NBA player shot analysis - FULL REPORT

May 5, 2024

1 Introduction to the project

1.1 Context

Incorporating advanced statistical analysis into our operations is crucial for staying competitive in the realm of American sports, particularly in the NBA. As technology continues to evolve, we recognize the importance of leveraging digital tracking tools to gather comprehensive data on player performance. By focusing on shot frequency and shooting efficiency among top NBA players, as identified by ESPN, we aim to gain valuable insights that can inform our strategic decisions and enhance our team's performance on the court. This project aligns with our commitment to utilizing data-driven approaches to drive success in the highly competitive landscape of professional basketball.

From a technical point of view:

This project entails harnessing cutting-edge digital tracking tools to capture real-time data on player movements during NBA games. We will employ sophisticated statistical analysis techniques to process the vast amount of information collected, focusing on shot frequency and shooting efficiency across various game situations and court locations. Additionally, predictive modeling techniques will be utilized to estimate the probability of shot success for each of the 20 esteemed NBA players included in the dataset. By leveraging advanced analytics and machine learning algorithms, we aim to extract actionable insights that can optimize player performance and inform strategic decision-making within our organization.

From an economic point of view:

Investing in this project holds significant economic potential for our organization within the sports industry. By leveraging data analytics to understand player performance and optimize strategic decision-making, we can gain a competitive edge on the court. Improved shot selection and efficiency among our players can lead to increased game success, fan engagement, and ultimately, revenue generation through ticket sales, merchandise, and sponsorships. Additionally, by demonstrating our commitment to data-driven approaches, we enhance our brand reputation and attract top talent, further bolstering our long-term economic viability and success in the market.

From a scientific point of view:

This project represents an opportunity to advance the scientific understanding of basketball performance through rigorous data analysis and predictive modeling. By examining shot data from top NBA players in various game contexts, we aim to uncover underlying patterns and trends that contribute to successful outcomes on the court. Through the application of statistical methods and machine learning algorithms, we can identify key factors influencing shot selection and effectiveness, contributing to the broader body of knowledge in sports analytics. Moreover, the insights gained from this research have the potential to inform coaching strategies, player development programs, and future scientific inquiries into sports performance optimization.

2 Understanding and manipulation of data

2.1 Framework

For this project, we utilized the NBA shot dataset spanning the years 1997 to 2020. The dataset contains comprehensive information on shot locations in NBA games, allowing for detailed analysis of shot frequency and efficiency among players during this period.

The dataset used in this project is freely available on Kaggle (https://www.kaggle.com/jonathangmwl/nba-shot-locations), a platform known for hosting various datasets for analysis and machine learning tasks. As such, it is accessible to anyone with an internet connection and an account on the Kaggle platform. The dataset is provided by the user “jonathangmwl” and can be accessed without any restrictions.

The dataset encompasses a considerable amount of data, capturing detailed shot information from NBA games spanning a 23-year period, ranging from 1997 to 2020. The exact size of the dataset, including the number of rows and columns, will be explored further in subsequent topics.

2.2 Relevance

The dataset contains a comprehensive array of features that encapsulate various aspects of shot-taking behavior in NBA games. Here’s a brief description of the key features included, along with their relevance for the classification problem:

Game-related features: Unique identifiers for each game, including game ID, event ID, and date of the game. While these features provide contextual information about when and where shots were taken, they are not directly relevant to the classification problem. However, they may indirectly influence player performance due to factors such as fatigue or opponent strength.

Player-related features: Unique identifiers for players, as well as their full names. While player identity is crucial for tracking individual performance, it may not directly impact the shot classification task unless specific player tendencies are considered in the modeling process.

Team-related features: Unique identifiers for teams participating in the game, including home and away teams. Similar to game-related features, team information provides contextual background but may not directly influence shot outcomes.

Shot-related features: Details about each shot taken, such as shot type (e.g., jump shot, layup), shot distance, shot zone (basic and area), shot zone range, and X-Y coordinates of shot location. These features are highly relevant for the classification problem as they directly characterize the shot-taking behavior of players. Shot type, distance, and location are likely to significantly influence the likelihood of a shot being successful, making them crucial predictors in the classification model.

Other features: Period of the game, minutes and seconds remaining in the period, season type (regular season or playoffs). While these features provide additional context about the game situation, their direct relevance to shot classification may be limited compared to shot-related features. However, game context, such as time remaining or playoff status, could indirectly influence shot outcomes by affecting player behavior or defensive strategies.

In summary, shot-related features, including shot type, distance, and location, are the most relevant predictors for the classification problem, as they directly characterize the shot-taking behavior of NBA players. Other contextual features, such as game-related and team-related features, may provide additional background information but are not as directly influential in predicting shot outcomes.

2.3 Problem Definition

We aim to predict the probability of a shot being made by each player, indicating whether a shot is successful or not. This problem naturally aligns with a binary classification task, where shots are categorized as either made or missed.

3 Pre-processing and feature engineering

Check the size of the dataset (number of rows and columns):

```
Dataset Size: (4729512, 22)
```

Display the first few rows of the dataset:

```
[4]:     Game ID  Game Event ID  Player ID Player Name     Team ID  \
     0  29700427            389        100  Tim Legler  1610612764
     1  29700427            406        100  Tim Legler  1610612764
     2  29700427            475        100  Tim Legler  1610612764
     3  29700427            487        100  Tim Legler  1610612764
     4  29700427            497        100  Tim Legler  1610612764

                 Team Name  Period  Minutes Remaining  Seconds Remaining  \
     0  Washington Wizards       4                 11                 22
     1  Washington Wizards       4                  9                 36
     2  Washington Wizards       4                  3                  7
     3  Washington Wizards       4                  1                 45
     4  Washington Wizards       4                  0                 45

       Action Type  … Shot Zone Area  Shot Zone Range Shot Distance X Location  \
     0   Jump Shot  …  Right Side(R)         8-16 ft.            15        117
     1   Jump Shot  …  Right Side(R)         8-16 ft.            14        143
     2   Jump Shot  …   Left Side(L)         8-16 ft.            10        -87
     3   Jump Shot  …      Center(C)  Less Than 8 ft.             5         -1
     4   Jump Shot  …  Right Side(R)         8-16 ft.            14         89

        Y Location  Shot Made Flag  Game Date  Home Team  Away Team     Season Type
     0         109               1   19980102        WAS        IND  Regular Season
     1          25               0   19980102        WAS        IND  Regular Season
     2          55               0   19980102        WAS        IND  Regular Season
     3          53               0   19980102        WAS        IND  Regular Season
     4         113               0   19980102        WAS        IND  Regular Season

     [5 rows x 22 columns]
```

Get the structure of the dataset:

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4729512 entries, 0 to 4729511
Data columns (total 22 columns):
 #   Column             Dtype
---  ------             -----
 0   Game ID            int64
 1   Game Event ID      int64
 2   Player ID          int64
 3   Player Name        object
 4   Team ID            int64
 5   Team Name          object
 6   Period             int64
 7   Minutes Remaining  int64
 8   Seconds Remaining  int64
 9   Action Type        object
 10  Shot Type          object
 11  Shot Zone Basic    object
 12  Shot Zone Area     object
 13  Shot Zone Range    object
 14  Shot Distance      int64
 15  X Location         int64
 16  Y Location         int64
 17  Shot Made Flag     int64
 18  Game Date          int64
 19  Home Team          object
 20  Away Team          object
 21  Season Type        object
dtypes: int64(12), object(10)
memory usage: 793.8+ MB
None
```

Summary statistics of numerical columns:

```
            Game ID  Game Event ID     Player ID       Team ID        Period  \
count  4.729512e+06   4.729512e+06  4.729512e+06  4.729512e+06  4.729512e+06
mean   2.314379e+07   2.501681e+02  1.639145e+05  1.610613e+09  2.477790e+00
std    5.521124e+06   1.589274e+02  3.733497e+05  8.595674e+00  1.139482e+00
min    2.000000e+07   1.000000e+00  3.000000e+00  1.610613e+09  1.000000e+00
25%    2.060015e+07   1.130000e+02  1.515000e+03  1.610613e+09  1.000000e+00
50%    2.120030e+07   2.450000e+02  2.550000e+03  1.610613e+09  2.000000e+00
75%    2.170117e+07   3.750000e+02  2.019370e+05  1.610613e+09  3.000000e+00
max    4.990009e+07   1.012000e+03  1.629760e+06  1.610613e+09  8.000000e+00

       Minutes Remaining  Seconds Remaining  Shot Distance    X Location  \
count       4.729512e+06       4.729512e+06   4.729512e+06  4.729512e+06
mean        5.332437e+00       2.873821e+01   1.208963e+01 -1.316958e+00
std         3.468664e+00       1.745678e+01   9.850088e+00  1.100864e+02
```

```
min          0.000000e+00       0.000000e+00    0.000000e+00 -2.500000e+02
25%          2.000000e+00       1.400000e+01    2.000000e+00 -6.000000e+01
50%          5.000000e+00       2.900000e+01    1.300000e+01  0.000000e+00
75%          8.000000e+00       4.400000e+01    2.100000e+01  5.600000e+01
max          1.200000e+01       5.900000e+01    8.900000e+01  2.500000e+02

         Y Location  Shot Made Flag     Game Date
count  4.729512e+06    4.729512e+06  4.729512e+06
mean   7.634400e+01    4.517832e-01  2.008996e+07
std    8.703236e+01    4.976698e-01  6.512593e+04
min   -5.200000e+01    0.000000e+00  1.997103e+07
25%    3.000000e+00    0.000000e+00  2.003120e+07
50%    3.800000e+01    0.000000e+00  2.009033e+07
75%    1.450000e+02    1.000000e+00  2.015013e+07
max    8.840000e+02    1.000000e+00  2.020031e+07
```

Check for missing values. If there are missing values, options are: include imputation, deletion, or using default values depending on the context.

```
Game ID              0
Game Event ID        0
Player ID            0
Player Name          0
Team ID              0
Team Name            0
Period               0
Minutes Remaining    0
Seconds Remaining    0
Action Type          0
Shot Type            0
Shot Zone Basic      0
Shot Zone Area       0
Shot Zone Range      0
Shot Distance        0
X Location           0
Y Location           0
Shot Made Flag       0
Game Date            0
Home Team            0
Away Team            0
Season Type          0
dtype: int64
```

We don't have any missing values.

Check is there a duplicates. If there are duplicated values, we can remove it.

```
[8]: 0
```

We don't have any duplicated values.

Let's create one big picture of the data to see what kind of dataset we have.

```
                  data_type  target  \
Game ID               int64       0
Game Event ID         int64       0
Player ID             int64       0
Player Name          object       0
Team ID               int64       0
Team Name            object       0
Period                int64       0
Minutes Remaining     int64       0
Seconds Remaining     int64       0
Action Type          object       0
Shot Type            object       0
Shot Zone Basic      object       0
Shot Zone Area       object       0
Shot Zone Range      object       0
Shot Distance         int64       0
X Location            int64       0
Y Location            int64       0
Shot Made Flag        int64       1
Game Date             int64       0
Home Team            object       0
Away Team            object       0
Season Type          object       0

                                                          description  \
Game ID                                  Unique id assigned to every game
Game Event ID               Unique id assigned to every event within a game
Player ID                               Unique id assigned to each player
Player Name                                    Shooting Players full name
Team ID                                   Unique id assigned to each team
Team Name                             The team of the player taking the shot
Period             The period of the game (out of four); each per…
Minutes Remaining                    Minutes remaining in period (out of 12)
Seconds Remaining  Seconds remaining in period-minute combination…
Action Type        Type of shot (ex. Jump Shot, Layup, Hookshot, …
Shot Type                                          Either 2pt or 3pt shot
Shot Zone Basic    General location of shot (ex. Left Corner 3, M…
Shot Zone Area     Area/Direction of shot (ex. Center, Left Side,…
Shot Zone Range    Grouping of shots based on range (ex. 8-16ft, …
Shot Distance                                Exact distance of shot in feet
X Location                                 Location of shot as X coordinate
Y Location                                 Location of shot as Y coordinate
Shot Made Flag                             1 (made shot) or 0 (missed shot)
Game Date                                                      Date of game
Home Team                                          Team name of the home team
Away Team                                          Team name of the away team
```

```
Season Type                              Regular Season or Playoffs

                   missing_data          type  \
Game ID                     0.0  quantitative
Game Event ID               0.0  quantitative
Player ID                   0.0  quantitative
Player Name                 0.0   categorical
Team ID                     0.0  quantitative
Team Name                   0.0   categorical
Period                      0.0  quantitative
Minutes Remaining           0.0  quantitative
Seconds Remaining           0.0  quantitative
Action Type                 0.0   categorical
Shot Type                   0.0   categorical
Shot Zone Basic             0.0   categorical
Shot Zone Area              0.0   categorical
Shot Zone Range             0.0   categorical
Shot Distance               0.0  quantitative
X Location                  0.0  quantitative
Y Location                  0.0  quantitative
Shot Made Flag              0.0  quantitative
Game Date                   0.0          date
Home Team                   0.0   categorical
Away Team                   0.0   categorical
Season Type                 0.0   categorical

                                                               category  \
Game ID                                                             NaN
Game Event ID                                                       NaN
Player ID                                                           NaN
Player Name                                                         NaN
Team ID                                                             NaN
Team Name                      36 teams (ex. Washington Wizards, etc)
Period                                       [1, 2, 3, 4, 5, 6, 7, 8]
Minutes Remaining                                                   NaN
Seconds Remaining                                                   NaN
Action Type          70 types (ex. Jump Shot, Layup, Hookshot, Dunk…
Shot Type                          ['2PT Field Goal' '3PT Field Goal']
Shot Zone Basic      ['Mid-Range' 'In The Paint (Non-RA)' 'Left Cor…
Shot Zone Area       ['Right Side(R)' 'Left Side(L)' 'Center(C)' 'R…
Shot Zone Range                                                     NaN
Shot Distance                                                       NaN
X Location                                                          NaN
Y Location                                                          NaN
Shot Made Flag                                                   [1, 0]
Game Date                                                           NaN
Home Team                                 36 teams (ex. LAL, ATL, etc)
Away Team                                 36 teams (ex. LAL, ATL, etc)
```

```
Season Type                            ['Regular Season' 'Playoffs']

                              comment
Game ID                           NaN
Game Event ID                     NaN
Player ID                         NaN
Player Name                       NaN
Team ID                           NaN
Team Name                         NaN
Period                            NaN
Minutes Remaining                 NaN
Seconds Remaining                 NaN
Action Type                       NaN
Shot Type                         NaN
Shot Zone Basic                   NaN
Shot Zone Area                    NaN
Shot Zone Range                   NaN
Shot Distance                     NaN
X Location                        NaN
Y Location                        NaN
Shot Made Flag                    NaN
Game Date            Should be datetime
Home Team                         NaN
Away Team                         NaN
Season Type                       NaN
```

3.1 Distributions of variables

Let's first look at the exact time frame we are looking and also tranform the date into a datetime format.

