistics from their previous three games, capturing recent performance trends and matchup dynamics.

The network architecture consists of five fully-connected layers with decreasing width to progressively extract higher-level patterns from the input data: Input layer: 1524 features $\rightarrow$ 512 neurons; Hidden layer 1: 512 $\rightarrow$ 256 neurons; Hidden layer 2: 256 $\rightarrow$ 128 neurons; Hidden layer 3: 128 $\rightarrow$ 64 neurons; Output layer: 64 $\rightarrow$ 1 neuron (point total prediction).

ReLU activation functions follow each hidden layer to introduce non-linearity and mitigate the vanishing gradient problem:

$$f(x) = \max(0, x) \tag{1}$$

The model is trained using the Adam Optimizer with a learning rate of 10^{-6} and weight decay regularization (coefficient = 10^{-5}) to prevent overfitting. We employ Mean Squared Error (MSE) as our loss function:

$$\mathcal{L}MSE = \frac{1}{n}\sum i = 1^{n}(y_i - \hat{y}i)^2 \tag{2}$$

where y_i represents the actual point total and $\hat{y}i$ is the predicted value. During training, we monitor both training and validation loss to ensure proper generalization.

3.3 Collaborative Filtering

Setup. Past NBA team matchups form a sparse matrix $R \in \mathbb{R}^{m \times n}$ whose entry r_{ij} is the total points when home team i played against visitor j. Collaborative filtering is commonly used by recommendation systems (i.e. Amazon and Netflix), where rows are “users," columns are "items," and entries r_{ij} predict user-item interaction (i.e. ratings) based on past user-item interactions. Likewise, our implementation treats home teams as "users," visitor teams as "items," and predicted cumulative points as the "interactions".

We approximate R with a rank-k model

$$\hat{r}_{ij} = \mu + b_i + b_j + \mathbf{p}_i^{\top}\mathbf{q}_j, \tag{3}$$

where μ is the global mean total, b_i and b_j are team-specific bias terms, and $\mathbf{p}_i, \mathbf{q}_j \in \mathbb{R}^k$ ($k = 10$) are latent “offence” and “defence” factors. Equation (3) thus corresponds to the low-rank factorisation $R \approx U\Sigma V^T$ with additive bias terms.

Model parameters minimise the ℓ_2-regularised loss

$$\mathcal{L} \;=\; \sum_{(i,j)\in\Omega} \big(r_{ij} - \hat{r}_{ij}\big)^2 + \lambda\big(\|\mathbf{p}_i\|^2 + \|\mathbf{q}_j\|^2 + b_i^2 + b_j^2\big),$$

with Ω the set of played games. Stochastic gradient descent updates, e.g. for $\mathbf{p}_i$, are $\mathbf{p}_i \leftarrow \mathbf{p}_i + \eta(e_{ij}\mathbf{q}_j - \lambda\mathbf{p}_i)$ where $e_{ij} = r_{ij} - \hat{r}_{ij}$. We use step size $\eta = 10^{-4}$ and $\lambda = 5 \times 10^{-3}$.

Because rosters and form shift rapidly, the model is retrained using various timeframes; the most recent w days of data. A grid search over $w \in \{3, \ldots, 21\}$ found $w = 3$ to 5 ($\approx$ 36-60 games) minimizes validation error. Finally, we use the `Surprise` `SVD` class (SGD optimiser, $k = 10$, 1000 epochs, η and λ as above).

