NBA Game Predictor with Feature Engineering

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Abstract

This study explores the application of various machine learning models to predict outcomes of NBA games, focusing on the challenges of feature selection and model overfitting. We employed logistic regression, support vector machines, feed-forward neural networks, and decision trees, each rigorously tuned to optimize performance. Our methodology emphasized careful feature selection to enhance model accuracy and generalizability. The results indicate that while traditional models like logistic regression and neural networks achieved moderate success, the decision tree model, despite its simplicity, provided valuable insights into feature importance and model transparency. The study also highlighted the potential of integrating non-numerical data to further improve predictive accuracy. Overall, our findings contribute to the ongoing discourse in sports analytics by demonstrating the effectiveness of methodical data processing and feature engineering in improving the predictive performance of machine learning models in sports outcomes.

1. Introduction

The realm of sports analytics, particularly in predicting the outcomes of NBA games, presents a complex challenge that intertwines vast datasets with the dynamic nature of sports. This paper delves into the application of advanced machine learning techniques to predict NBA game outcomes, emphasizing the critical role of feature engineering in enhancing model performance.

1.1. Problem Statement

Predicting the outcomes of NBA games involves analyzing various factors such as team statistics, player performance, and historical data. The inherent unpredictability of sports events, compounded by the voluminous and multifaceted nature of sports data, makes accurate prediction particularly challenging. This project aims to address these challenges by applying sophisticated machine learning models, with a focus on the potent role of feature engineering in improving prediction accuracy.

1.2. Feature Engineering Techniques

Feature engineering stands as a cornerstone of our approach, significantly influencing the efficacy of the predictive models employed. In this project, we explored several feature engineering techniques to refine our models' input data, thereby enhancing their predictive accuracy. These techniques include:

- **Data Preprocessing:** Initial steps involved handling missing values and normalizing data to ensure model stability and performance.
- **Feature Selection:** We employed methods like recursive feature elimination and principal component analysis to identify and retain the most relevant features, reducing dimensionality and avoiding model overfitting.
- **Feature Transformation:** Techniques such as logarithmic transformations and polynomial features were used to modify feature scales and relationships, aiming to better capture the nonlinear dependencies between variables.
- **Feature Creation:** New features were derived from existing data, such as calculating moving averages of player performance metrics, to provide models with more informative inputs.

1.3. Model Implementation and Results

We implemented multiple machine learning models, including logistic regression, support vector machines, decision trees, and neural networks. Each model was rigorously tuned and evaluated using a dataset meticulously prepared through our feature engineering processes. The logistic regression model, enhanced through feature engineering, showed a notable improvement in accuracy compared to baseline models. This underscores the effectiveness of our feature engineering strategies in tackling the predictive challenges of NBA game outcomes.

1.4. Conclusion

The integration of comprehensive feature engineering techniques significantly contributed to the predictive accuracy of

our models. This study not only advances the field of sports analytics by providing a robust methodological framework for game outcome prediction but also highlights the transformative impact of feature engineering in handling complex predictive tasks in machine learning.

The desired output of our machine learning model is binary: a '1' represents a win for the home team, while a '0' indicates a loss. This binary outcome helps streamline the prediction process, making it straightforward and specifically tailored to assessing home team advantage, a well-recognized factor in sports analytics.

The motivation behind selecting this problem stems from a desire to deepen the understanding of NBA analytics. By identifying which statistical measures most effectively predict game outcomes, we can offer deeper insights into the dynamics of winning in professional basketball. This not only aids teams in strategizing and game preparation but also enhances the analytical tools available to the broader sports community. In doing so, our project bridges the gap between historical data and predictive accuracy, shedding light on the evolving nature of competitive basketball.

Our final models included logistic regression and neural networks, which were evaluated against a baseline model that used only three-point shooting percentages—a statistic commonly regarded as a strong predictor of game outcomes. The results demonstrated that our refined logistic regression model, which considered a broader array of statistics, outperformed the neural network model, achieving an accuracy of 60%. This accuracy, while modest, represents a significant improvement over the baseline and highlights the potential for more nuanced analytics in sports prediction. The study uncovered interesting dynamics, such as the negative impact of offensive rebounds on game outcomes, suggesting that not all intuitively positive statistics are beneficial in predicting wins. These findings underscore the complexity of sports analytics and the value of machine learning in uncovering less obvious insights that can influence game strategy and betting practices.

2. Related Work

In recent research on NBA game prediction using machine learning, several approaches and challenges have emerged, providing valuable insights for comparing methodologies and findings. Here's a breakdown of key observations from the related work:

2.1. Feature Selection and Data Processing

Alexander Fayad's project focused on using monthly statistics from the NBA as predictors. This approach underscores the challenge of acquiring and processing relevant data for predictive modeling in sports analytics. Notably, the emphasis on recent data and the simplification of mathematical complexity highlight the importance of data quality over quantity (Towards Data Science).

2.2. Graph Convolutional Networks (GCN)

Researchers introduced a novel approach using Graph Convolutional Networks (GCNs) to predict NBA game outcomes. By leveraging the spatial representation of teams in a graph structure, this method offers a sophisticated analysis of team dynamics and interactions. In contrast, traditional statistical data and machine learning models, without incorporating relational dynamics between teams as graph data, were employed in our project (MDPI).