```
[18]:     Game ID  Game Event ID  Player ID Player Name     Team ID  \
      0  29700427            389        100  Tim Legler  1610612764
      1  29700427            406        100  Tim Legler  1610612764
      2  29700427            475        100  Tim Legler  1610612764
      3  29700427            487        100  Tim Legler  1610612764
      4  29700427            497        100  Tim Legler  1610612764

                  Team Name  Period  Minutes Remaining  Seconds Remaining  \
      0  Washington Wizards       4                 11                 22
      1  Washington Wizards       4                  9                 36
      2  Washington Wizards       4                  3                  7
      3  Washington Wizards       4                  1                 45
      4  Washington Wizards       4                  0                 45

        Action Type  … Shot Zone Area  Shot Zone Range Shot Distance X Location  \
      0   Jump Shot  …  Right Side(R)        8-16 ft.            15         117
      1   Jump Shot  …  Right Side(R)        8-16 ft.            14         143
```

```
2   Jump Shot  …   Left Side(L)        8-16 ft.             10        -87
3   Jump Shot  …      Center(C)  Less Than 8 ft.             5         -1
4   Jump Shot  …  Right Side(R)        8-16 ft.             14         89

   Y Location  Shot Made Flag  Game Date  Home Team Away Team     Season Type
0         109               1 1998-01-02        WAS       IND  Regular Season
1          25               0 1998-01-02        WAS       IND  Regular Season
2          55               0 1998-01-02        WAS       IND  Regular Season
3          53               0 1998-01-02        WAS       IND  Regular Season
4         113               0 1998-01-02        WAS       IND  Regular Season

[5 rows x 22 columns]
```

```
Timestamp('1997-10-31 00:00:00')
```

```
Timestamp('2020-03-11 00:00:00')
```

```
Our data looks at the time period from 1997 to 2020
```

3.2 Balanced/imbalanced Dataset

To check if the dataset is balanced in terms of shot made and shot missed instances, we can calculate the proportion of shots made (positive class) versus shots missed (negative class) in the dataset. Let's perform this analysis:

```
[20]: Shot Made Flag
      0    0.548217
      1    0.451783
      Name: proportion, dtype: float64
```

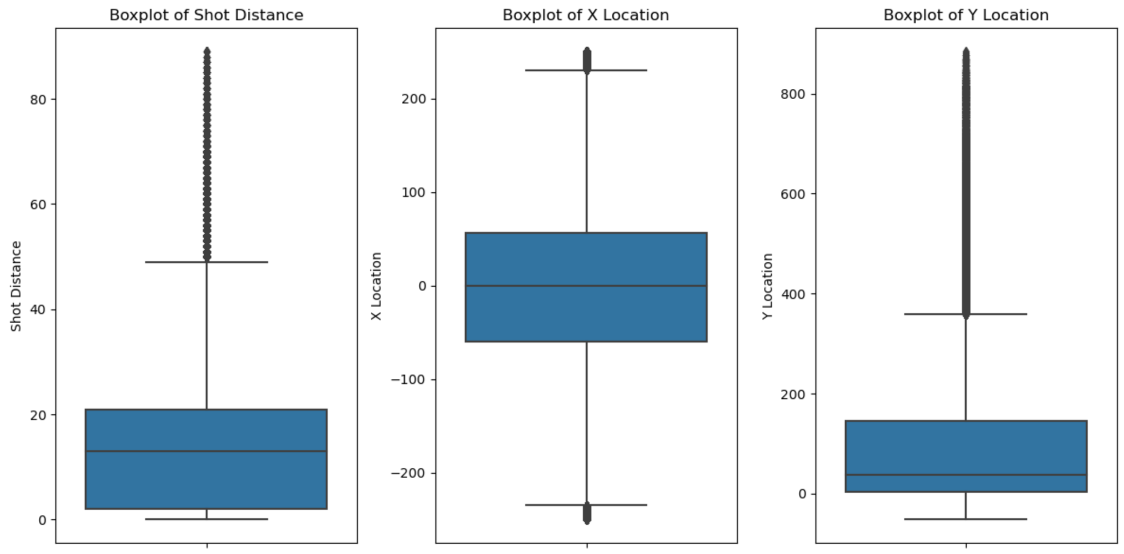
The dataset displays a proportion of shots made at around 0.45 and shots missed at 0.55, suggesting a slight imbalance in class distribution. However, with a difference of only 0.1 between the two proportions, some may not consider it significantly imbalanced. In instances where the split between classes is close to 50/50, explicit balancing techniques like oversampling or undersampling may not be necessary. Given these considerations, we can interpret the dataset as balanced and proceed accordingly.

3.3 Outliers

Identify if there are any outliers in the dataset, especially in numerical features like shot distance, X and Y locations. Outliers might affect the model's performance and need to be handled appropriately, for example, by removing them or transforming them using some techniques.

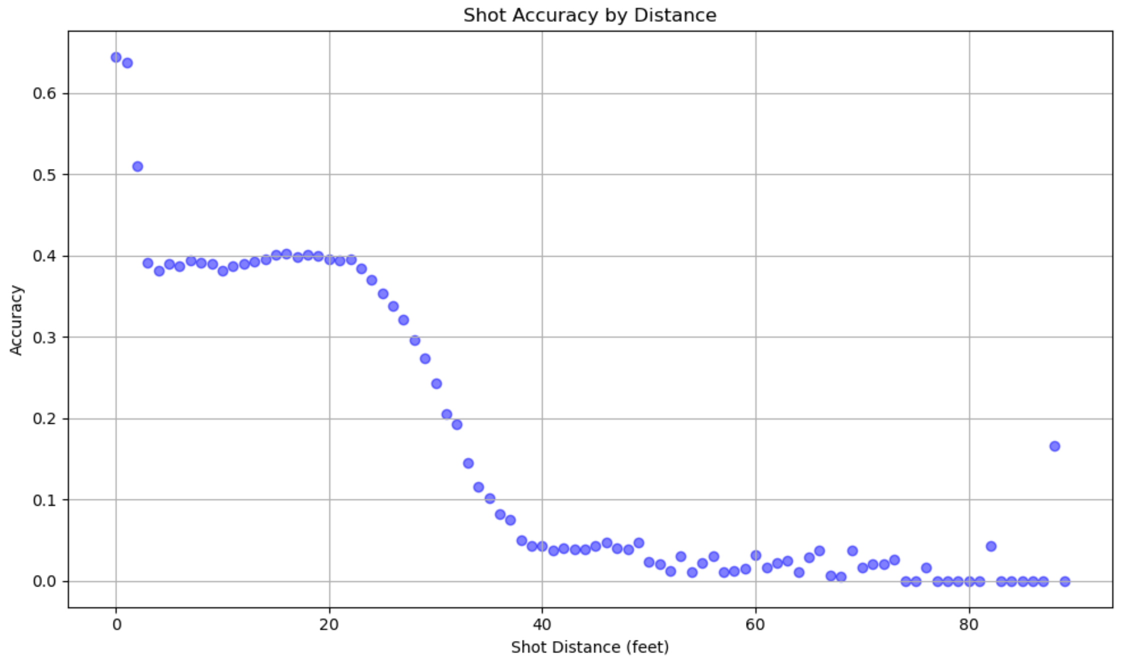
```
Shot Distance  has  6774  outliers
X Location  has  130902  outliers
Y Location  has  15160  outliers
```

Additionally, visualization techniques such as box plots can provide a graphical representation of outliers, aiding in their identification and interpretation.



It seems that the outliers identified statistically may not necessarily reflect true anomalies in the data, as certain locations and distances are indeed realistic in the context of basketball shots. While shots taken from distances greater than 50 feet may be statistically considered outliers due to their low frequency, they actually indicate a scarcity of attempts from such distances. Similarly, Y location values exceeding 350 feet may appear as statistical outliers, but they represent realistic shooting positions. As for the X location, although there are fewer data points observed on both sides (left and right) beyond +/-220 feet, these values are genuine and should be taken into account when building models.

Let's explore shot distance further through another visualization.



The graph above shows something interesting about how accurate NBA players are with their shots. Usually, we expect accuracy to drop as the shot gets farther from the basket. But between 5 to 25 feet away, accuracy stays about the same. There could be a few reasons. Players practice free throws a lot, which are taken from 15 feet away, so they're pretty good at shots from nearby distances. Also, defenders guard differently depending on how close the shooter is to the basket, which might make closer shots harder. But between 5 to 25 feet, these factors seem to balance out. So, even though we might think farther shots are always harder, this graph shows that's not always the case. It gives us a new perspective on how distance affects shooting accuracy.

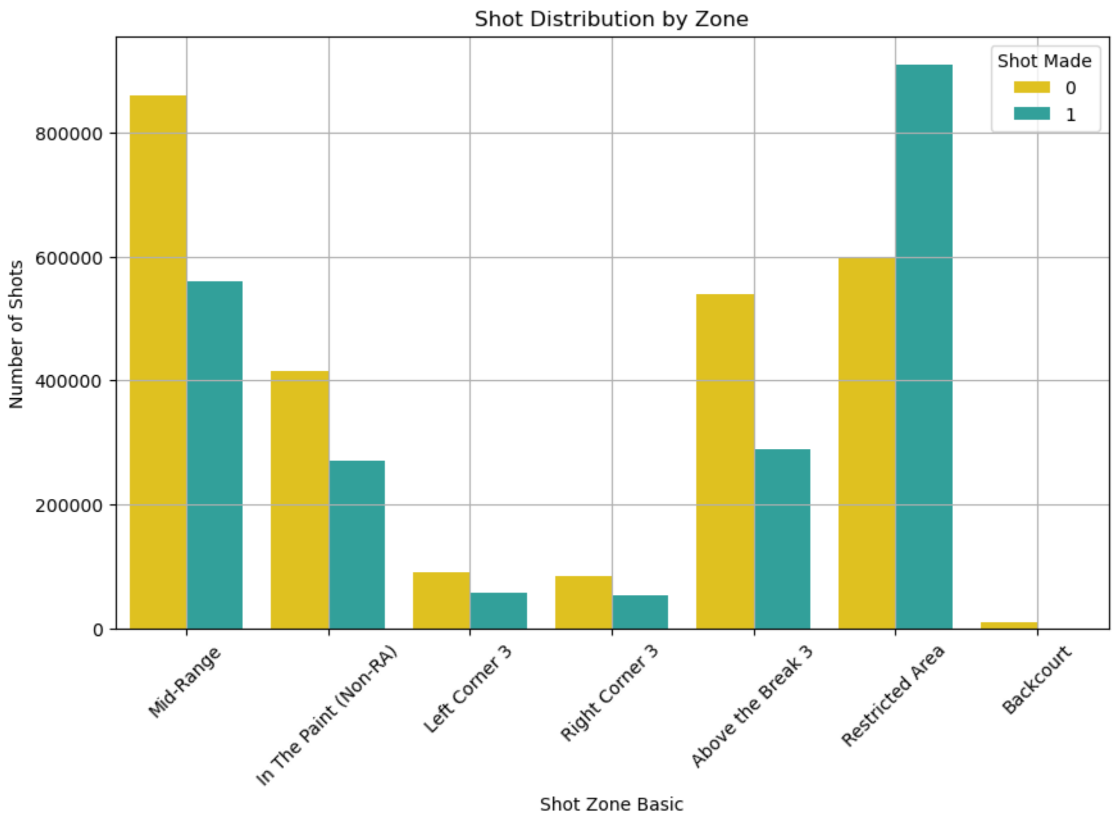
In terms of outliers, the extreme value observed at the far right end of the graph, with an accuracy of approximately 0.18 points, could be considered an outlier. This is likely a scenario where a player hastily attempts a long-range shot as time expires, resulting in a low success rate. While these shots occasionally find success, they occur infrequently.

3.4 Normalization and Standardization

During the data exploration phase, we are primarily focused on understanding the data distribution, identifying outliers, and gaining insights into feature relationships. We will not perform normalization and standardization during this phase as they can alter the data distribution and make it harder to interpret visualizations. Therefore, we will skip normalization and standardization during data exploration and apply them later during preprocessing, just before training the model.

4 Visualizations and Statistics

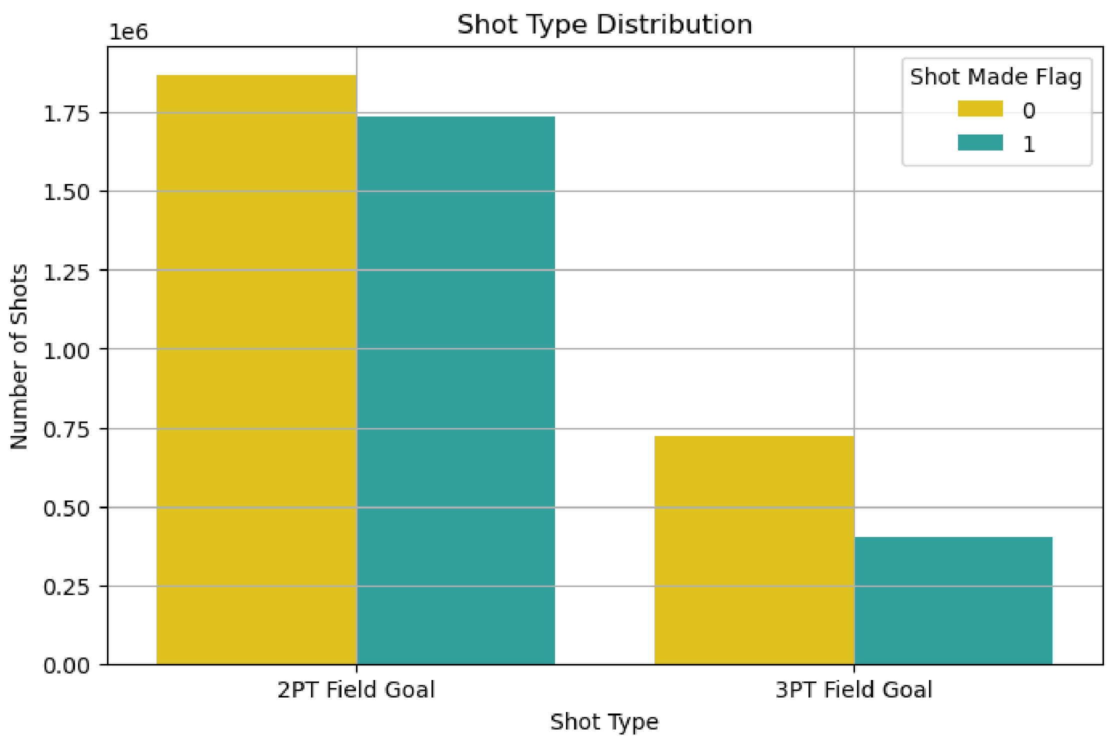
Let's generate some visualizations to gain further insights.



This count plot displays the distribution of both made and missed shots for each shot zone basic. The bars grouped by shot outcome (made or missed), with different colors representing each outcome. This visualization provides a clear comparison between the number of made and missed shots in each shot zone basic.

The shot accuracy in the Restricted Area stands out as notably higher when compared to other areas.

This graph shows something interesting about how accurate NBA players are with their shots. Usually, we expect accuracy to drop as the shot gets farther from the basket. But between 5 to 25 feet away, accuracy stays about the same. There could be a few reasons. Players practice free throws a lot, which are taken from 15 feet away, so they're pretty good at shots from nearby distances. Also, defenders guard differently depending on how close the shooter is to the basket, which might make closer shots harder. But between 5 to 25 feet, these factors seem to balance out. So, even though we might think farther shots are always harder, this graph shows that's not always the case. It gives us a new perspective on how distance affects shooting accuracy.

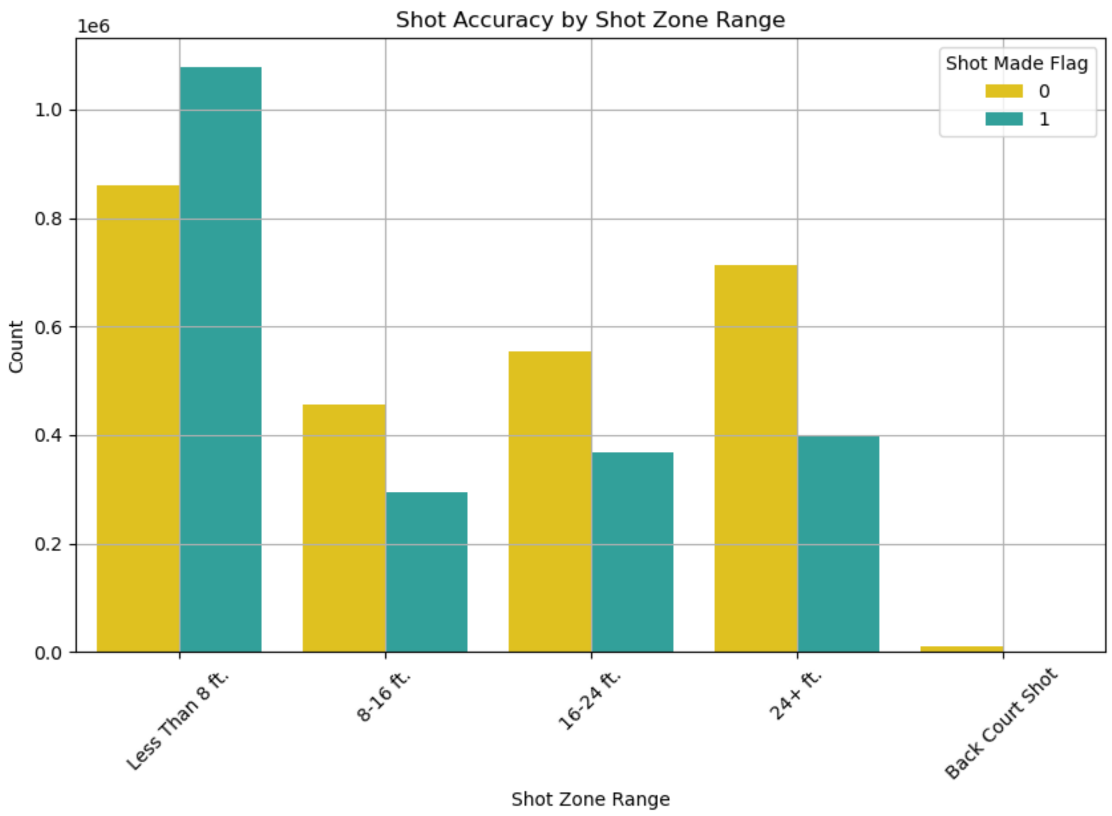


The plot reveals a substantial discrepancy in the distribution of shot types. The majority of shots taken are ‘2PT Field Goals’, outnumbering ‘3PT Field Goals’ by approximately threefold. Consequently, the differing proportions between these shot types indicate a notable disparity in the frequency of attempts between two-point and three-point shots.

This observation underscores the importance of analyzing shooting efficiency and strategy across different shot types. Further exploration into the factors influencing shot selection and success rates for both two-point and three-point shots can offer valuable insights into player performance and strategic decision-making during NBA games.

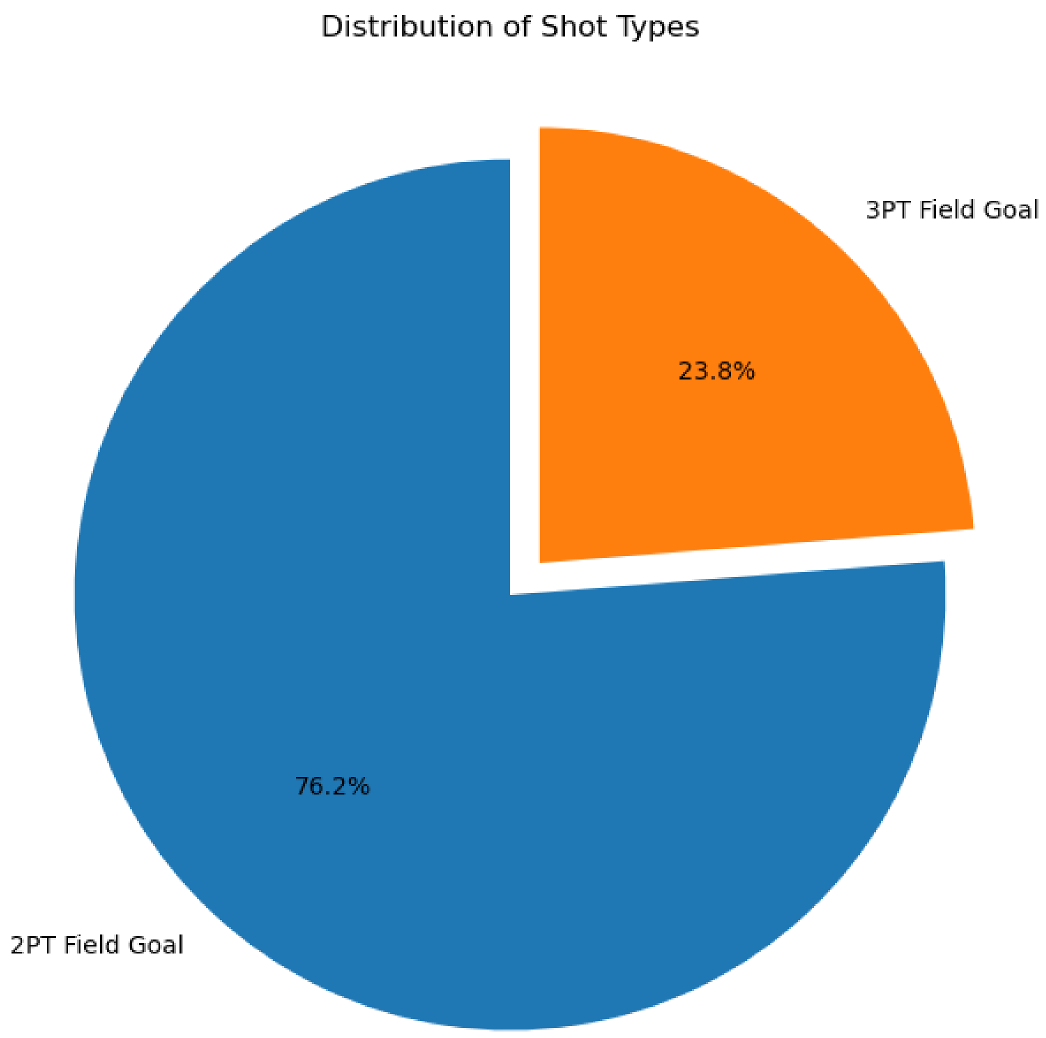
From the heatmap, we can discern patterns in shot selection and shooting accuracy across different court regions. Areas with a higher density of gold points indicate regions where players have successfully made shots, while areas with a higher density of blue points suggest regions where shots were missed more frequently.

Analyzing the shot heatmap provides valuable insights into player positioning, shooting tendencies, and areas of strength or weakness on the court. Further investigation into spatial patterns can inform strategic decisions related to player positioning, defensive strategies, and offensive playcalling in basketball games.

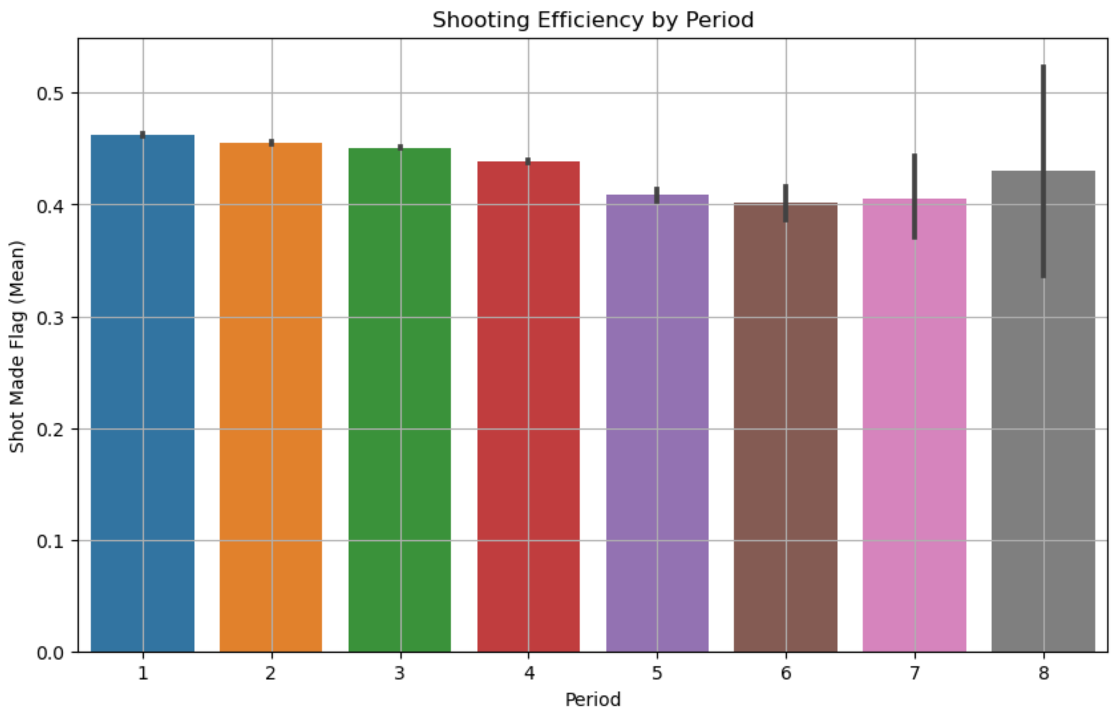


The plot highlights a distinct pattern in shot accuracy based on shot zone range. Shots taken in the nearest area (less than 8 ft. from the basket) exhibit notably higher accuracy compared to shots attempted from further distances. This observation suggests that players tend to have a higher likelihood of making shots when positioned closer to the basket.

The decline in shot accuracy with increasing distance from the basket aligns with the inherent difficulty of making shots from greater distances, attributed to factors such as shot angle, defensive pressure, and player skill. Understanding these patterns in shot accuracy across different shot zones is crucial for player positioning, offensive strategies, and shot selection during basketball games.



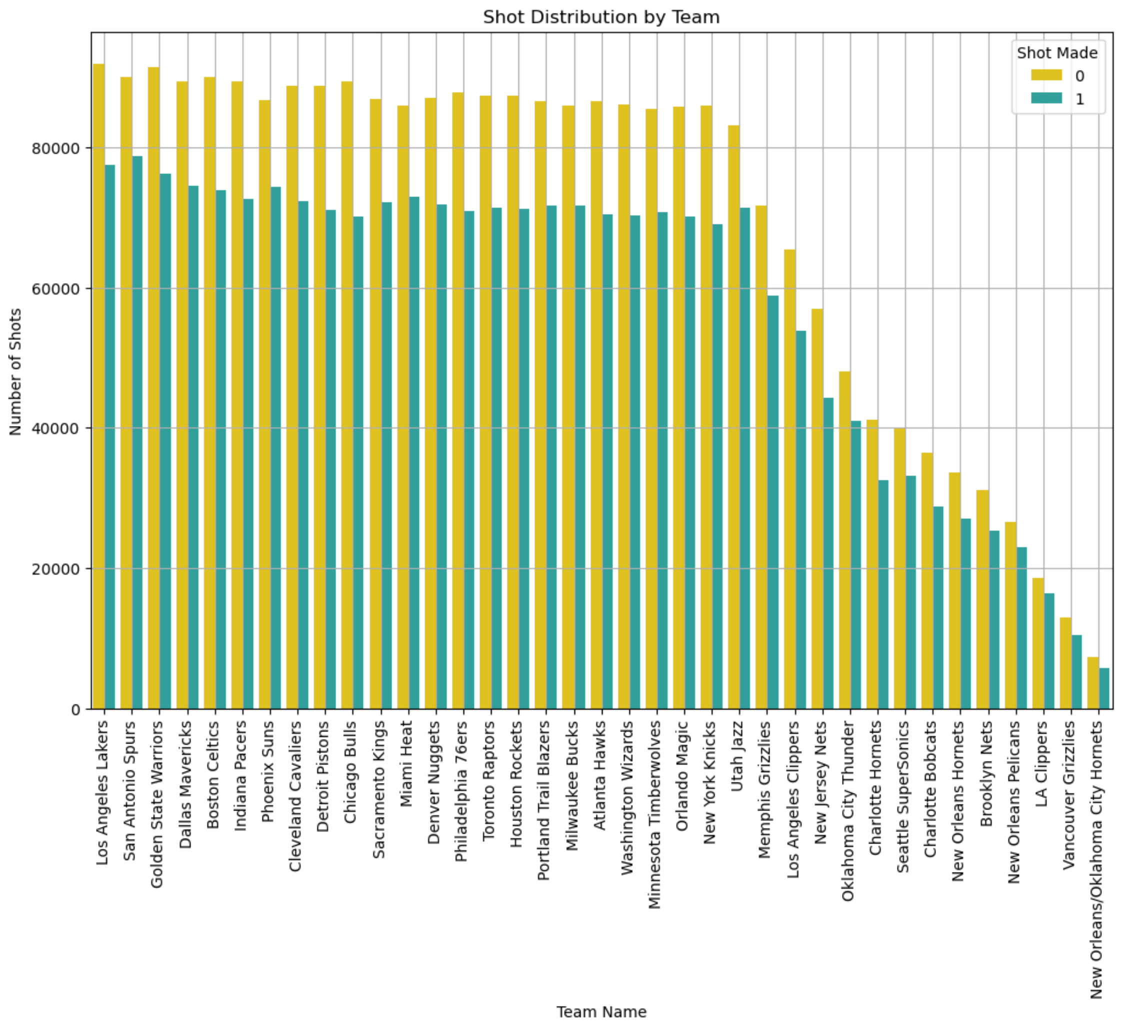
From the visualization, it's evident that over three-quarters of the shots taken are 2-point shots, while the remaining proportion represents 3-point shots. This distribution underscores the prevalence of 2-point field goal attempts in NBA gameplay, reflecting the traditional emphasis on scoring close to the basket.



Periods (1-4): Shooting efficiency remains stable, with consistent mean values and low variability. This suggests reliable shooting performance in the initial stages of the game.

Overtime-Periods (5-6): There is a slight decrease in shooting efficiency, accompanied by a small increase in variability. Shooting performance becomes moderately less consistent during these periods.

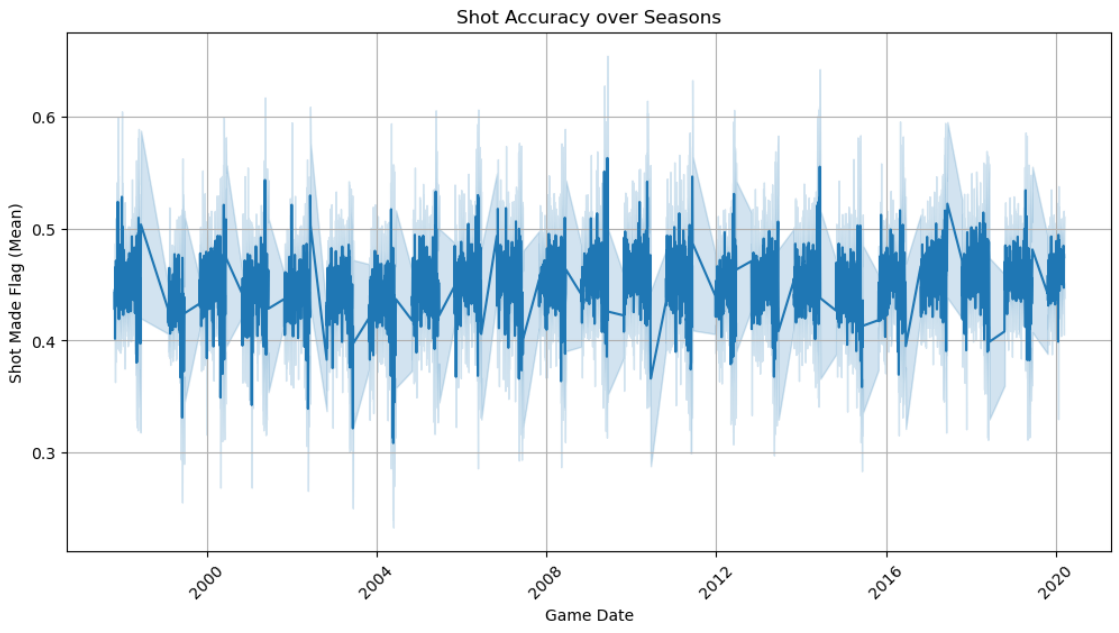
Overtime-Periods (7-8): Shooting efficiency experiences a sharper decline, with shorter columns indicating lower mean values and longer error bars indicating higher variability. Shooting performance becomes less consistent and more variable as the game progresses.



The shot distribution by team visualization offers insights into the distribution of shots made and missed by NBA teams, showcasing their offensive strategies and efficiency.

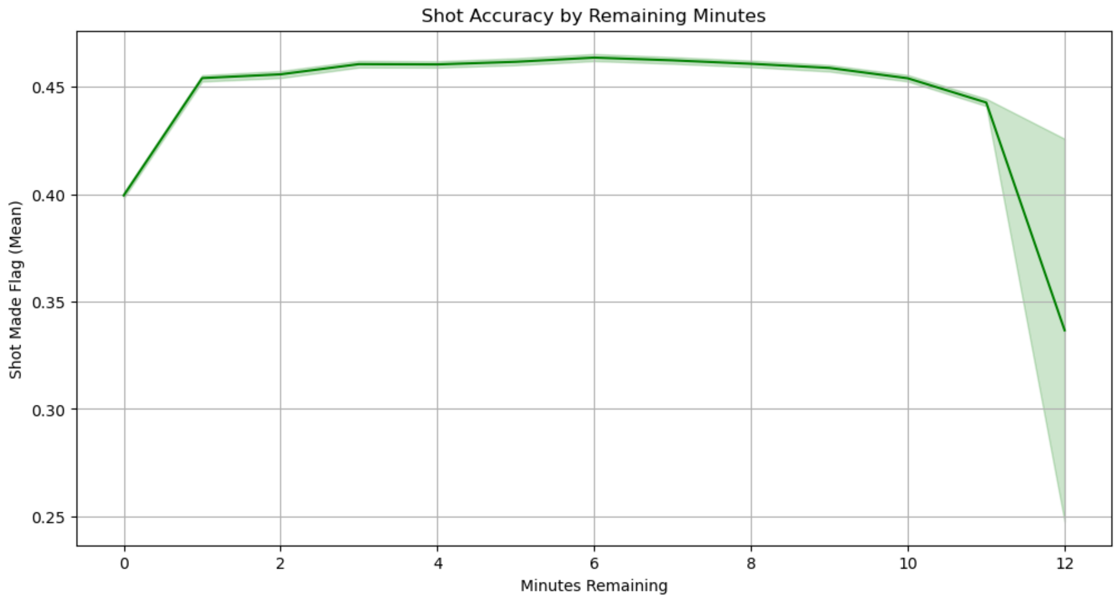
Upon analysis, we observe notable variations in shot distributions across different teams. Teams like LAL, SAS, GSW, and DM demonstrate impressive shot distributions, suggesting a well-balanced offensive strategy and efficient shot selection. In contrast, teams such as NOCH, VG, and LAC exhibit comparatively poor shot distributions, hinting at potential inefficiencies or tactical shortcomings in their offensive approach.

The shot distribution by team visualization provides valuable insights into the offensive dynamics and strategic tendencies of NBA teams. Further exploration may involve examining the factors contributing to variations in shot distribution, such as player roles, coaching philosophies, and offensive systems employed by each team.

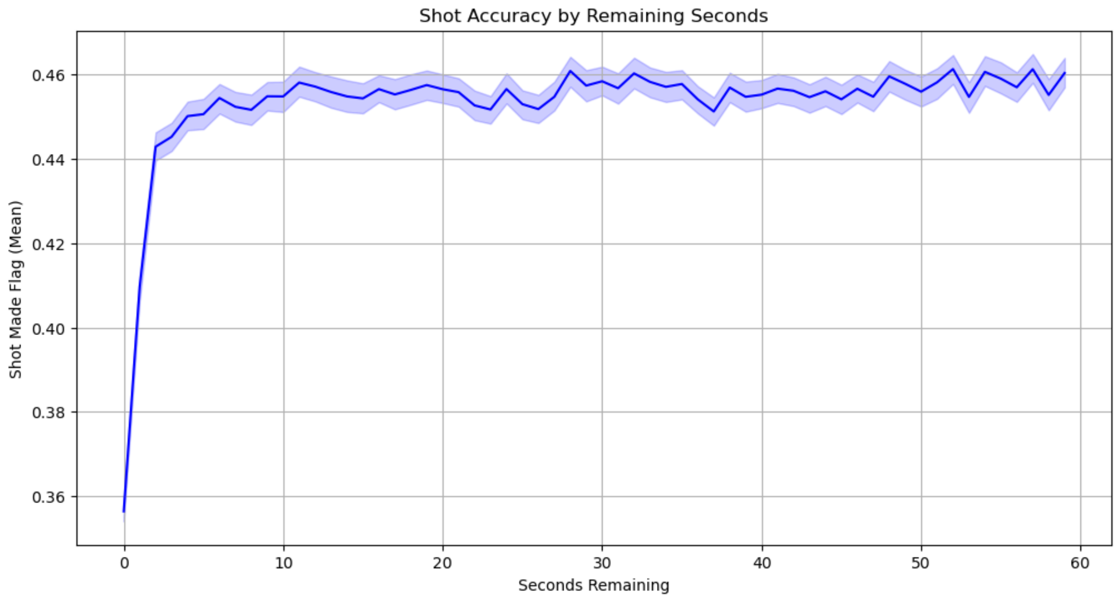


The shot accuracy over seasons visualization tracks the trend of shot accuracy throughout the seasons of NBA gameplay. The line plot depicts the mean shot accuracy (proportion of shots made) over time, with the x-axis representing the game dates and the y-axis representing the mean shot made flag.

By monitoring shot accuracy trends over seasons, NBA teams can adapt their training regimens, gameplay strategies, and roster management approaches to enhance performance and achieve sustained success on the court.



The graph reveals interesting insights into how shot accuracy evolves over the course of the game. The slight fluctuations in shot accuracy during the early minutes may reflect the teams' strategies, adjustments, or warm-up period. As the game progresses, we observe a gradual decline in shot accuracy, possibly due to increased fatigue, defensive pressure, or higher stakes in critical game moments. The narrowing confidence interval towards the end of the game indicates heightened certainty in shot accuracy estimation during crunch time, where players' decisions and execution become more decisive in determining game outcomes. This visualization underscores the importance of time management and strategic decision-making in basketball games, as they can significantly impact shot outcomes and ultimately, game results.



The graph provides insights into how shot accuracy varies as the game clock winds down. The fluctuations in shot accuracy over different time intervals may reflect various game dynamics, including offensive strategies, defensive pressure, and players' performance under time constraints. The relatively stable shot accuracy observed towards the end of the game (around the last minute) indicates players' ability to maintain composure and execute shots effectively in high-pressure situations. This visualization underscores the significance of time management and decision-making in basketball, as players must navigate the game's final moments with precision to secure favorable outcomes.

5 Stages of the project

5.1 Classification of the problem

1. Type of Machine Learning Problem: The machine learning problem in this project is a classification task. Specifically, it involves predicting whether a given NBA shot will be made or missed based on various features related to the shot.

2. Task Related to the Project: The project is related to NBA shot analysis, which falls under sports analytics. The specific task is to analyze and predict the outcome of shots taken during NBA games, focusing on whether a shot will result in a successful make or a miss.

3. Main Performance Metric: The main performance metric used to compare different machine learning models in this project is accuracy. Accuracy is chosen as the main metric because it provides a straightforward measure of how often the model's predictions are correct out of all predictions made. In the context of NBA shot analysis, accuracy helps evaluate the overall effectiveness of the model in predicting whether a shot will be made or missed.

4. Additional Performance Metrics: In addition to accuracy, other quantitative performance metrics are used to evaluate the models' performance comprehensively. These metrics include:

   Precision: It measures the ratio of true positive predictions to the total number of positive predictions. In the context of NBA shot analysis, precision helps assess the model's ability to correctly identify made shots among all shots predicted as made.

   Recall (Sensitivity): It calculates the ratio of true positive predictions to the total number of actual positives. In the NBA shot analysis, recall evaluates the model's capability to capture all made shots, indicating its sensitivity to identifying positive instances (made shots).

   F1 Score: The F1 score is the harmonic mean of precision and recall. It provides a balanced measure of a model's performance, considering both false positives and false negatives. This metric is useful in scenarios where we want to balance precision and recall, such as in the NBA shot analysis task where correctly identifying both made and missed shots is crucial.

   Area Under the ROC Curve (AUC-ROC): This metric evaluates the model's ability to distinguish between classes (made and missed shots) across various threshold values. A higher AUC-ROC value indicates a better-performing model in terms of class separation and predictive power.

   These additional metrics help in gaining a more nuanced understanding of the model's performance beyond just accuracy, taking into account factors like false positives, false negatives, and the balance between precision and recall.

In summary, the NBA shot analysis project involves a classification task where the goal is to predict whether a given shot will be made or missed. The main performance metric used is accuracy, supplemented by other quantitative metrics like precision, recall, F1 score, and AUC-ROC to provide a comprehensive evaluation of the machine learning models employed in the analysis.

5.2 Model choice and optimization

1. Algorithms Explored: In the NBA shot analysis project, several machine learning algorithms were experimented with to find the most suitable model for predicting shot outcomes. The algorithms tried include:

Logistic Regression, Support Vector Machines (SVM), Random Forests, Boosting, Bagging, Convolutional Neural Networks (CNN)

2. Selection of Models: Among the various algorithms tested, the models selected for further optimization and evaluation were Random Forests and Boosting. These models were chosen for the following reasons:

Random Forests: Random Forests are robust and effective for classification tasks, especially when dealing with a large number of features (as is often the case in sports analytics datasets). They are less prone to overfitting compared to individual decision trees and can handle non-linear relationships well.

Boosting: Boosting algorithms are known for their ability to build strong predictive models by combining weak learners sequentially. They perform well in capturing complex patterns and can often outperform other algorithms in terms of predictive accuracy.

3. Parameter Optimization Techniques: Parameter optimization techniques such as Grid Search and Cross-Validation were employed to fine-tune the selected models. Grid Search was used to explore different combinations of hyperparameters for each model, such as the number of trees, maximum depth, learning rate, etc.

4. Testing Advanced Models: Apart from traditional machine learning algorithms like Random Forests and Boosting, advanced ensemble methods such as Bagging and Boosting were also tested in the project.

   Bagging (Random Forest with Bagging): Bagging involves creating multiple bootstrap samples of the training data and training a separate model on each sample. In this project, a variation of Bagging was tested using Random Forests with bagging, which can further improve model robustness and reduce variance.

   Boosting: Boosting algorithms were considered as advanced models due to their ability to sequentially improve the model's performance by focusing on correcting errors made by previous models. Boosting techniques can often lead to superior predictive performance compared to standalone models like logistic regression or SVM.

   Convolutional Neural Networks (CNNs): CNN explored as part of the algorithm selection process for their unique ability to capture spatial patterns in data, particularly in image-based datasets. In the context of NBA shot analysis, CNNs were evaluated to determine their effectiveness in extracting features from shot images or related visual data.

These advanced models were tested to explore their potential for enhancing the predictive accuracy and generalization capability of the NBA shot analysis model.

In conclusion, the model selection process in the NBA shot analysis project involved experimenting with various algorithms such as Logistic Regression, SVM, Random Forests, Boosting, Bagging and CNN. Random Forests and Boosting were chosen based on their performance, suitability for the task, and potential for optimization. Parameter optimization techniques like Grid Search and Cross-Validation were utilized to fine-tune these models, and advanced techniques such as Bagging and Boosting were also explored to improve predictive accuracy and model robustness.

6 Preprocessing NBA player shot dataset for modeling purposes

In the Report1 we undertook essential preprocessing steps and conducted exploratory data analysis through visualization techniques. Our focus now shifts towards building machine learning models to gain deeper insights and make predictions based on our dataset. However, before we delve into model development, it's crucial to ensure that our data is adequately prepared. This involves transforming qualitative attributes into quantitative representations, normalizing features, and other necessary preparations to optimize the performance of our models.

In this part, we will carry out these preliminary tasks, laying the groundwork for our subsequent modeling endeavors. By converting qualitative attributes to quantitative ones and applying normalization techniques, we aim to create a clean and standardized dataset that is well-suited for machine learning analysis.

Our ultimate goal is to generate preprocessed and refined training and testing datasets. These datasets will lay the groundwork for our modeling endeavors, facilitating the smooth progression of building and assessing machine learning models in the subsequent phases of our project.

6.1 Categorical variable transformation and feature normalization

In machine learning and statistical modeling, the quality and format of input data significantly impact the performance and accuracy of predictive models. When working with datasets that contain categorical variables (attributes that represent qualitative characteristics) transforming these variables into numerical representations becomes imperative. Categorical variable transformation enables machine learning algorithms to interpret and analyze these variables effectively, allowing for meaningful insights and accurate predictions.

Furthermore, to ensure fair and optimal treatment of different features during model training, it is essential to normalize numerical features. Feature normalization standardizes the scale of input features, preventing certain variables from dominating the model training process due to their larger magnitude. By scaling features to a common range or distribution, feature normalization promotes stability, convergence, and improved generalization of machine learning models.

In summary, the process of categorical variable transformation and feature normalization is fundamental in preparing datasets for machine learning tasks, ensuring that models can effectively learn from and generalize to new data.

6.1.1 Transform attributes with high cardinality

Convert attributes, which have very large number of unique values.

Let's look at the unique valkues of 'Action Type' column.