3.4 Long Short Term Memory Networks (LSTMs)

Overview Each LSTM cell processes an input vector x_t, the previous hidden state h_{t-1}, and the cell state c_{t-1}, producing updated states h_t and c_t. The underlying equations are:

$$i_t = \sigma\big(W_i x_t + U_i h_{t-1} + b_i\big) \qquad \text{(input gate)} \tag{4}$$

$$f_t = \sigma\big(W_f x_t + U_f h_{t-1} + b_f\big) \qquad \text{(forget gate)} \tag{5}$$

$$o_t = \sigma\big(W_o x_t + U_o h_{t-1} + b_o\big) \qquad \text{(output gate)} \tag{6}$$

$$\tilde{c}_t = \tanh\big(W_c x_t + U_c h_{t-1} + b_c\big) \qquad \text{(cell input)} \tag{7}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \qquad \text{(new cell state)} \tag{8}$$

$$h_t = o_t \odot \tanh(c_t) \qquad \text{(new hidden state)} \tag{9}$$

$\sigma(\cdot)$ is the logistic sigmoid and $\tanh(\cdot)$ is the hyperbolic tangent. W_i, U_i, and b_i are learned parameters.

- One LSTM layer, which reads the input sequence and returns only the final hidden state.
- A dropout layer applied to the output to reduce overfitting.
- Fully-connected dense layer with ReLU activation.
- Dropout layer with the same rate as the previous.
- Output layer with a single unit and linear activation for regression.

The model is compiled with an Adam optimizer and uses MSE loss and mean absolute error (MAE) as metrics.

4 Experiments

4.1 Baseline Model (Random Forest)

Our Baseline Random Forest model is trained on games from the 2007-2008 season, validated against 2008-2009, and tested against 2009-2010. Each game has 1525 features, the same as each other model, except also adding a time variable.

Hyperparameter	Value
Number of trees, T	150
Maximum tree depth	1
Split criterion	Mean Squared Error (MSE)

Table 1: Hyperparameters for the LSTM model.

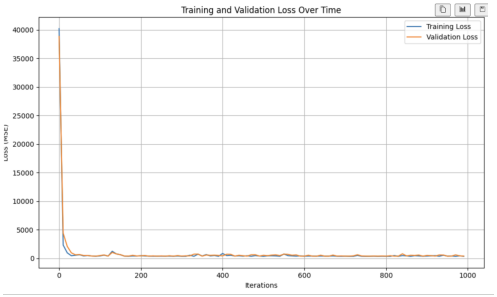
Dataset	**Loss**
Train	1280.88
Validation	811.99
Test	5178.90

Table 2: Final model losses.

4.2 Fully Connected Neural Networks

We evaluate our fully connected neural network on NBA seasons 2012–2018, using 2012–2016 seasons for training (5,069 games), 2016–2017 for validation (1,260 games), and 2017–2018 for testing (1,264 games). The model processes 1,524 features per game, representing both teams' performance statistics from their previous three games. We train for 1,000 epochs using SGD with a learning rate of 10^{-5} and weight decay of 10^{-6} for regularization. The model shows convergence within 100 epochs, demonstrating its ability to capture the underlying patterns in the data despite the inherently high-variance nature of NBA scoring totals.

Loss Accuracy	**Train MSE**	**Test MSE**
Neural Network	332.99	369.38



4.3 Collaborative Filtering

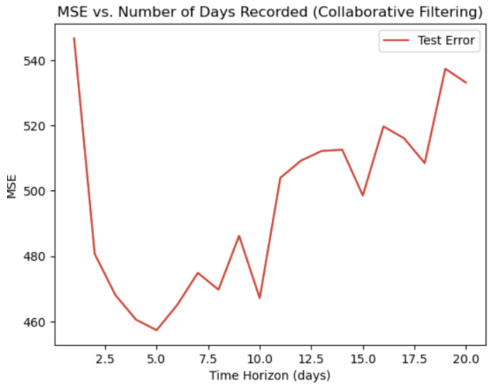
While our model has similar results to the original neural network, our model converges in 30 epochs while the original paper converges in ~100-150 epochs.

Experimental setup. We evaluate the CF pipeline on NBA games from the 2007–08 through 2017–18 seasons. The model uses a sliding window approach where, at the start of each game-day, only matches from the preceding w days are visible (with w varied from 1 to 20 days to determine the optimal window size). Metrics are computed *chronologically* to avoid look-ahead bias, with the model being retrained for each new window of games.