2.3. Challenges with Traditional Models

Traditional machine learning models such as logistic regression, support vector machines, and neural networks have shown varying success rates in predicting NBA game outcomes. Studies have reported success rates ranging from 60

2.4. Comparative Analysis

Our approach distinguishes itself through a rigorous focus on feature engineering and the exclusion of direct game outcome indicators, which are often included in other models. By prioritizing broader performance metrics and uncovering less obvious statistical influences on game results, our model aims to provide both reliable predictions and insightful analysis for real-world betting scenarios.

3. Dataset and Evaluation

3.1. Dataset

Our study leverages two principal datasets collected from Kaggle, game_data.csv and team_details.csv, which collectively form the foundation of our predictive analysis on NBA game outcomes. These datasets were meticulously selected to provide a comprehensive overview of both game-specific statistics and team-related information, enabling a multifaceted approach to understanding the dynamics of basketball games.

The game_data.csv dataset is a detailed compilation of statistics from individual NBA games, with each row representing a unique game. This dataset is structured to include a wide

array of variables that capture the performance metrics of both teams and their players within a game. Key features of this dataset include:

- Team Identifiers: team_id_home and team_id_away denote the unique identifiers for the home and away teams, respectively.
- Win/Loss Outcomes: wl_home and wl_away provide binary indicators of win or loss outcomes for the home and away teams.
- Performance Metrics: Detailed statistics for both teams, such as field goals made (fgm_home, fgm_away), field goals attempted (fga_home, fga_away), and three-point field goals made (fg3m_home, fg3m_away), among others.
- Aggregate Statistics: Comprehensive metrics like total rebounds (reb_home, reb_away), assists (ast_home, ast_away), and total points scored (pts_home, pts_away).

In contrast, the team_details.csv dataset offers a broader perspective on each NBA team, encapsulating essential foundational and operational attributes. Each row corresponds to a different team, with variables that include:

- Team ID: A unique identifier for each team (team_id).
- Descriptive Attributes: Information such as the team's abbreviation (abbreviation), nickname (nickname), founding year (yearfounded), and city (city).
- Operational Details: Insights into the team's arena (arena), arena capacity (arenacapacity), ownership (owner), general management (generalmanager), and head coaching (headcoach)
- Digital Footprint: Links to the team's official social media pages on Facebook (facebook), Instagram (instagram), and Twitter (twitter).

This dataset provides valuable context on the historical and organizational aspects of each team, which can indirectly influence game performance and outcomes.

3.2. Data Preprocessing

In the data preprocessing phase of our study, we implemented a series of strategic transformations to refine our primary datasets, thereby enhancing the robustness and predictive accuracy of our model. The primary focus was on stabilizing the variability inherent in single-game data and enriching the dataset with contextual team performance metrics. This was achieved through two main preprocessing steps: computing team average statistics and augmenting game data with these statistics.

3.2.1. Computing Team Average Statistics

The first step in our preprocessing involved computing average statistics for each team across multiple seasons. This approach was designed to mitigate the fluctuations seen in single-game performance metrics, which can be influenced by transient factors such as player injuries or short-term form. By aggregating these statistics over a longer period, we obtain a more stable and representative measure of a team's capabilities.

The computation was performed using the following code snippet:

```
average_stats = combined_stats.groupby(
                'team_id').agg(lambda x:
                x.mean()).reset_index()
```

Here, `combined_stats` is a DataFrame containing game-level statistics for all teams. The `groupby` method groups the data by `team_id`, and the `agg` function applies the mean function to each group, effectively calculating the average of each statistic for each team. This method ensures that the derived metrics, such as three-point percentages and free throw percentages, reflect a more consistent performance level, providing a solid foundation for predictive modeling.

3.2.2. Augmenting Game Data with Team Stats

The second preprocessing step involved enhancing the game dataset by merging it with the computed team averages. This augmentation process integrates historical performance data into the game-specific dataset, allowing each game entry to be contextualized with the average statistics of both the home and away teams.

The merging process was facilitated by the following code:

```
df_merged = pd.merge(df_games,
            df_team_avg_home,
            how="left", ...)
```

In this step, `df_games` represents the original game data, and `df_team_avg_home` contains the team averages. The merge operation is performed such that each game record is supplemented with the corresponding team statistics, ensuring that the dataset includes comprehensive features for both participating teams.

3.2.3. Advantages of Augmented Data

The augmentation of game data with team average statistics offers several significant advantages:

1. **Enhanced Model Accuracy**: By incorporating team averages, the model can make predictions based on a richer set of features that include not only game-specific data but also historical performance metrics. This leads to a more nuanced understanding of each team's strengths and weaknesses.

2. **Reduction of Overfitting**: The variability in single-game data can lead to overfitting, where a model learns noise rather than the underlying pattern. Averaging statistics over multiple seasons reduces this risk, making the model more generalizable to new, unseen data.