```
There is 70 Action Type values.
```

```
[51]: Action Type
      Jump Shot                      2570552
      Layup Shot                      609190
      Driving Layup Shot              293150
      Pullup Jump shot                137984
      Hook Shot                        91485
                                     …
      Driving Reverse Dunk Shot          217
      Running Bank Hook Shot             187
      Turnaround Finger Roll Shot        127
      Running Reverse Dunk Shot          102
      Putback Reverse Dunk Shot           10
      Name: count, Length: 70, dtype: int64
```

Most machine learning algorithms operate with quantitative variables, hence the need to convert these values into numerical representations. With 70 unique action types, employing one-hot encoding would introduce an excessive number of additional columns, which is impractical. As we lack expertise in NBA terminology to group similar action types for discretization or feature engineering, our best option would be to utilize frequency encoding in this scenario. Instead of creating binary indicator variables for each unique action type, we could encode each action type based on its frequency in the dataset. This approach replaces each action type with the proportion of shots that belong to that category. This can be useful if certain action types occur more frequently than others and we want to capture that information in the model.

Step 1. Calculate the frequency of each unique action type.

Step 2. Replace each action type with its frequency in the dataset

These values represent the proportions of each category in the dataset, where the sum of all proportions would be equal to 1. In the context of frequency encoding for machine learning, using normalize=True ensures that each category's encoding represents its relative frequency in the dataset, making it suitable for capturing the distribution of categorical variables in a normalized manner.

Let's do the same for 'Team Name' column.

```
There is 37 Team Name values.
```

```
[55]: array(['Washington Wizards', 'Utah Jazz', 'San Antonio Spurs',
              'Atlanta Hawks', 'Toronto Raptors', 'Portland Trail Blazers',
              'New York Knicks', 'Houston Rockets', 'Phoenix Suns', 'Miami Heat',
              'Cleveland Cavaliers', 'Milwaukee Bucks', 'Los Angeles Clippers',
              'Philadelphia 76ers', 'Denver Nuggets', 'Golden State Warriors',
              'Orlando Magic', 'Dallas Mavericks', 'Seattle SuperSonics',
              'Sacramento Kings', 'Los Angeles Lakers', 'Vancouver Grizzlies',
              'Charlotte Hornets', 'New Jersey Nets', 'Chicago Bulls',
              'Indiana Pacers', 'Boston Celtics', 'Detroit Pistons',
              'Minnesota Timberwolves', 'Memphis Grizzlies',
              'New Orleans Hornets', 'Charlotte Bobcats',
              'New Orleans/Oklahoma City Hornets', 'Oklahoma City Thunder',
              'Brooklyn Nets', 'New Orleans Pelicans', 'LA Clippers'],
             dtype=object)
```

With the same reason as for 'Action Type', we can do feature encoding for 'Team Name', 'Home Team' and 'Away Team' columns. This time we will create function and will use that.

In our dataset 'Team ID' and 'Team Name' contains exactly the same information. Let's remove 'Team ID' column.

6.1.2 Transform other categorical attributes

Now, let's proceed to the next task. We have some categorical columns that need to be dichotomized. This involves transforming these categorical variables into "quantitative" variables that can be interpreted by a machine learning model.

In our dataset 'Shot Type', 'Shot Zone Basic', 'Shot Zone Area', 'Shot Zone Range', 'Season Type' columns contain qualitative values. Let's transform them.

We will use One Hot Encoding technique to encode a qualitative variable.

Step 1. Perform one-hot encoding for each categorical column

Step 2. Concatenate the one-hot encoded columns with the original DataFrame

Step 3. Drop the original categorical columns

6.1.3 Transform quantitative attributes, which have unique id values

In our dataset ‘Player ID’ and ‘Player Name’ contains exactly the same information. Let’s remove ‘Player Name’ column.

Let’s investigate ‘Game ID’, ‘Game Event ID’, ‘Player ID’ columns. These contain unique identifiers and lack inherent numerical meaning, it’s important to handle them appropriately for machine learning tasks.

Since these unique identifiers are repeated and associated with different instances or records in our dataset, then they can be considered as categorical variables rather than unique identifiers. In this case, we can apply feature encoding techniques to represent these categorical variables numerically.

Frequency encoding can indeed be applied to our unique identifiers.

6.2 Transform date attribute

Let’s transform date value to more readable format.

```
Timestamp('1997-10-31 00:00:00')
```

```
Timestamp('2020-03-11 00:00:00')
```

```
Our data looks at the time period from 1997 to 2020
```

The approach to handling date features in classification models is generally similar across different types of classifiers, including logistic regression. Date objects cannot be directly used as predictors in classification models, as these models require numerical input features.

Therefore, regardless of the specific classification model we are using, we typically need to perform feature engineering on the date column to extract relevant numerical features.

There are some common approaches to feature engineering with date data in classification models. We will use Extract Components. This approach extracts relevant components from the date, such as year, month, day, day of the week. These components can then be encoded as numerical features.

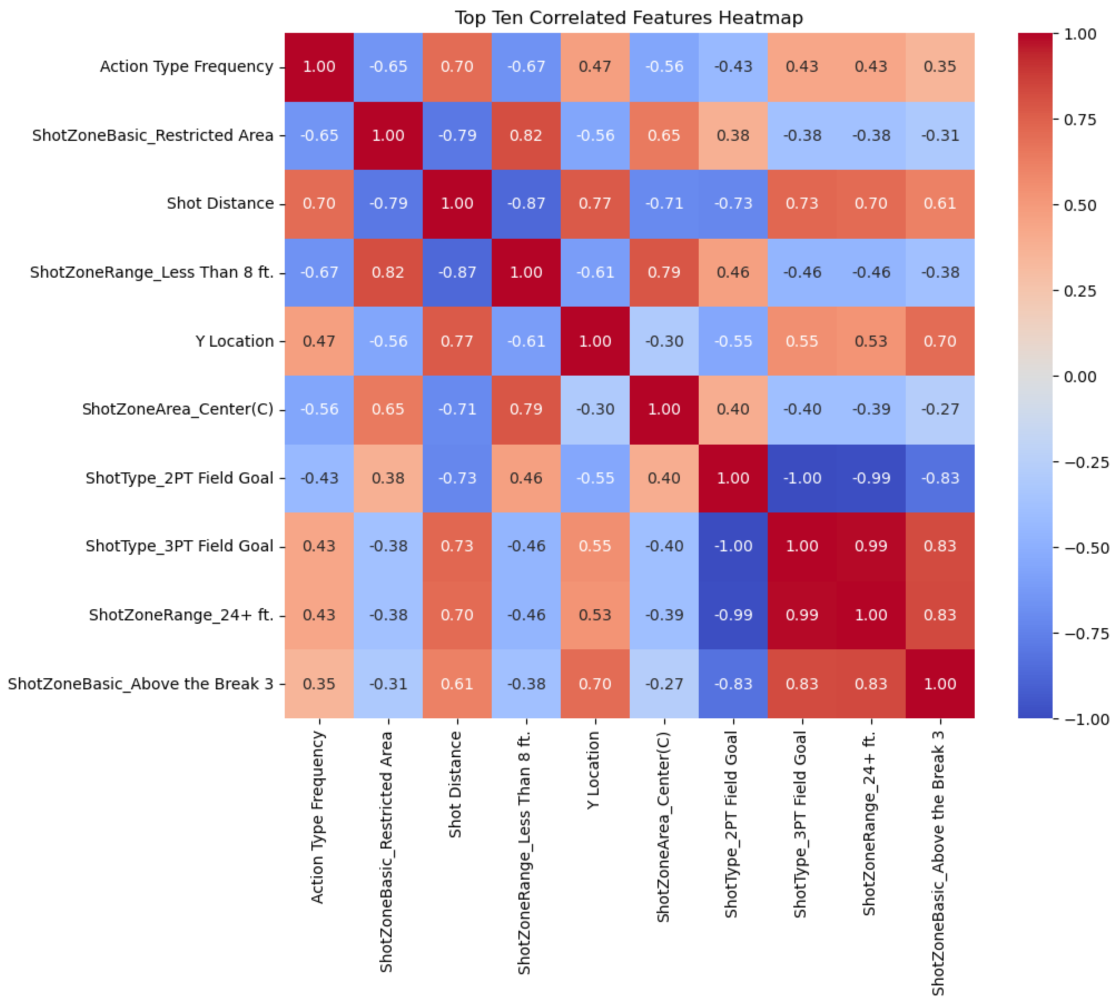
Display the DataFrame with extracted components.