Prediction accuracy. Table 3 reports the Mean Squared Error (MSE) of the CF model against three baselines:

Table 3: Mean Squared Error (MSE) of CF model vs. baselines

Method	**Train MSE ↓**	**Test MSE**
Collaborative Filtering	2.85	369.84



This plot shows the MSE when considering different sized windows of data (last X number of days). Based on this plot, we can infer that a window of 3-5 days is optimal because it balances prioritizing relevant information of sports athletes with having a sufficient amount of data to inform our model.

4.4 Long Short Term Memory Networks (LSTMs)

Our Long Short Term Memory (LSTM) model is trained on games from the 2012-2013, 2013-2014, 2014-2015, and 2015-2016 seasons, validated against 2016-2017, and tested against 2017-2018. Each game has 1524 features.

Hyperparameter	Value
Number of LSTM units	128
Dense layer size	64
Dropout rate	0.10
Batch size	5
Number of epochs	30
Optimizer	Adam
Loss function	MSE
Patience	5 epochs

Table 4: Hyperparameters for the LSTM model.

Dataset	**Loss**
Train	546.63
Validation	399.40
Test	398.29

Table 5: Final model losses.

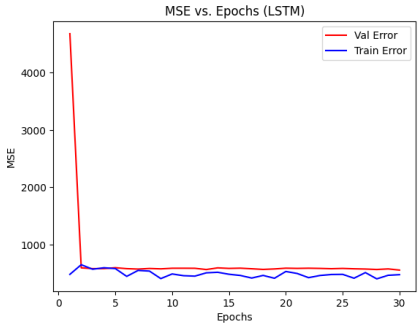


Figure 1: LSTM Loss (MSE) across 30 epochs

5 Conclusion

5.1 Discussion

Overall, Neural Networks had the best test MSE, at 369.38. LSTM posted similar results (test MSE = 398.29) by modeling temporal dependencies, and the Random Forest Baseline model performed much worse than the other models. Collaborative filtering remains competitive with the two better models, but its reliance on very recent data, with an optimal 3–5 day window, may require frequent retraining, which could be inefficient when compared to other models. The deeper models demanded more training time and hyperparameter searching, whereas collaborative filtering could be retrained quickly but missed broader factors, leading to poorer results.

The superior performance of the fully connected network (MSE = 369.38) suggests that capturing non-linear interactions among hundreds of box-score features is critical. Furthermore, the LSTM's similar performance (MSE = 398.29) indicates that short-term temporal patterns carry predictive signal, and working on better utilizing longer-range dependecies may help. Furthermore, the competitive performance of collaborative filtering highlights the value of latent team-vs-team interactions, yet its dependence on a narrow 3–5 day retraining window raises concerns about model drift. The random forest, while easier to interpret and faster to train, fails to model the complex interactions that drive high-variance NBA scoring, resulting in suboptimal accuracy.

Below are a table and chart that represent our final losses:

Dataset	Train Loss (MSE)	Val Loss (MSE)	Test Loss (MSE)
Random Forest	1280.88	811.99	5178.90
Collaborative Filtering	2.85	N/A	457.32
Neural Networks	332.99	369.41	369.38
LSTM	546.63	399.40	398.29

Table 6: Our Model Losses Comparison

Figure 2: Loss Comparison Chart (Logarithmic)

5.1.1 Future Work

With more time and resources, we could improve upon the work done in this paper in the following ways:

Firstly, we could use more diverse data and richer contextual features. For example, we could include features such as player-level statistics, injury reports, rest days, back-to-back indicators, and more.

We could also consider using different model architectures such as transformer-based sequence models. We could feed the past T games for each team into a Transformer encoder with positional embeddings and attention headers, allowing the model to weight non-contiguous games while not being limited by a fixed window. We could also consider using graph neural networks (GNNs) as they offer a natural way to model all of our model matchups.

Lastly, we could consider building a real-time deployment pipeline that retrains based on live odds and in-game stats. This extension would create the most impact on real sports bettors, but may be difficult to use in practice.

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