3. **Improved Contextual Analysis**: The augmented data allows the model to consider the context of each team's long-term performance trends, which is crucial for assessing how teams might perform under various game conditions.

Overall, the preprocessing steps of computing team averages and augmenting game data are critical for preparing our dataset for effective model training. These methods not only stabilize the input data but also enrich the feature set, thereby laying a solid foundation for building a robust predictive model.

3.3. Data Splitting Strategy

In our project, a critical step towards ensuring the robustness and generalizability of our predictive model was the strategic division of our dataset into training, development, and testing sets. This division was executed with a proportion of 70%, 15%, and 15% respectively. Such a split facilitates a comprehensive evaluation framework, allowing for iterative model training, fine-tuning, and final evaluation on unseen data.

3.3.1. Training, Development, and Testing Sets

- **Training Set (70%)**: This subset is used for the initial training of our model. It provides a broad range of data points for the model to learn from, encompassing various scenarios and outcomes from the historical game and team data.

- **Development Set (15%)**: Also known as the validation set, this subset is crucial for model tuning and hyperparameter optimization. It acts as a proxy for the test set during the model development phase, enabling the assessment of model performance and the identification of overfitting.

- **Testing Set (15%)**: The testing set is reserved for the final evaluation of the model. It consists of data that the model has never seen during the training or development phases, serving as a critical measure of the model's predictive power and generalizability to new data.

3.3.2. Feature Engineering: Baseline vs. Tuned Feature Sets

In our project, we have implemented feature engineering techniques to create two distinct versions of our feature set: `X_baseline` and `X_tuned`. These feature sets are designed to evaluate the impact of different levels of feature complexity on the predictive accuracy of our model.

X_baseline The `X_baseline` feature set is intentionally simplistic, utilizing only the three-point percentage (`fg3_pct`) as its sole metric. This feature was chosen due to the significant impact that three-point shooting efficiency has on the outcomes of basketball games. The simplicity of `X_baseline` allows us to establish a baseline performance level for our predictive models, against which more complex models can be compared.

X_tuned Conversely, the `X_tuned` feature set is much more comprehensive, incorporating a wide range of team performance metrics that provide a deeper insight into both offensive and defensive aspects of the game. This feature set includes:

- **Home Team Metrics:**
  - `fg3_pct_home_avg`: Average three-point shooting percentage at home.
  - `ft_pct_home_avg`: Average free throw percentage at home.
  - `oreb_home_avg`: Average offensive rebounds per game at home.
  - `dreb_home_avg`: Average defensive rebounds per game at home.
  - `ast_home_avg`: Average assists per game at home.
  - `reb_home_avg`: Average total rebounds per game at home.
  - `stl_home_avg`: Average steals per game at home.
  - `blk_home_avg`: Average blocks per game at home.
  - `tov_home_avg`: Average turnovers per game at home.
- **Away Team Metrics:**
  - `fg3_pct_away_avg`: Average three-point shooting percentage away.
  - `ft_pct_away_avg`: Average free throw percentage away.

- `oreb_away_avg`: Average offensive rebounds per game away.
- `dreb_away_avg`: Average defensive rebounds per game away.
- `ast_away_avg`: Average assists per game away.
- `reb_away_avg`: Average total rebounds per game away.
- `stl_away_avg`: Average steals per game away.
- `blk_away_avg`: Average blocks per game away.
- `tov_away_avg`: Average turnovers per game away.

It is crucial to note that while the 'X_baseline' and 'X_tuned' datasets refer to the same data entries, the 'X_tuned' dataset encompasses a more extensive set of features compared to the 'X_baseline'. The following table summarizes the distribution of data entries across the different sets for both the baseline and tuned versions:

Table 1. Data Splitting Summary

Dataset	Training Set	Development Set	Testing Set
X_baseline	2488	533	534
X_tuned	2488	533	534

These metrics were selected to provide a holistic view of team performance, encompassing various aspects of gameplay that are critical to understanding and predicting the outcomes of NBA games. By using these detailed metrics in the `X_tuned` feature set, our model can leverage nuanced data points that reflect the strategic and operational effectiveness of the teams, thereby enhancing the predictive accuracy and depth of our analysis.

3.4. Evaluation Metrics

In the evaluation phase of our project, we utilized a set of metrics to rigorously assess the performance of our predictive models. These metrics are designed to provide a multifaceted view of model effectiveness, encompassing various aspects of prediction accuracy and error types. Among these, Accuracy was chosen as our primary metric due to its straightforward representation of overall model performance.

Accuracy is defined as the proportion of true results (both true positives and true negatives) in the total number of cases examined. It offers a clear and intuitive measure of how often the model is correct across both classes, making it particularly useful in scenarios where the classes are balanced. As our primary metric, Accuracy serves as the initial indicator of model success, guiding our evaluation of which model is considered "better" in terms of overall predictive capability.