```
[66]:   Game Date  Year  Month  Day  Day_of_Week
     0 1998-01-02  1998      1    2            4
     1 1998-01-02  1998      1    2            4
     2 1998-01-02  1998      1    2            4
     3 1998-01-02  1998      1    2            4
     4 1998-01-02  1998      1    2            4
```

Remove ‘Game Date’ column.

6.3 Correlation matrix

Now that we have transformed all features into numeric values, we can proceed to create a correlation matrix specifically for the 'Shot Made Flag' target variable.

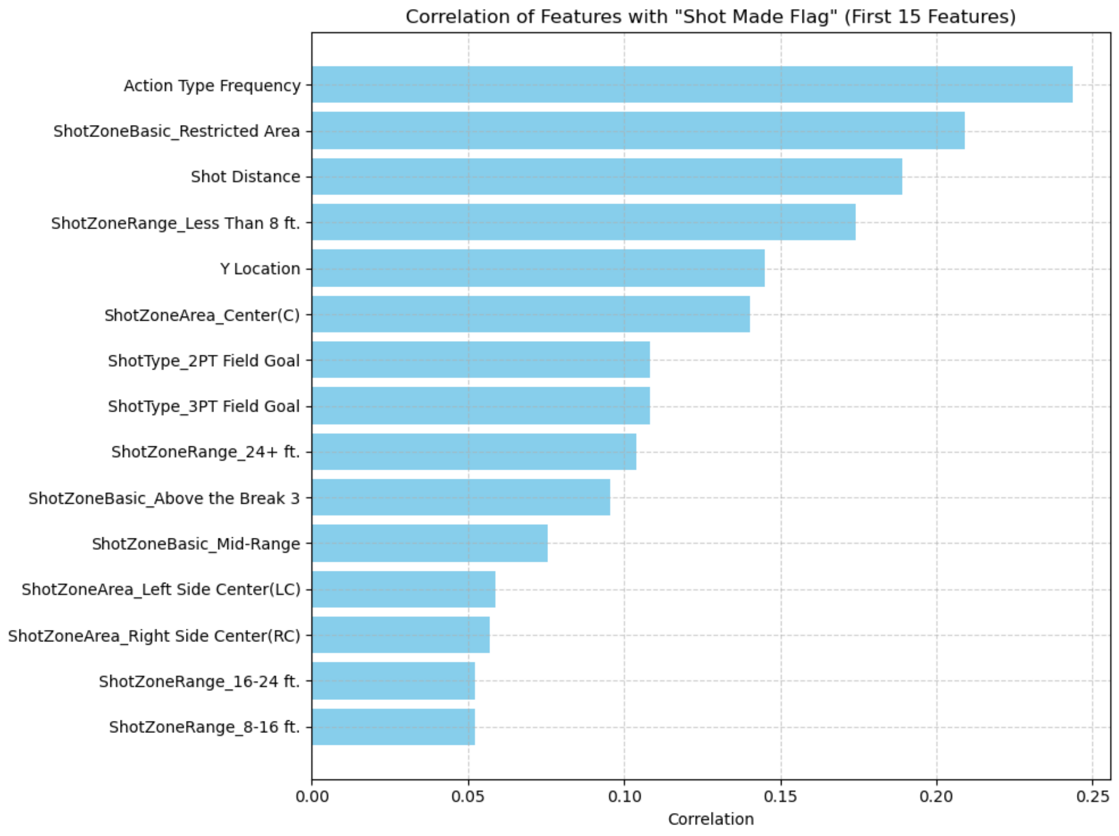


One can see by viewing these map that for an NBA player to increase his chances of making a shot, he should be as close as possible to the basket (ShotZoneRange_Less Than 8 ft., ShotZoneBasic_Restricted Area).

The high correlation coefficient of 0.99 between 'ShotType_3PT Field Goal' and 'ShotZoneRange_24+ ft.' signifies a strong relationship between attempting three-point shots and shooting from beyond the 24-foot mark on the court. This suggests that NBA players who frequently attempt three-pointers are more likely to do so from long distances, beyond the traditional three-point line. Coaches and analysts may use this insight to strategize offensive plays that leverage players' shooting abilities from long range, optimizing scoring opportunities based on shot selection and player positions on the court.

Let's create a plot showcasing the first 15 features that are correlated most with the target variable

‘Shot Made Flag’.



The correlation plot highlights the features most strongly correlated with ‘Shot Made Flag’.

‘Action Type Frequency’ shows a high positive correlation, suggesting that the frequency of specific actions during a shot attempt significantly impacts shot success.

‘ShotZoneBasic_Restricted Area’ and ‘Shot Distance’ also exhibit strong positive correlations, indicating that shots taken from restricted areas and shorter distances are more likely to be made.

Furthermore, ‘ShotType_2PT Field Goal’ and ‘ShotType_3PT Field Goal’ reflect the influence of shot type on success rates, with both two-point field goals (2PT) and three-point field goals (3PT) having an equal impact on shot success rates.

6.4 Split train and test parts

Let’s create a data DataFrame in which we will store the features and create the target data variable.

In order to test the performance of the classification model, it is necessary to select a part of the data that is dedicated to the evaluation and that is therefore not taken into account in the training of the model. To do this, the data must be systematically divided into a training set (X_train and y_train) and a test set (X_test and y_test).

Usually, the test set size is between 15% and 30% of the total amount of data. The choice of the distribution depends mainly on the quantity and quality of the available data. We will choose 20%.

Let's randomly divide the matrices into a training set and a test set corresponding to 80% and 20% of the total amount of available data respectively. Add the argument random_state = 66 for randomness reproducibility.

To build a classification model, we need to train our model on the training set only.

We intend to store these training and testing sets in a file for later use in modeling tasks. Ensuring consistency, all models will be trained on these identical sets. This approach will provide us with a clearer understanding of each model's performance under the same conditions, aiding in the determination of the most effective model.

6.5 Conclusion for preprocessing

We converted all categorical attributes to quantitative. Our dataset ready for further modeling.

[82]:
```
Period                                  int64
Minutes Remaining                       int64
Seconds Remaining                       int64
Shot Distance                           int64
X Location                              int64
Y Location                              int64
Shot Made Flag                          int64
Action Type Frequency                 float64
Team Name_Frequency                   float64
Home Team_Frequency                   float64
Away Team_Frequency                   float64
ShotType_2PT Field Goal                 int64
ShotType_3PT Field Goal                 int64
ShotZoneBasic_Above the Break 3         int64
ShotZoneBasic_Backcourt                 int64
ShotZoneBasic_In The Paint (Non-RA)     int64
ShotZoneBasic_Left Corner 3             int64
ShotZoneBasic_Mid-Range                 int64
ShotZoneBasic_Restricted Area           int64
ShotZoneBasic_Right Corner 3            int64
ShotZoneArea_Back Court(BC)             int64
ShotZoneArea_Center(C)                  int64
ShotZoneArea_Left Side Center(LC)       int64
ShotZoneArea_Left Side(L)               int64
ShotZoneArea_Right Side Center(RC)      int64
ShotZoneArea_Right Side(R)              int64
ShotZoneRange_16-24 ft.                 int64
ShotZoneRange_24+ ft.                   int64
ShotZoneRange_8-16 ft.                  int64
ShotZoneRange_Back Court Shot           int64
ShotZoneRange_Less Than 8 ft.           int64
```

```
SeasonType_Playoffs                         int64
SeasonType_Regular Season                   int64
Game ID_Frequency                         float64
Game Event ID_Frequency                   float64
Player ID_Frequency                       float64
Year                                        int32
Month                                       int32
Day                                         int32
Day_of_Week                                 int32
dtype: object
```

For now, our focus has been on converting categorical attributes into quantitative representations. We'll defer the scaling process to the appropriate modeling stage, where each model can adopt its own scaling approach (Standardization, MinMax Scaling or other type of scaling) based on its requirements and the characteristics of the data. The current emphasis has been on ensuring that our data is prepared in a format conducive to modeling, with further considerations such as feature scaling left for subsequent stages tailored to each specific model.

6.6 Save train-test sets in a file

Save the train and test sets in a new 'joblib' file.

```
New joblib file generated successfully.
```

7 NBA player shot analysis with Logistic Regression

In this section, we will dive into the logistic regression model. The packages utilized will include pandas and scikit-learn, along with its sub-packages linear_model, preprocessing, and joblib.

This task centers on exploring the parameters that may impact the shot outcomes of NBA players. The dataset under analysis comprises quantitative variables.

7.1 Pre-processing and feature engineering

Read the train and test sets from the file 'NBA Shot Locations 1997 - 2020-Report2-train-test.joblib'.

7.2 Standardization

Let's see min and max values of some columns.

```
Minimum values:
X Location                     -250.000000
Y Location                      -52.000000
Action Type Frequency             0.000002
ShotType_2PT Field Goal           0.000000
ShotZoneRange_Less Than 8 ft.     0.000000
Player ID_Frequency               0.000000
dtype: float64

Maximum values:
```

```
X Location                          250.000000
Y Location                          881.000000
Action Type Frequency                 0.543513
ShotType_2PT Field Goal               1.000000
ShotZoneRange_Less Than 8 ft.         1.000000
Player ID_Frequency                    0.006390
dtype: float64
```

To ensure optimal performance of our model, it would be advisable to perform scaling before applying logistic regression classification. Since we have columns with values between [-250, 250] and [0, 1], it's crucial to scale them appropriately to ensure that all features contribute equally to the model training process.

In our case, since we have both negative and positive values in some columns, and logistic regression is not sensitive to the scale of features, we can consider using Standard Scaling. Standard Scaling will transform our features to have a mean of 0 and a standard deviation of 1, without bounding them to a specific range like [-1, 1] or [0, 1].

Note: we will only scale the numerical features and not the encoded categorical features or the target column 'Shot Made Flag'. Also, the scaling is not necessary for columns generated from frequency encoding as their values are already in the range [0, 1].

Note: This technique scales the features to have a mean of 0 and a standard deviation of 1. Since the date components are already in different units (e.g., year, month, day), they may not benefit from standard scaling. In fact, applying standard scaling to these components could distort their meaning.

7.3 Classification by logistic regression

Let's create a clf Classifier, using the LogisticRegression method of the linear_model package. Then train the algorithm on the training set (X_train and y_train).

```
[87]: LogisticRegression(C=0.001, max_iter=1000, solver='liblinear')
```

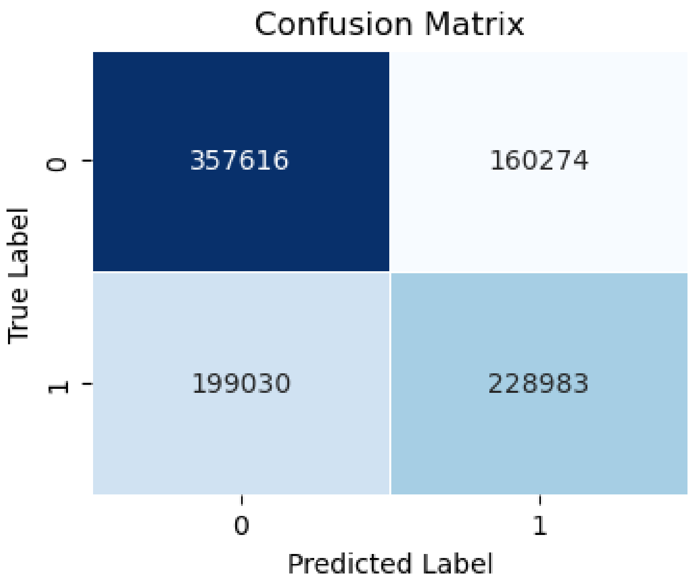
7.4 Evaluation of the classification model

7.4.1 Confusion matrix

Now it is possible to calculate the prediction for the data in the test set, and construct the confusion matrix.

Predict the data in the test set and store it in the variable y_pred.

Create and display the confusion matrix cm.



The confusion matrix, above, illustrates that the number of good classifications (on the diagonal) is greater than the number of bad classifications.

Is it the model that is unsuitable for this type of data or is it the parameterization that is unsuitable?

Many machine learning algorithms, such as Logistic regression, rely on hyperparameters that are not always obvious to determine in order to obtain the best performance on a given dataset.

Unlike the simple parameters of the model which are directly derived from the data (e.g. the coefficients of a regression), the hyperparameters make it possible to decide on the structure of the model and must be set before training it.

In most cases, when several hyperparameters are to be set, and one does not know which ones to use to obtain the best possible model, the most efficient strategy is to create a search grid. We indicate the parameters to be varied. Then the parameters are crossed and a model is created and evaluated for each possible combination by cross validation.

Create a dictionary parameters containing the possible values taken for the parameter:

```
[94]: {'C': [0.01, 1, 100], 'penalty': ['l2'], 'solver': ['liblinear']}
```

Apply the function model_selection.GridSearchCV() to the clf model, specifying in the param_grid argument the parameter grid created above. Return the classifier thus created in grid_clf. The scoring argument allows us to choose the metric we want to use to evaluate the performance of the models, by default it is accuracy.

Train grid_clf on the training set, (X_train, y_train). Save the results in the grid object.

Following results displays all possible combinations of hyperparameters and the average performance of the associated model by cross validation.

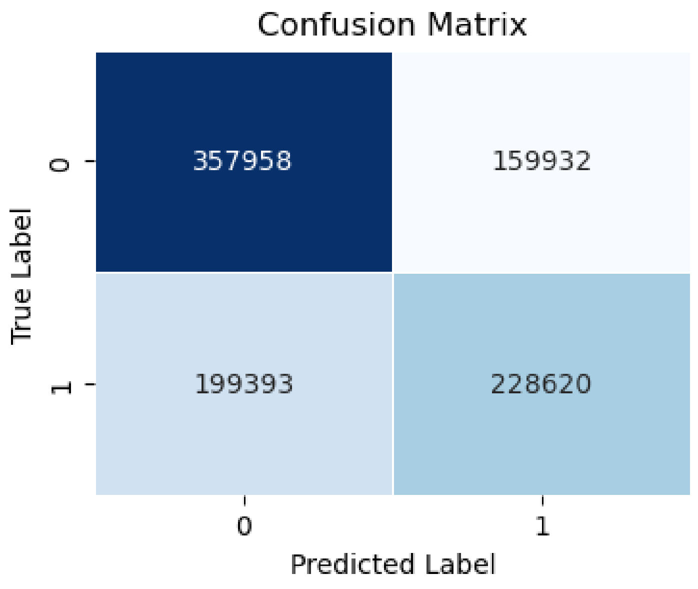
```
                                                  params  mean_test_score
```

```
0  {'C': 0.01, 'penalty': 'l2', 'solver': 'liblin…        0.620353
1   {'C': 1, 'penalty': 'l2', 'solver': 'liblinear'}        0.620370
2  {'C': 100, 'penalty': 'l2', 'solver': 'libline…        0.620349
```

The best_params_ attribute of the created model allows to display the parameters having given the best score and retained by default.

```
{'C': 1, 'penalty': 'l2', 'solver': 'liblinear'}
```

Now make class predictions using the grid_clf model on the test set and store them in the y_pred variable, and print a confusion matrix from these predictions.



The confusion matrix is non-significantly better than that obtained at the beginning of this paragraph. The tuning of hyperparameters is thus a very useful and essential step when creating models, especially when one has several important hyperparameters, such as Logistic regression, and is thus not to be neglected.

7.4.2 Accuracy score

The accuracy of a model is a metric often used in classification and corresponds to the number of well classified elements out of the total number of shots. It can be computed by using the score attribute of the classifier (clf).

Let's create a new classifier with the best parameters, fit it on the training data and calculate accuracy on test and train sets.

```
[102]: LogisticRegression(C=1, solver='liblinear')
```

```
0.6201248965274452
This logistic regression model achieved an accuracy of approximately 62.01% on
the test set.
```

If we do accuracy test also on train set then we will have more or less same result.

```
0.6203674851180447
This logistic regression model achieved an accuracy of approximately 62.04% on
the train set.
```

Save the best model to a file.

```
[106]: ['model_best_lr.joblib']
```

7.4.3 Classification report

The function classification_report() of the sklearn.metrics sub-module allows to display some of these additional metrics, with as arguments the vector of true labels, and the vector of predicted labels.

Display the classification report of our predictions.