In addition to Accuracy, we also considered the following metrics to ensure a comprehensive evaluation:

- **Precision**: Measures the proportion of correctly predicted positive observations to the total predicted positives. It is crucial for scenarios where the cost of false positives is high, helping us understand the model's ability to identify only relevant instances as positive.
- **Recall**: Quantifies the proportion of actual positives correctly identified by the model. This metric is vital in situations where missing a positive instance carries a significant penalty, providing insight into the model's capability to capture all relevant instances.
- **F1 Score**: The harmonic mean of Precision and Recall, offering a balance between the two. It becomes critical when an equilibrium between Precision and Recall is desired, ensuring that the model does not excessively favor one over the other.

The rationale behind selecting Accuracy as our primary metric lies in its ability to provide a quick and clear measure of model performance, especially useful in our balanced class scenario. However, to address the limitations of relying solely on Accuracy and to ensure a holistic view of model performance, we also incorporate Precision, Recall, and the F1 Score into our evaluation framework. This approach allows us to capture a detailed picture of model effectiveness, considering both the benefits of correct predictions and the costs associated with prediction errors.

4. Methods

4.1. Baseline Methods

We employ two baseline methods for rigorous evaluation:

Baseline Models: Models trained on the dataset X_baseline serve as our primary baseline. In contrast, models trained on X_tuned are considered comparison methods.

Comparison with Vegas Money-Line Odds: To assess our model's effectiveness, we'll compare performance against Vegas money-line odds. In sports betting, exceeding a 55% prediction accuracy can yield long-term profitability. Models consistently surpassing this 55% accuracy threshold will demonstrate improvement over conventional betting odds. This comparison offers both statistical and financial evaluation benchmarks.

4.2. Logistic Regression

In our study, we employed logistic regression, a fundamental yet powerful linear classifier, to model the relationship between our feature set and the binary outcome variable. The

implementation was facilitated by the `scikit-learn` library, a widely used tool in the machine learning community for its efficiency and ease of use.

4.2.1. Parameters and Hyperparameters

The logistic regression model in `scikit-learn` is highly customizable with several parameters and hyperparameters that can be tuned to optimize performance. For our experiments, we focused on the following key hyperparameters:

- **L1 Ratios:** This parameter is crucial when using Elastic Net regularization (a combination of L1 and L2 regularization). It determines the balance between L1 and L2 regularization, with values closer to 1 favoring L1, and values closer to 0 favoring L2. We experimented with ratios of $\{0.1, 0.5, 0.9\}$ to explore their impact on model performance.
- **Maximum Iterations:** This parameter specifies the maximum number of iterations for the solvers to converge. We tested a range of values: $\{100, 500, 1000, 2000, 5000\}$ to find an optimal balance between computational efficiency and model accuracy.

4.2.2. Hyperparameter Tuning

Hyperparameter tuning was conducted through exhaustive grid search, where each combination of L1 ratio and maximum iterations was evaluated. The process can be summarized in the following steps:

1. Initialize two logistic regression models with identical settings but different training data sets (baseline and pre-fined).
2. For each combination of L1 ratio and maximum iterations:
   (a) Set the hyperparameters for both models.
   (b) Train each model on its respective training set.
   (c) Evaluate the models on a development set, calculating accuracy, precision, recall, and F1 score.
3. Identify the combination of hyperparameters that yields the best performance based on accuracy or any other chosen metric.

This methodical approach allowed us to systematically explore the hyperparameter space and select the most effective settings for our logistic regression models.

4.2.3. Rationale for Hyperparameter Choices

The choice of hyperparameters was driven by the goal of overcoming limitations identified in our midterm report. By adjusting the L1 ratio, we aimed to find an optimal balance between model complexity and generalization ability, thus addressing overfitting or underfitting issues. The exploration of maximum iterations was intended to ensure that the solver had sufficient opportunity to converge to a solution, thereby improving model reliability.

4.2.4. Libraries Used

The implementation of our logistic regression models was primarily based on the `LogisticRegression` class from the `scikit-learn` library. This choice was motivated by the library's robustness, efficiency, and the comprehensive range of functionalities it offers for machine learning tasks.

4.3. Support Vector Machine (SVM)

Support Vector Machine (SVM) is a powerful and versatile supervised machine learning algorithm used for classification and regression tasks. In our project, we utilized the SVM classifier from the `scikit-learn` library to enhance our predictive modeling capabilities beyond the logistic regression model.

4.3.1. Parameters and Hyperparameters

The SVM classifier offers several parameters that can be tuned to optimize the model's performance. For our experiments, we focused on the following key hyperparameters:

- **C (Regularization Parameter):** The C parameter trades off correct classification of training examples against maximization of the decision function's margin. Higher C values lead to a smaller margin and can help the model better classify all training points correctly. We tested values $\{0.1, 1, 10\}$.
- **Kernel:** The kernel type can be linear, polynomial, radial basis function (rbf), or sigmoid. We experimented with {'linear', 'rbf', 'sigmoid'} to investigate how different kernels impact the performance.
- **Shrinking:** This is a heuristic method used to speed up training. We tested both {True, False} to determine the effect of this parameter on the training efficiency and model accuracy.

4.3.2. Hyperparameter Tuning

Hyperparameter tuning was conducted through a systematic grid search approach, where each combination of C, kernel type, and shrinking option was evaluated. The process can be summarized in the following steps:

1. Initialize two SVM models with identical settings but different training data sets (baseline and pre-fined).

2. For each combination of C, kernel, and shrinking:
   (a) Set the hyperparameters for both models.
   (b) Train each model on its respective training set.
   (c) Evaluate the models on a development set, calculating accuracy, precision, recall, and F1 score.
3. Identify the combination of hyperparameters that yields the best performance based on accuracy or any other chosen metric.

This exhaustive search allowed us to explore various configurations and select the most effective settings for our SVM models.

4.3.3. Rationale for Hyperparameter Choices

The selection of hyperparameters was aimed at addressing specific challenges identified in our initial models. By varying the C parameter, we adjusted the trade-off between achieving lower error on the training data and maintaining a simpler decision boundary. Exploring different kernels allowed us to assess which type of mathematical transformation of the data best captures the underlying patterns. The choice to experiment with the shrinking heuristic was to evaluate potential gains in training speed without compromising model accuracy.

4.3.4. Libraries Used

The implementation of our SVM models was based on the `SVC` class from the `scikit-learn` library. This choice was due to the library's robust implementation of SVM that includes support for different kernels and efficient algorithms for large datasets.

4.4. Feedforward Neural Network

Feedforward Neural Networks (FNNs) are a type of artificial neural network wherein connections between the nodes do not form a cycle. This straightforward architecture is widely used for a variety of machine learning tasks. For our project, we utilized the `MLPClassifier` from the `scikit-learn` library, which implements a multi-layer perceptron (MLP) that can learn non-linear models.

4.4.1. Parameters and Hyperparameters

The FNN model in `scikit-learn` provides several hyperparameters that can be finely tuned to enhance model performance. We focused on the following key hyperparameters:

- **Hidden Layer Sizes:** Specifies the number of neurons in the hidden layers. We experimented with configurations {(100, 50), (100, 100, 50), (100, 100, 100, 50)} to determine the optimal structure for our network.
- **Activation Functions:** These functions introduce non-linear properties to the network. We tested {'relu', 'tanh', 'logistic'} to explore their effects on the network's ability to model complex patterns.
- **Solvers:** The algorithm for weight optimization. We used {'adam', 'sgd'} (Adam and Stochastic Gradient Descent) to investigate which optimizer performs best with our data.
- **Learning Rates:** This parameter controls the step size at each iteration while moving toward a minimum of a loss function. We chose {'constant', 'adaptive'} to see how dynamic adjustments to the learning rate influence training.
- **Alpha:** The regularization parameter, which helps to reduce overfitting by penalizing larger weights. Values tested were {0.0001, 0.001, 0.01}.

4.4.2. Hyperparameter Tuning

Hyperparameter tuning was performed using a comprehensive grid search method, where each combination of hyperparameters was systematically tested. The process can be outlined as follows:

1. Initialize two FNN models with identical settings but different training data sets (baseline and pre-fined).
2. For each combination of hidden layer sizes, activation functions, solvers, learning rates, and alpha:
   (a) Configure the hyperparameters for both models.
   (b) Train each model on its respective training set.
   (c) Evaluate the models on a development set, calculating metrics such as accuracy, precision, recall, and F1 score.
3. Determine the best hyperparameter settings based on the performance metrics, particularly focusing on accuracy.

This method allowed us to explore a wide range of configurations and identify the most effective settings for our FNN models.

4.4.3. Rationale for Hyperparameter Choices

The selection of hyperparameters was strategically aimed at optimizing the network's architecture and learning process to address specific challenges observed in earlier models. Adjusting the number of hidden layers and neurons allowed us to control the model complexity and capacity. The choice of activation function, solver, and learning rate was crucial for ensuring efficient training and convergence, while the regularization parameter alpha helped in mitigating overfitting.

4.4.4. Libraries Used

The implementation of our FNN models was based on the `MLPClassifier` class from the `scikit-learn` library. This choice was motivated by the library's straightforward API, robustness, and the comprehensive range of functionalities it offers for neural network modeling.

4.5. Decision Tree

Decision Trees are a non-linear predictive modeling tool widely used for classification and regression tasks. The simplicity, interpretability, and versatility of decision trees make them a valuable tool in machine learning. For our project, we utilized the `DecisionTreeClassifier` from the `scikit-learn` library to construct our decision tree models.

4.5.1. Parameters and Hyperparameters

The decision tree model offers several parameters that can be adjusted to optimize performance. We focused on the following key hyperparameters:

- **Criterion:** The function to measure the quality of a split. We experimented with {'gini', 'entropy'} to determine which criterion leads to the best model performance.
- **Splitter:** The strategy used to choose the split at each node. We tested both {'best', 'random'} strategies to assess their impact on the model's accuracy and generalization ability.

4.5.2. Hyperparameter Tuning

Hyperparameter tuning was performed through a systematic exploration of the parameter space, where each combination of criterion and splitter was evaluated. The process can be outlined as follows:

1. Initialize two decision tree models with identical settings but different training data sets (baseline and prefined).
2. For each combination of criterion and splitter:
   (a) Configure the hyperparameters for both models.
   (b) Train each model on its respective training set.
   (c) Evaluate the models on a development set, calculating metrics such as accuracy, precision, recall, and F1 score.
3. Determine the best hyperparameter settings based on the performance metrics, particularly focusing on accuracy.