```
              precision    recall  f1-score   support

           0       0.64      0.69      0.67    517890
           1       0.59      0.53      0.56    428013

    accuracy                           0.62    945903
   macro avg       0.62      0.61      0.61    945903
weighted avg       0.62      0.62      0.62    945903
```

The precision and recall scores provide insights into the model's ability to correctly classify instances of each class. In this case, the precision for class 0 (0.64) is higher than that for class 1 (0.59), indicating that the model is better at correctly identifying instances of class 0. However, the recall for class 0 (0.69) is higher than that for class 1 (0.53), indicating that the model is better at capturing a higher proportion of true instances for class 0 compared to class 1.

7.4.4 ROC curve

By default, the predict() method of a classifier in the case of a logistic regression classifies shot result as positive when the probability of belonging to the positive class is greater than the threshold of 0.5, and negative otherwise. Sometimes, we may want to modify this classification threshold.

Let's say we want to change threshold to 0.4.

In that case the lower the classification threshold, the more the number of shot-mades classified as 1 increases, so the sensitivity will increase. On the other hand, a shot-made is classified as 0 only if the probability that it belongs to this class is higher than 0.6, which increases the precision of the null class but decreases the specificity.

Another very efficient tool to evaluate the performance of a model is the ROC curve. The ROC curve (for Receiver Operating Characteristic) is the ideal tool to summarize the performance of a binary classifier according to all possible thresholds. It avoids the time-consuming task of predicting classes for different thresholds, and evaluating the confusion matrix for each of these thresholds.

Graphically, the ROC measure is represented as a curve which gives the true positive rate, the sensitivity, as a function of the false positive rate, the antispecificity (= 1 - specificity). Each classification threshold value will provide a point on the ROC curve, which will go from (0, 0) to (1, 1).

The closer the curve is to the (0,1) point (top left), the better the predictions. A model with sensitivity and specificity equal to 1 is considered perfect.

The area under the curve (AUC: Area Under the Curve) is very useful. In a single number it summarizes the ability of the model to distinguish the negative class from the positive class (Non Admitted / Admitted).

An AUC score of 0.5 means that the model is not better than a random classification, an AUC score of 1.0 means a perfectly predictive model, and an AUC of 0.0 is perfectly anti-predictive (very rare).

The sklearn.metrics module contains the function roc_curve() which returns an array of false positive rates (anti-specificity), an array of true positive rates (sensitivity), and an array of classification thresholds taking values between 0 and 1. It takes as argument the vector of labels we want to predict, a vector of probabilities to belong to the positive class and the argument pos_label, which allows to choose which label is defined as positive.

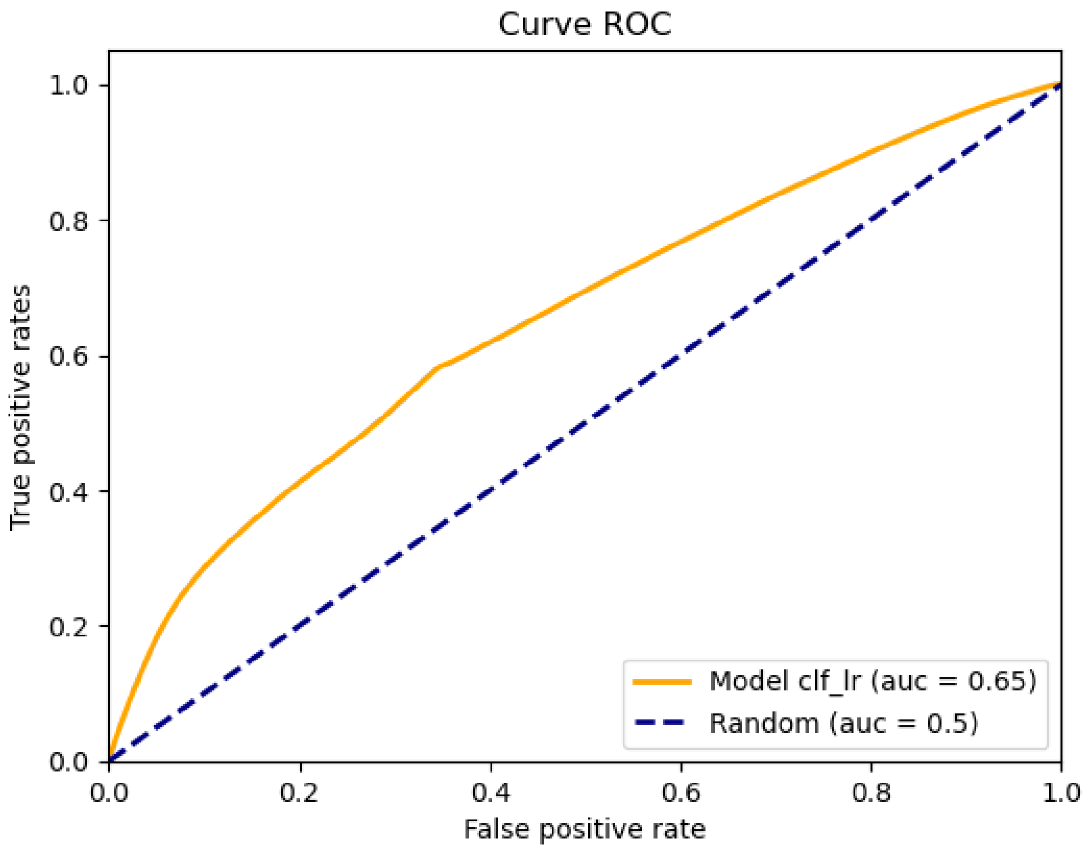
The function auc() of the same module computes the area under the curve when given as arguments a vector of false positive rates and a vector of the same size of true positive rates.

Step 1. Apply the roc_curve() function to y_test and the second column of probs, specifying that the positive label in our case is 1. Store the returned results in the fpr, tpr, thresholds tables.

Step 2. Calculate in roc_auc the AUC corresponding to the values of fpr and tpr.

```
[108]: 0.6531505047507934
```

From the variables fpr, tpr and roc_auc, create a reproduction of the graph.



While a ROC AUC of 0.65 suggests that the model has some predictive ability, further analysis and consideration of specific requirements are needed to determine its suitability for practical applications. Additionally, exploring alternative models or optimization strategies may help improve performance further.

7.5 Conclusion for Logistic Regression

The accuracy of the logistic regression model on the test dataset was observed to be approximately 62%. This indicates that the model correctly classified 62% of instances.

To gain a deeper understanding of the model's performance, various evaluation metrics were employed, including confusion matrix, accuracy, precision, recall, F1-score, and ROC curve analysis.

While the logistic regression classification model achieved a moderate level of accuracy, ongoing refinement and evaluation are necessary to develop a robust and reliable predictive model for the given task.

8 NBA player shot analysis with Support Vector Machine (SVM)

Our investigation into using Support Vector Machine (SVM) models revealed challenges with training on our large dataset of 4.7 million rows. The training process failed to execute, indicating that

SVM may not be suitable for this task given the scale of our data. This is primarily due to the computational complexity of SVM, which scales significantly with both the number of features and observations. In our case, with 4.7 million observations, the computational burden became impractical, with the running time scaling up to O(n_features x n^3_observations), resulting in an overwhelming number of operations—roughly estimated at 100 quintillion—required to process the data.

9 NBA player shot analysis with Boosting and Bagging

In this section, we will dive into the boosting and bagging algorithms. Boosting and Bagging methods are "meta-algorithms" whose approach is to combine several machine learning algorithms into a predictive model, in order to reduce their variance or bias, and improve the final performance.

Both methods work in a similar way, and consist of 2 main steps:

1) Build different simple Machine Learning models on subsets of the original data.
2) Produce a new model from the assembly of the previous ones.

9.1 Pre-processing and feature engineering

The package sklearn.ensemble allows to implement the AdaBoost algorithm in the case of multi-class classification, in particular the class AdaBoostClassifier, which allows to create a classifier using by default a simple decision tree as initial classification rule.

Read the train and test sets from the file 'NBA Shot Locations 1997 - 2020-Report2-train-test.joblib'.

9.2 Boosting

Boosting is a set of methods that essentially aim to reduce the bias of simple and weak Machine Learning models and convert them into a stable and powerful model.

There are many different boosting algorithms. The most popular is the AdaBoost algorithm (for Adaptive Boosting) developed by Freund & Schapire (1997). It works as follows:

We choose a "weak" classification rule. The idea is to apply this rule several times by judiciously assigning a different weight to the observations at each iteration.

- The weights of each observation are initialized to 1/ for the estimation of the first model.
- They are then updated for each iteration. The importance of an observation is unchanged if the observation is well ranked; otherwise it increases with the measured quality of fit of the model.
- The final aggregation is a combination of the obtained estimators weighted by the quality of fit of each model.

9.3 Supervised decision tree classification

Let's create a clf Classifier, using the DecisionTreeClassifier method with parameter max_depth = 3. Then train the algorithm on the training set (X_train and y_train).

```
[112]: DecisionTreeClassifier(max_depth=3)
```

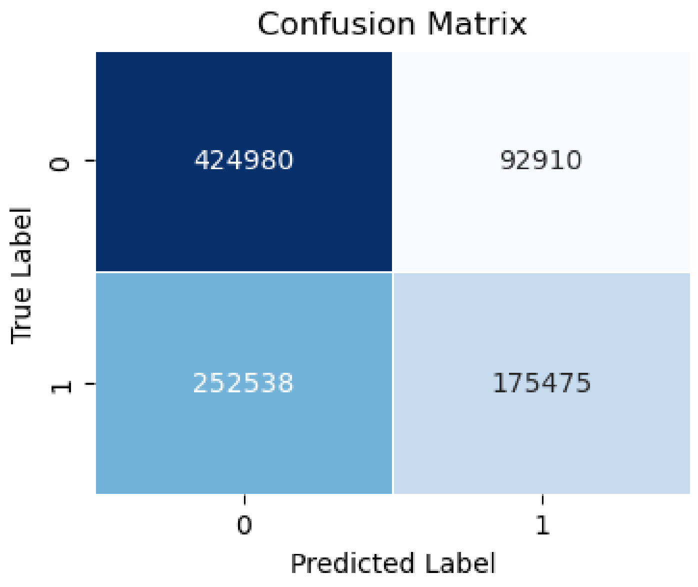
9.3.1 Evaluation of the first classification model

First, we will evaluate the model by computing its average accuracy on the train and test sets.

```
0.6347955340029581
This decision tree model achieved an accuracy of approximately 63.48% on the
test set.
```

```
0.6355870810118065
This decision tree model achieved an accuracy of approximately 63.56% on the
train set.
```

The rate of good prediction is relatively moderate. For better clarity of the predictions made, a confusion matrix should be displayed.



```
[118]: ['model_dt.joblib']
```

9.4 Boosting Algorithm

The objective of this part is to create a new classification model from sequences of decision trees like dtc defined above.

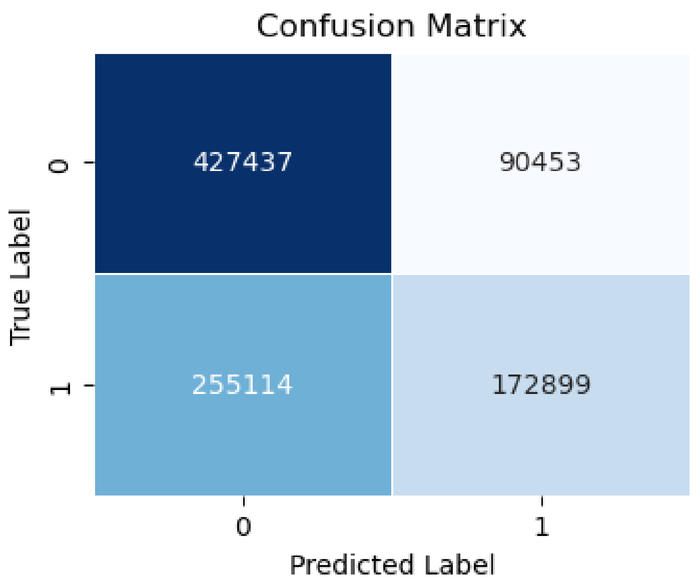
Create a classifier again, using the AdaBoostClassifier class. Train the algorithm. Calculate the accuracy of the new classification model on the test sample.

```
/Users/mihrandovlatyan/anaconda3/lib/python3.11/site-
packages/sklearn/ensemble/_weight_boosting.py:519: FutureWarning: The SAMME.R
algorithm (the default) is deprecated and will be removed in 1.6. Use the SAMME
algorithm to circumvent this warning.
  warnings.warn(
[120]: AdaBoostClassifier(estimator=DecisionTreeClassifier(max_depth=3),
                          n_estimators=2)
```

```
0.6346697282913787
This boosting model achieved an accuracy of approximately 63.47% on the test
set.
```

```
0.6354211019161864
This boosting model achieved an accuracy of approximately 63.54% on the train
set.
```

Print the confusion matrix of the test set.



The results obtained are the as the simple decision tree. Adaboost is an algorithm applicable to many domains by a good choice of basic classifiers. This technique is adapted to multi-label problems and allows to classify outliers well.

```
[125]: ['model_boosting.joblib']
```

9.5 Bagging or Bootstrap AGGregatING

The term Bagging comes from the contraction of Boostrap Aggregating. The general method of Bagging consists mainly in training a model on different subsets of the same size as the initial sample, using the Bootstrap technique, i.e. a random draw with discount. The method thus builds a set of independent estimators, unlike Boosting, which are then aggregated (or bagged) into a meta-model, with a majority vote for the classification, and a mean for the regression.

Unlike Boosting, choosing a large number of estimators will not result in additional risk of over-fitting. Indeed, the higher the number of estimators, the more the bias of the final model will be equivalent to the average of the aggregated biases and the variance will decrease as the estimators that are aggregated will be decorrelated. It is therefore in our interest to choose the highest possible number of estimators, depending on the time we wish to allow for the training process.

The prediction error computed, in general, for Bagging methods is the so-called Out Of Bag (OOB) error, i.e. for each observation the average of the errors for all the models trained on a bootstrap sample of which it is not a part is computed. This technique helps to prevent over-fitting.

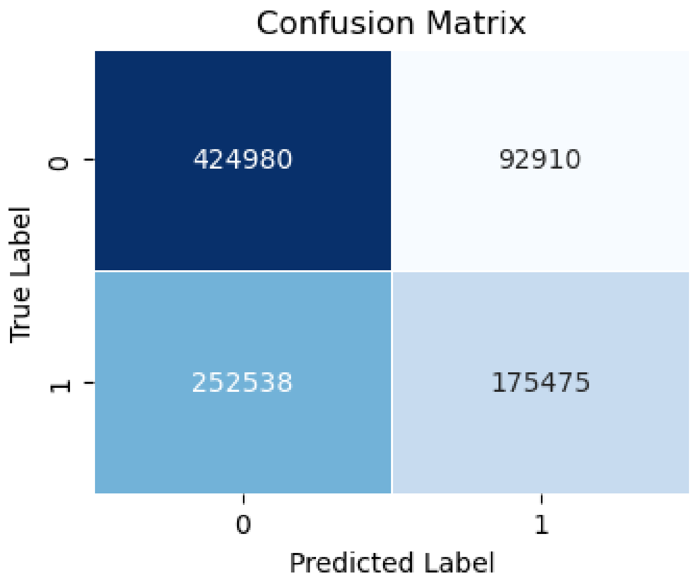
Create a classifier again, using the BaggingClassifier class. Train the algorithm. Print the Out Of Bag error of the model.

```
[126]: BaggingClassifier(estimator=DecisionTreeClassifier(max_depth=3))
```

Calculate the accuracy of the new classification model on the test and train samples.

```
0.6347955340029581
This bagging model achieved an accuracy of approximately 63.48% on the test set.
0.6355870810118065
This bagging model achieved an accuracy of approximately 63.56% on the train
set.
```

Print the confusion matrix of the test set.



The results obtained with Bagging are the same as the first models.

Create a dictionary parameters containing the possible values taken for the parameter:

```
[130]: {'max_features': [0.5, 1.0],
        'max_samples': [0.5, 1.0],
        'n_estimators': [10, 20]}
```

Following results displays all possible combinations of hyperparameters and the average performance of the associated model by cross validation.

```
                                              params  mean_test_score
0  {'max_features': 0.5, 'max_samples': 0.5, 'n_e…         0.626650
1  {'max_features': 0.5, 'max_samples': 0.5, 'n_e…         0.627056
2  {'max_features': 0.5, 'max_samples': 1.0, 'n_e…         0.625253
3  {'max_features': 0.5, 'max_samples': 1.0, 'n_e…         0.626787
4  {'max_features': 1.0, 'max_samples': 0.5, 'n_e…         0.635916
5  {'max_features': 1.0, 'max_samples': 0.5, 'n_e…         0.635587
6  {'max_features': 1.0, 'max_samples': 1.0, 'n_e…         0.635587
7  {'max_features': 1.0, 'max_samples': 1.0, 'n_e…         0.635587

Best hyperparameters: {'max_features': 1.0, 'max_samples': 0.5, 'n_estimators':
10}
```

Evaluate the best model from best_estimator_ attribute on the test and train sets.

```
0.6347955340029581
This bagging model achieved an accuracy of approximately 63.48% on the test set.

0.6355870810118065
This bagging model achieved an accuracy of approximately 63.56% on the train
set.
```

```
[137]: ['model_best_bagging.joblib']
```

Bagging is a simple and robust ensemble method that reduces variance when predictors are unstable. Its estimation of the prediction error by Bootstrap prevents over-fitting.

9.6 Conclusion for Boosting and Bagging

The accuracy of the bagging and boosting models on the test dataset was observed to be approximately 63%. This indicates that the models correctly classified 63% of instances.

To gain a deeper understanding of the model's performance, various evaluation metrics were employed, including confusion matrix, accuracy.

While the bagging and boosting models achieved a moderate level of accuracy, ongoing refinement and evaluation are necessary to develop a robust and reliable predictive model for the given task.

10 NBA player shot analysis with Random Forests

In this section, we will create Random Forests model. The packages used will be pandas, scikit-learn and its subpackages, namely ensemble, and joblib.

This task centers on exploring the parameters that may impact the shot outcomes of NBA players. The dataset under analysis contains quantitative variables.

10.1 Classification by random forests

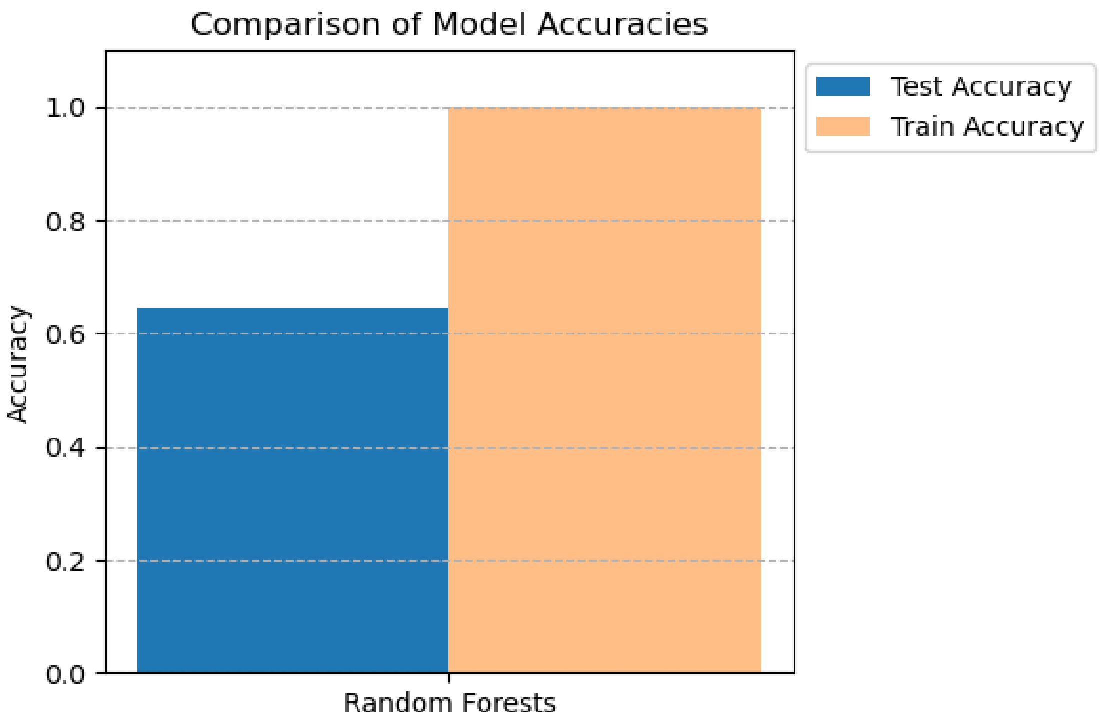
Let's create a clf Classifier, using the RandomForestClassifier method of the ensemble package. Then train the algorithm on the training set (X_train and y_train).

```
[140]: RandomForestClassifier(n_jobs=-1, random_state=321)
```

10.2 Evaluation of the classification model

```
0.6445935788341933
This random forests model achieved an accuracy of approximately 64.46% on the
test set.
```

```
0.9999994714041541
This random forests model achieved an accuracy of approximately 100.00% on the
train set.
```



These numbers indicate that our Random Forest classifier is overfitting the training data, as it performs nearly perfectly on the training set but struggles to generalize to new, unseen data (as evidenced by the lower testing accuracy). It might be beneficial to explore methods to reduce overfitting, such as hyperparameter tuning, feature selection, or using more data for training if possible.

Create a dictionary parameters containing the possible values taken for the parameter.

```
[144]: {'max_depth': [10],
         'min_samples_leaf': [1, 2],
         'min_samples_split': [2, 3],
         'n_estimators': [5, 10],
         'n_jobs': [-1]}
```

Apply the function model_selection.GridSearchCV() to the clf model, specifying in the param_grid argument the parameter grid created above. Return the classifier thus created in grid_clf. The scoring argument allows us to choose the metric we want to use to evaluate the performance of the models, by default it is accuracy.

Train grid_clf_rf on the training set, (X_train, y_train). Save the results in the grid object.

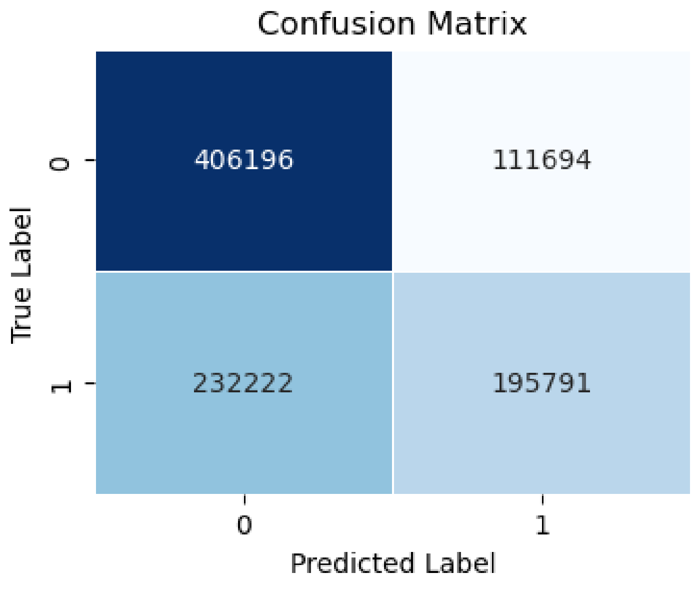
Following results displays all possible combinations of hyperparameters and the average performance of the associated model by cross validation.

```
                                               params  mean_test_score
0  {'max_depth': 10, 'min_samples_leaf': 1, 'min_…        0.637314
1  {'max_depth': 10, 'min_samples_leaf': 1, 'min_…        0.640048
2  {'max_depth': 10, 'min_samples_leaf': 1, 'min_…        0.636880
3  {'max_depth': 10, 'min_samples_leaf': 1, 'min_…        0.638332
4  {'max_depth': 10, 'min_samples_leaf': 2, 'min_…        0.634464
5  {'max_depth': 10, 'min_samples_leaf': 2, 'min_…        0.637940
6  {'max_depth': 10, 'min_samples_leaf': 2, 'min_…        0.634464
7  {'max_depth': 10, 'min_samples_leaf': 2, 'min_…        0.637940
```

The best_params_ attribute of the created model allows to display the parameters having given the best score and retained by default.

```
{'max_depth': 10, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators':
10, 'n_jobs': -1}
```

Now make class predictions using the grid_clf model on the test set and store them in the y_pred variable, and print a confusion matrix from these predictions.



The confusion matrix is non better than that obtained at the beginning of this paragraph. This because we used ‘max_depth’ = 10 in grid search, while in first result we have ‘max_depth’ = None. This allows the trees to expand until all leaves are pure or until all leaves contain less than min_samples_split samples, effectively allowing the trees to grow without any depth limit.

The tuning of hyperparameters is thus a very useful and essential step when creating models, especially when one has several important hyperparameters, such as random forests, and is thus not to be neglected.

Evaluate the best model from best_estimator_ attribute on the test and train sets.

```
0.6364151503906849
This random forests model achieved an accuracy of approximately 63.64% on the
test set.
```

```
0.6382379891791145
This random forests model achieved an accuracy of approximately 63.82% on the
train set.
```

```
[154]: ['model_best_rf.joblib']
```

10.2.1 Classification report

The function classification_report() of the sklearn.metrics sub-module allows to display some of these additional metrics, with as arguments the vector of true labels, and the vector of predicted labels.

Display the classification report of our predictions.

```
              precision    recall  f1-score   support

           0       0.64      0.78      0.70    517890
           1       0.64      0.46      0.53    428013

    accuracy                           0.64    945903
   macro avg       0.64      0.62      0.62    945903
weighted avg       0.64      0.64      0.63    945903
```

The F1-score is the harmonic mean of precision and recall and provides a balanced measure of the model's performance. For class 0, the F1-score is 0.70, while for class 1, it is 0.53. This suggests that the model achieves a better balance between precision and recall for class 0 compared to class 1.

The overall accuracy of the model is 64%, indicating that approximately 64% of all instances are correctly classified.

10.3 Conclusion for Random Forests

The accuracy of the random forests model on the test dataset was observed to be approximately 64%. This indicates that the model correctly classified 64% of instances.

To gain a deeper understanding of the model's performance, various evaluation metrics were employed, including confusion matrix, accuracy, precision, recall, F1-score.

While the random forests classification model achieved a moderate level of accuracy, ongoing refinement and evaluation are necessary to develop a robust and reliable predictive model for the given task.

11 Comparison of basic Models

11.1 Comparison of Hyperparameters for each Model

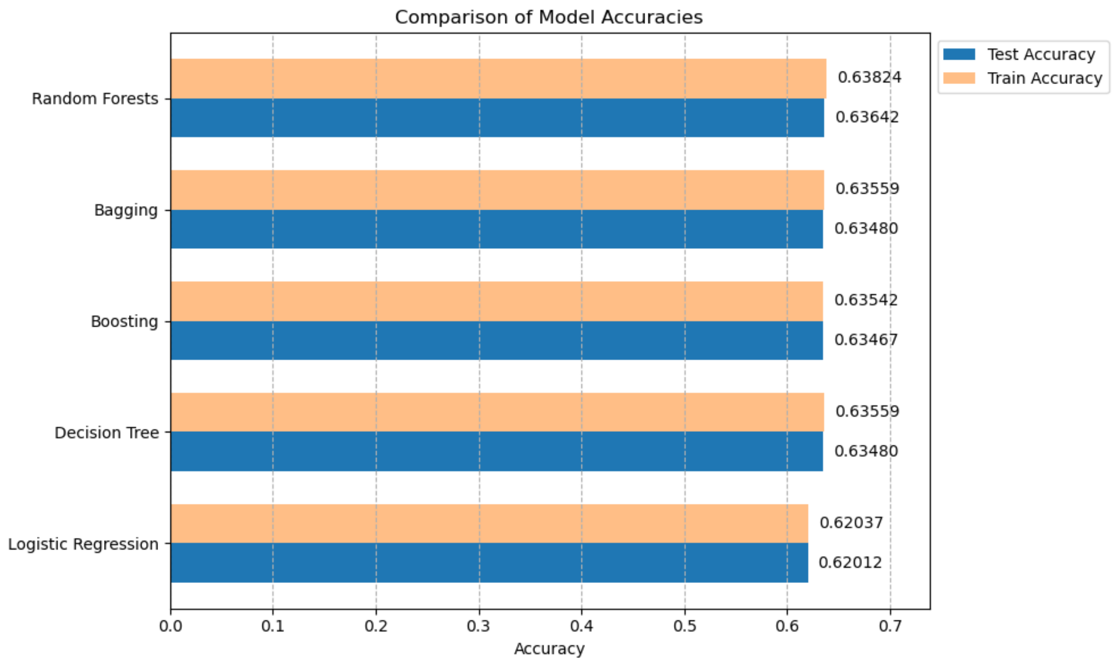
Hyperparameter Space for each Model

Model Type	Hyperparameters
Logistic Regression	C: [0.01, 1, 100], penalty: l2, solver: liblinear
Bagging	max_features: [0.5, 1.0], max_samples: [0.5, 1.0], n_estimators: [10, 20]
Random Forests	max_depth: 10, min_samples_leaf: [1, 2], min_samples_split: [2, 3], n_estimators: [5, 10],

Best Hyperparameters of each Model

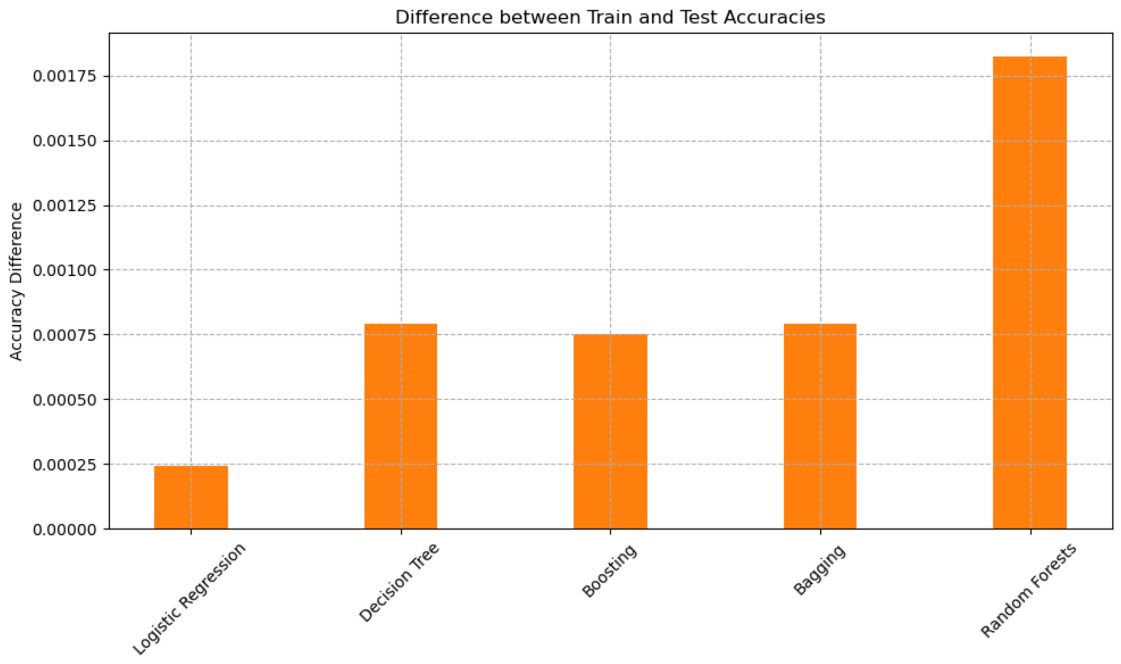
Model Type	Best Hyperparameters
Logistic Regression	C: 1, penalty: l2, solver: liblinear
Bagging	max_features: 1.0, max_samples: 0.5, n_estimators: 10
Random Forests	max_depth: 10, min_samples_leaf: 1, min_samples_split: 2, n_estimators: 10, n_jobs: -1

11.2 Comparison of Accuracies for each Model



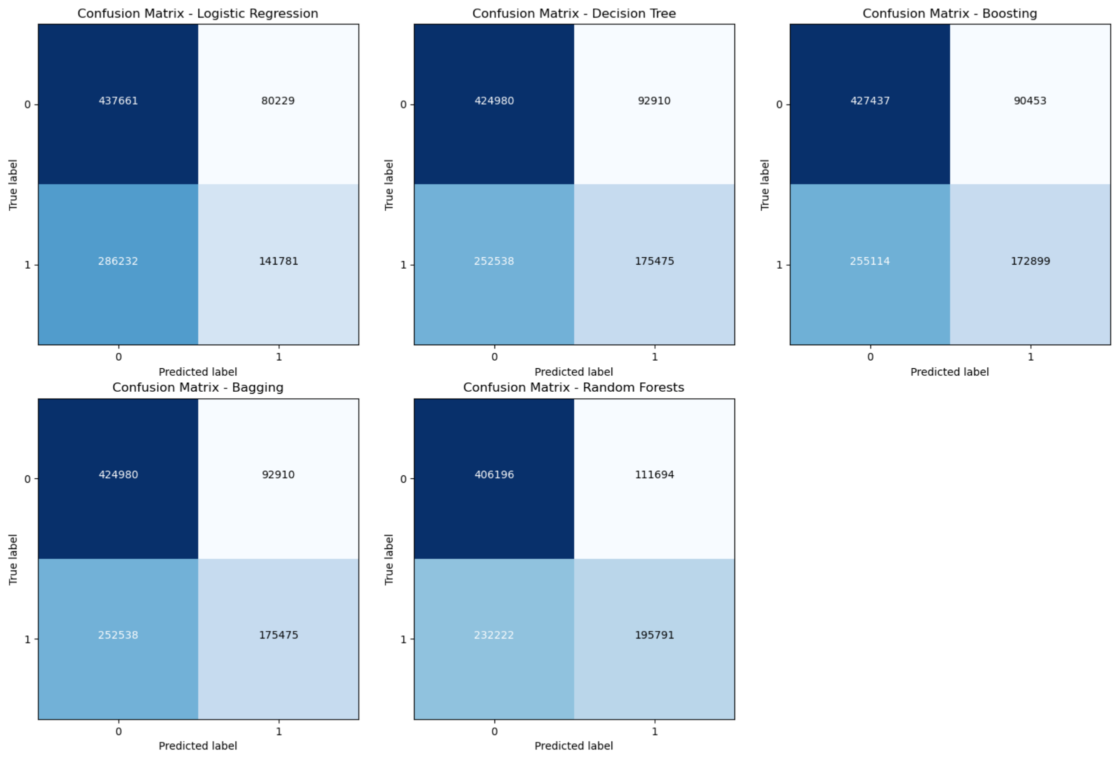
Note: Random Forest model showed the highest accuracy score for the training and test data sets.

Since the train and test accuracies are very close, making it difficult to visually distinguish them in a bar chart, we are going to use a different type of plot that emphasizes the comparison more clearly. We will plot the difference between train and test accuracies for each model. This can highlight cases where overfitting or underfitting occurs.



Note: Random Forest model has the highest accuracy difference between train and test sets, but that is not high to say that we have an overfitting.

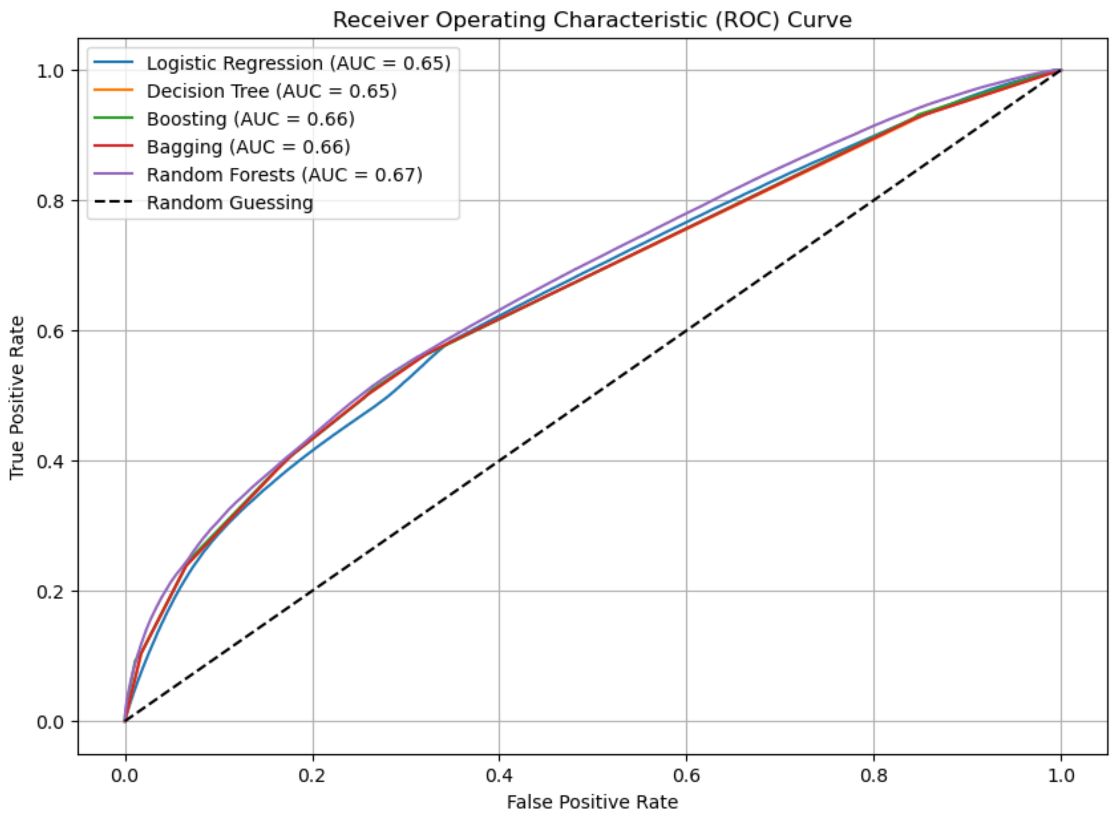
11.3 Comparison of Confusion Matrix for each Model



Note: The illustration of confusion matrices reveals a relatively big number of true positives for Random Forests model.

11.4 Comparison of ROC Curves for each Model