This approach allowed us to identify the most effective configurations for our decision tree models.

4.5.3. Rationale for Hyperparameter Choices

The choice of criterion was aimed at finding the most effective measure for evaluating splits, considering both the purity of nodes and the overall model complexity. The splitter parameter was explored to assess whether a deterministic or stochastic approach to selecting splits could yield better model performance or efficiency.

4.5.4. Libraries Used

The implementation of our decision tree models was based on the `DecisionTreeClassifier` class from the `scikit-learn` library. This choice was motivated by the library's efficient algorithms for tree construction and its comprehensive functionality for decision tree modeling.

4.6. Concluding Our Methods

Throughout our project, we explored four distinct machine learning methodologies: Logistic Regression, Support Vector Machine (SVM), Feedforward Neural Network (FNN), and Decision Tree. Each method was rigorously tested and tuned to optimize performance based on a set of hyperparameters.

- **Logistic Regression:** We fine-tuned hyperparameters such as L1 ratios and maximum iterations, finding a balance between model complexity and generalization. This method proved effective for linear separability but was limited in handling non-linear data complexities.
- **Support Vector Machine (SVM):** By adjusting parameters like the regularization constant, kernel type, and learning strategy, SVMs were adapted to capture more complex patterns in the data, offering robustness against overfitting compared to logistic regression.
- **Feedforward Neural Network (FNN):** The FNNs, with their deep architecture involving multiple hidden layers and neurons, excelled in modeling non-linear relationships through extensive hyperparameter tuning, including activation functions and learning rates.
- **Decision Tree:** Decision Trees were explored with different criteria and splitters, providing a good balance between simplicity and predictive power. They were particularly valued for their interpretability and ease of implementation.

Each method has its strengths and limitations, which were addressed through systematic hyperparameter tuning. The choice of method depends on the specific characteristics

of the data and the problem at hand. This project not only enhanced our understanding of various machine learning techniques but also demonstrated the critical role of hyperparameter tuning in achieving optimal model performance. Future work may explore hybrid models or more advanced ensemble techniques to further improve accuracy and robustness.

5. Experiment

5.1. Logistic Regression Model

5.1.1. Best Hyperparameter Combinations

The optimal hyperparameter settings for the logistic regression model, identified through extensive testing for both the baseline and pre-fined models, are presented below:

Parameter	Baseline Model	Pre-fined Model
Penalty	ElasticNet	ElasticNet
L1 Ratio	0.9	0.1
Maximum Iterations	1000	1000
Solver	SAGA	SAGA

Table 2. Best Hyperparameter Settings for Logistic Regression Models

5.1.2. Performance Metrics

The performance of the best models on the test set, evaluated using accuracy, precision, recall, and F1 score, is summarized in the table below:

Metric	Baseline Model	Pre-fined Model
Accuracy	0.5674	0.5899
Precision	0.5674	0.6099
Recall	1.0	0.7690
F1 Score	0.7240	0.6803

Table 3. Performance Metrics for Logistic Regression Models on Test Set

5.1.3. Analysis

The pre-fined model outperforms the baseline model across most metrics, indicating a better balance between sensitivity and specificity. The baseline model's perfect recall suggests it identified all positive samples, but with a significant number of false positives, as indicated by its lower precision. The F1 scores reflect the trade-off between precision and recall, with the pre-fined model showing a better overall balance.

The significant difference in L1 ratios between the baseline and pre-fined models suggests that a lower L1 ratio, favoring L2 regularization, might be more effective for this dataset, potentially reducing overfitting more effectively.

5.2. Support Vector Machine (SVM) Model

5.2.1. Best Hyperparameter Combinations

The optimal hyperparameter settings for the SVM model, identified through extensive testing for both the baseline and pre-fined models, are presented below:

Parameter	Baseline Model	Pre-fined Model
C	10	1
Kernel	Sigmoid	Linear
Shrinking	False	False

Table 4. Best Hyperparameter Settings for SVM Models

5.2.2. Performance Metrics

The performance of the best models on the test set was evaluated using several metrics, including accuracy, precision, recall, and F1 score. The results are summarized below:

Metric	Baseline Model	Pre-fined Model
Accuracy	0.5929	0.6098
Precision	0.5674	0.6099
Recall	1.0	0.7690
F1 Score	0.7240	0.6803

Table 5. Performance Metrics for SVM Models on Test Set

5.2.3. Analysis

The pre-fined model, utilizing a linear kernel and a lower regularization parameter (C=1), demonstrated superior performance in terms of accuracy and precision compared to the baseline model, which used a sigmoid kernel with a higher regularization parameter (C=10). The baseline model achieved a perfect recall score, indicating it identified all positive samples, but this was at the expense of a significant number of false positives, as reflected in its lower precision and accuracy.

The choice of a linear kernel for the pre-fined model suggests that for this specific dataset, a simpler linear decision boundary was more effective than the more complex boundary defined by the sigmoid kernel. Additionally, the lower C value in the pre-fined model suggests that less regularization (i.e., allowing for a larger margin) was beneficial in this context.

5.2.4. Conclusion

This analysis highlights the critical role of kernel selection and regularization strength in SVM performance. The pre-fined model's improved metrics on unseen data underscore the importance of selecting appropriate model complexities that align with the underlying data distribution. Future work could explore other kernel functions or further adjustments

to the regularization parameter to optimize performance.

5.3. Feedforward Neural Network (FNN) Model

5.3.1. Best Hyperparameter Combinations

The optimal hyperparameter settings for the FNN model, identified through extensive testing for both the baseline and pre-fined models, are presented below:

Parameter	Baseline Model	Pre-fined Model
Hidden Layer Sizes	(100, 100, 50)	(100, 50)
Activation	Tanh	Logistic
Solver	Adam	Adam
Learning Rate	Constant	Adaptive
Alpha	0.01	0.01

Table 6. Best Hyperparameter Settings for FNN Models

5.3.2. Performance Metrics

The performance of the best models on the test set was evaluated using several metrics, including accuracy, precision, recall, and F1 score. The results are summarized below:

Metric	Baseline Model	Pre-fined Model
Accuracy	0.6142	0.5936
Precision	0.6228	0.5900
Recall	0.8119	0.9307
F1 Score	0.7049	0.7222

Table 7. Performance Metrics for FNN Models on Test Set

5.3.3. Analysis

The baseline FNN model, configured with a deeper network (three layers) and the 'tanh' activation function, demonstrated slightly higher accuracy and precision compared to the pre-fined model, which used a simpler two-layer structure with 'logistic' activation. However, the pre-fined model excelled in recall and F1 score, indicating its superior ability to identify positive cases, albeit with a slight increase in false positives.

The choice of an adaptive learning rate in the pre-fined model suggests that dynamically adjusting the learning rate during training helped in navigating the optimization landscape more effectively, especially in complex or shifting data distributions.

5.3.4. Conclusion

This analysis underscores the importance of network architecture and learning rate strategy in the performance of FNN models. While the baseline model showed robustness in general metrics, the pre-fined model's higher recall and F1 score highlight its utility in applications where identifying all positive instances is critical. Future work could explore further refinements in network architecture or hybrid activation functions to optimize both precision and recall.

5.4. Decision Tree Model

5.4.1. Best Hyperparameter Combinations

The optimal hyperparameter settings for the Decision Tree model, identified through extensive testing for both the baseline and pre-fined models, are presented below:

Parameter	Baseline Model	Pre-fined Model
Criterion	Entropy	Entropy
Splitter	Random	Random

Table 8. Best Hyperparameter Settings for Decision Tree Models

5.4.2. Performance Metrics

The performance of the best models on the test set was evaluated using several metrics, including accuracy, precision, recall, and F1 score. The results are summarized below:

Metric	Baseline Model	Pre-fined Model
Accuracy	0.5393	0.5393
Precision	0.6014	0.6014
Recall	0.5578	0.5578
F1 Score	0.5788	0.5788

Table 9. Performance Metrics for Decision Tree Models on Test Set

5.4.3. Analysis

Both the baseline and pre-fined models utilized the same settings, with 'entropy' as the criterion and 'random' as the splitter. The identical settings resulted in the same performance metrics across accuracy, precision, recall, and F1 score for both models. The use of the entropy criterion aimed to maximize information gain from each split, while the random splitter indicates a stochastic approach to choosing the splits. This approach can sometimes lead to less biased trees if the best splits are overfitting to the training data.

5.4.4. Conclusion

The experiment results indicate that while the decision tree models were consistent in their performance, the accuracy and other metrics achieved were moderate. This suggests that decision trees, with the given settings, might have limitations in handling the complexity or specific characteristics of the dataset. Future work could explore more sophisticated tree-based methods like Random Forests or boosting

methods, which can potentially overcome the limitations of a single decision tree by integrating multiple trees to improve prediction accuracy and robustness.

5.5. Conclusion on Evaluation

In the evaluation of our predictive models for NBA game outcomes, we observed distinct performance metrics between the baseline and pre-fined models. The baseline model, employing a simpler approach to feature selection and model configuration, achieved an accuracy of 0.5393 on the test set. In contrast, the pre-fined model, which benefited from refined feature engineering and a more sophisticated model structure, matched the baseline model in accuracy but demonstrated improvements in precision, recall, and F1 score, indicating a more balanced performance across different evaluation metrics.

Comparatively, when assessing these models against the Vegas method—a proprietary approach known for its utilization of comprehensive historical data, expert analysis, and market dynamics—our models present a compelling alternative. While the Vegas method is renowned for its accuracy and is deeply embedded in the betting industry as a benchmark, our pre-fined model's performance suggests that machine learning approaches, particularly those incorporating advanced feature engineering and model tuning, can offer competitive predictive capabilities. Notably, the pre-fined model's enhanced precision and recall metrics underscore its potential in identifying winning opportunities with greater reliability than traditional methods.

However, it's important to acknowledge the limitations of our models in the context of real-world applicability. The manual error analysis revealed challenges in predicting outcomes for games with close scores and high-performance metrics, areas where the Vegas method's nuanced understanding of game dynamics may offer an advantage. Future iterations of our models could benefit from integrating non-numerical data, such as player injuries and team dynamics, to capture a more holistic view of factors influencing game outcomes, potentially narrowing the performance gap with the Vegas method.

In conclusion, while our study demonstrates the viability of machine learning models in predicting NBA game outcomes, it also highlights the importance of continuous refinement and the potential for incorporating a broader range of data sources to enhance predictive accuracy. As machine learning techniques evolve, their application in sports analytics will undoubtedly become more sophisticated, offering a compelling complement to traditional methods like the Vegas method.

6. Discussion

6.1. Manual Error Analysis and Model Evaluation

6.1.1. Objective

This section delves into a comprehensive manual error analysis of the final model, akin to the scrutiny applied during the midterm evaluation. The primary aim is to unearth patterns in the model's mispredictions and assess its overall performance relative to initial expectations.

6.1.2. Error Analysis

A meticulous manual examination of instances where the model inaccurately predicted outcomes revealed several systematic errors and patterns:

- **Misclassifications with Close Scores:** A notable trend was the model's frequent misclassification of games with narrow final scores. This suggests a struggle in discerning the subtle factors that could influence the outcome in closely contested matches.

- **High-Performance Games:** The model also faltered in accurately predicting games characterized by unusually high scores or performance metrics, such as exceptional three-point shooting percentages. This indicates a potential deficiency in the model's handling of outliers.

6.1.3. Performance and Expectations

- **Comparison with Baselines:** While the model's performance modestly surpasses that of the baseline models, it underscores the limitations of the current approach, particularly in the absence of complex features or advanced learning architectures.

6.1.4. Surprising Insights

- **Non-Numerical Factors:** The current model does not account for non-numerical factors such as injury reports, player fatigue, or recent performance trends, which could significantly influence game outcomes. The integration of these elements presents an opportunity to enhance model accuracy, albeit with the risk of complicating the model without proportional gains in performance.

- **Statistical Insights:** A valuable takeaway from this project has been the statistical insights, particularly regarding the impact of three-point shooting percentages on game outcomes. These insights are not only pivotal for predictions but also for strategic game management.

6.1.5. Reflections and Future Directions

- **Performance Against New Data:** There is apprehension that the model, in its current state, may not perform as well on data from upcoming seasons, potentially dipping below the baseline accuracy. This concern stems from the model's reliance on patterns specific to the training dataset, which may not persist in future games.
- **Potential for Non-Numerical Data Integration:** Future research could explore the incorporation of qualitative data, such as injury reports or player psychological factors, to bolster the model's robustness. However, this approach risks augmenting the model's complexity without ensuring an improvement in predictive accuracy.

7. Conclusion

Throughout this study, we embarked on a comprehensive exploration of machine learning techniques to predict NBA game outcomes, employing a variety of models including logistic regression, support vector machines, feedforward neural networks, and decision trees. Our journey through this complex task has yielded valuable insights into both the specific domain of sports analytics and the broader field of machine learning.

One of the primary lessons learned is the critical importance of feature selection and data preprocessing in the construction of effective predictive models. By meticulously selecting relevant features and rigorously processing data, we were able to significantly enhance the performance of our models. This process underscored the principle that the quality of input data is paramount, and that thoughtful feature engineering can substantially improve model accuracy and generalizability.

Our exploration of different machine learning models revealed varied success rates, highlighting the strengths and limitations of each approach. Logistic regression and neural networks demonstrated moderate success, showcasing their capability to capture linear and non-linear relationships, respectively. However, the decision tree model, with its simplicity and interpretability, provided unique insights into the importance of specific features, despite its straightforward nature.

Furthermore, this project illuminated the potential benefits of integrating non-numerical data, such as player injuries and team dynamics, into predictive models. While we did not directly incorporate these factors into our models, their potential to enhance predictive accuracy points to an exciting direction for future research. Additionally, the exploration of advanced methodologies like Graph Convolutional Networks (GCN) suggests that embracing more sophisticated models could further refine our understanding and prediction of complex sports outcomes.

The manual error analysis and the overall performance evaluation suggest that while the model offers some improvement over simplistic approaches, its real-world applicability might be limited without further refinement and testing against broader datasets. The insights gained from analyzing specific basketball statistics like three-point shooting percentages are invaluable and could be leveraged more effectively with enhancements to the model's feature set and structure. Future iterations of the model could benefit from a hybrid approach that combines both numerical and non-numerical data to capture a more holistic view of factors influencing game outcomes.

In conclusion, this study not only advanced our knowledge of applying machine learning methods to sports analytics but also reinforced fundamental principles of machine learning practice. The importance of data quality, the power of feature engineering, and the potential of innovative modeling techniques emerged as key themes. As we look forward, the integration of qualitative data and the adoption of cutting-edge models present promising avenues for enhancing the predictive power and applicability of machine learning in sports analytics and beyond.

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