```
/Users/mihrandovlatyan/anaconda3/lib/python3.11/site-
packages/sklearn/ensemble/_weight_boosting.py:519: FutureWarning: The SAMME.R
algorithm (the default) is deprecated and will be removed in 1.6. Use the SAMME
algorithm to circumvent this warning.
  warnings.warn(
```



Note. The ROC shows that all models struggle to increase sensitivity without disproportionately increasing specificity. As our goal is to increase recall, this means that these models will further increase false positives significantly. In addition, the AUC shows us that the overall accuracy across all models is similarly.

12 NBA player shot analysis with Deep Learning (CNN, LeNet architecture)

The main objective of this part is to perform a reproduction of the Convolutional Neural Network (CNN) algorithm LeNet5 on Python with the Keras module. The LeNet architecture is one of the simplest to implement and one of the most important in Deep Learning as it is the backbone of many more complex models.

The LeNet architecture was introduced by Yann LeCun in November 1998. We will construct the architecture of the LeNet network, then we will train this algorithm on the same data as in the previous models. The LeNet network includes two convolution layers, two pooling layers, and dropout layers.

Read the train and test sets from the file ‘NBA Shot Locations 1997 - 2020-Report2-train-test.joblib’.

12.1 Standardization

To ensure optimal performance of our model, it would be advisable to perform scaling before applying our classification. We will only scale the numerical features and not the encoded categorical features or the target column ‘Shot Made Flag’. Also, the scaling is not necessary for columns generated from frequency encoding as their values are already in the range [0, 1].

Show the dimension of train dataset.

```
[21]: (3783609, 39)
```

By reducing the dimensionality of the data, PCA can help in capturing the most important features or patterns in the data, which can lead to improved model performance. It can also help in mitigating issues like overfitting, especially when the original dataset has a large number of features.

```
[23]: (3783609, 20)
```

Transform the X_train data into a 4-dimensional array (nb_images, width, height, depth). Each data point will be resized to the format (4, 5, 1). Apply the same transformation to the X_test data.

Let’s define some callbacks which will regulate our model training.

Create the CNN model with LeNet architecture.

Compile the model and show the summary.

```
Model: "functional_1"


 Layer (type)                        Output Shape                    Param #

 input_layer (InputLayer)            (None, 4, 5, 1)                       0

 conv2d (Conv2D)                     (None, 4, 5, 128)                 1,280

 max_pooling2d (MaxPooling2D)        (None, 2, 2, 128)                     0

 conv2d_1 (Conv2D)                   (None, 2, 2, 64)                 73,792

 max_pooling2d_1 (MaxPooling2D)      (None, 1, 1, 64)                      0

 flatten (Flatten)                   (None, 64)                            0

 dense (Dense)                       (None, 128)                       8,320

 dropout (Dropout)                   (None, 128)                           0

 dense_1 (Dense)                     (None, 64)                        8,256

 dropout_1 (Dropout)                 (None, 64)                            0
 dense_2 (Dense)                  (None, 32)                    2,080

 dropout_2 (Dropout)              (None, 32)                        0

 dense_3 (Dense)                  (None, 1)                        33


 Total params: 93,761 (366.25 KB)

 Trainable params: 93,761 (366.25 KB)

 Non-trainable params: 0 (0.00 B)
```

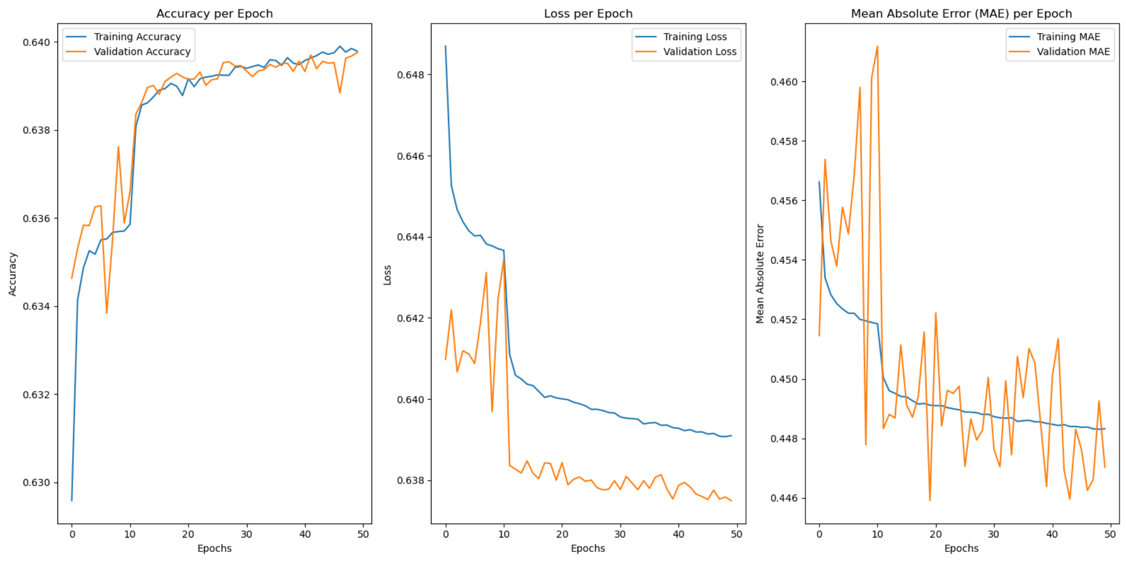
```
None
```

Train the model.

```
Epoch 1/50 - loss: 0.6487 - accuracy: 0.6296 - val_loss: 0.6410 - val_accuracy:
0.6346
Epoch 11/50 - loss: 0.6437 - accuracy: 0.6359 - val_loss: 0.6434 - val_accuracy:
0.6366
Epoch 21/50 - loss: 0.6400 - accuracy: 0.6392 - val_loss: 0.6384 - val_accuracy:
0.6391
Epoch 31/50 - loss: 0.6396 - accuracy: 0.6394 - val_loss: 0.6378 - val_accuracy:
0.6393
Epoch 41/50 - loss: 0.6393 - accuracy: 0.6396 - val_loss: 0.6379 - val_accuracy:
0.6393
Training duration: 112 min 51 sec
```

Save the history object to a file that later we can use it.

Display the training history for each epoch.



Evaluate the model on test data.

```
29560/29560             23s
762us/step - accuracy: 0.6406 - loss: 0.6373 - mean_absolute_error: 0.4494
Test Accuracy: 63.99%
```

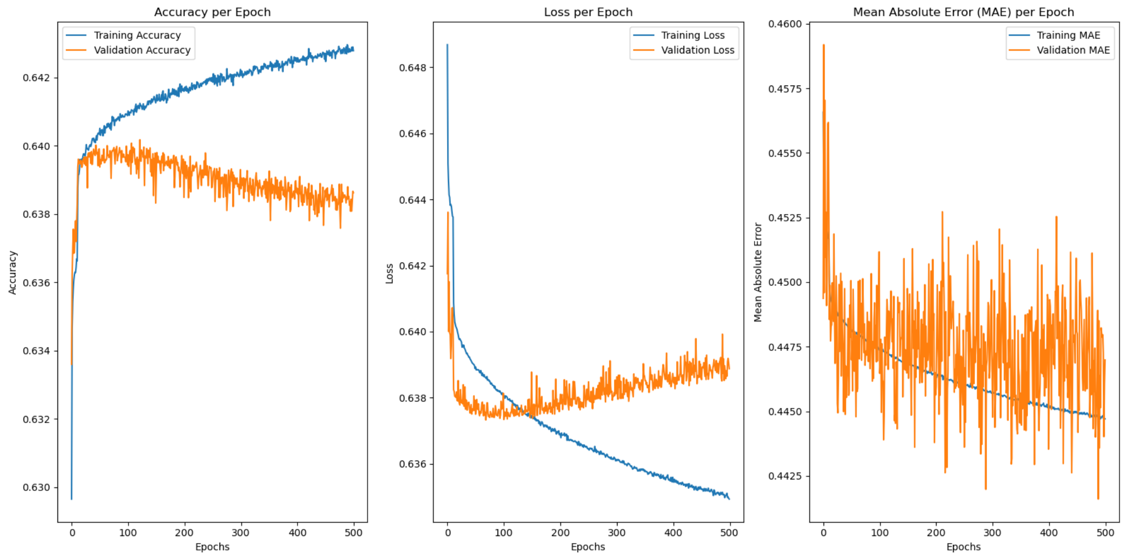
Display a detailed evaluative report of the model's performance using the classification report function.

```
29560/29560             22s
746us/step
              precision    recall  f1-score   support

           0       0.63      0.81      0.71    517890
           1       0.66      0.43      0.52    428013

    accuracy                           0.64    945903
   macro avg       0.64      0.62      0.62    945903
weighted avg       0.64      0.64      0.62    945903
```

12.1.1 Curiosity training on Epoch = 500

In the previous diagram, you might notice a small jump in accuracy starting from Epoch 12, followed by a gradual increase. Intrigued by this observation, we ran the same code with an Epoch value of 500 to explore how much further the accuracy could improve. Here are the results.

```
Epoch 1/500 - loss: 0.6487 - accuracy: 0.6297 - val_loss: 0.6418 - val_accuracy: 0.6336
Epoch 101/500 - loss: 0.6380 - accuracy: 0.6410 - val_loss: 0.6373 - val_accuracy: 0.6397
Epoch 201/500 - loss: 0.6369 - accuracy: 0.6417 - val_loss: 0.6381 - val_accuracy: 0.6393
Epoch 301/500 - loss: 0.6361 - accuracy: 0.6421 - val_loss: 0.6386 - val_accuracy: 0.6387
Epoch 401/500 - loss: 0.6355 - accuracy: 0.6426 - val_loss: 0.6386 - val_accuracy: 0.6386
Epoch 491/500 - loss: 0.6351 - accuracy: 0.6427 - val_loss: 0.6385 - val_accuracy: 0.6385
Training duration: 1236 min 37 sec
```



The model's performance during training and validation shows several key trends across different metrics. Initially, both training and test accuracies show an improvement up to a certain epoch, reaching their peak values. However, beyond this point, the trends diverge: while the training accuracy continues to improve slightly, the test accuracy starts to decrease gradually. This divergence indicates a potential issue with overfitting, where the model may be learning to perform well on the training data but struggles to generalize to new, unseen data.

12.1.2 Hyperparameters

We also simluated grid search behaviour for CNN to get the best accuracy result:

Please note that the training process took a few days to complete.

```
 ---------------------------------------------------------
| Hyperparameters                                         |
|---------------------------------------------------------|
| optimizers: [Adam, RMSprop],                            |
| activations: [relu, leaky_relu],                        |
| batch_sizes: [128, 256],                                |
| epochs: 40,                                             |
| conv_layers (Conv2D, MaxPooling2D pairs): [1, 2],       |
| dense_layers (Dense, Dropout pairs): [1, 2]             |
 ---------------------------------------------------------
```

Best Hyperparameter was:

```
 -------------------------------------------------------------------------------------------
| Best Hyperparameter    | Training |    Val    |  Loss   |   Val   |  MAE    |   Val   | Learning
|                        | Accuracy | Accuracy |        |  Loss  |        |   MAE  |   Rate
|-----------------------------------------------------------------------------------------------
| optimizers: Adam,      |  0.6412  |  0.6399  | 0.6369 | 0.6373 | 0.4464 | 0.4466 |  0.0001
| activations: leaky_rel |          |          |        |        |        |        |
| batch_sizes: 256,      |          |          |        |        |        |        |
| epochs: 40,            |          |          |        |        |        |        |
| conv_layers (pair): 2, |          |          |        |        |        |        |
| dense_layers (pair): 1 |          |          |        |        |        |        |
 -----------------------------------------------------------------------------------------------
```

```
Adam, activation: leaky_relu
Training with batch size: 256
Training with 2 Conv2D layers
Training with 1 Dense layers
Epoch 40/40
14780/14780            102s 7ms/step
- accuracy: 0.6412
- loss: 0.6369
- mean_absolute_error: 0.4464
- val_accuracy: 0.6399 - val_loss: 0.6373
- val_mean_absolute_error: 0.4466
- learning_rate: 1.0000e-04
```

12.2 Conclusion for LeNet Architecture

While achieving an accuracy of approximately 64% with the CNN model on the test dataset is notable, it's important to note that this performance is comparable to or in line with what we typically observe with basic models such as Logistic Regression or Random Forests. These traditional machine learning models are known for their simplicity and often provide competitive results on many datasets, especially when the data has a moderate level of complexity.

The fact that the CNN model's accuracy is around 64% suggests that while convolutional neural networks can offer advantages in certain scenarios, they may not always outperform simpler models on every dataset. Factors such as dataset size, feature representation, and model hyperparameters can influence the relative performance of different models.

It's crucial to consider the trade-offs between model complexity, computational resources, and performance when choosing a modeling approach. In some cases, a simpler model like Logistic Regression or Random Forests may suffice, especially if interpretability or computational efficiency is a priority.

13 NBA player shot analysis with Deep Learning (PyTorch framework)

PyTorch framework developed by Facebook, Nvidia and a some institutional partners such as University of Oxford and ENS, Paris. There are many reasons for having chosen this framework over others. Primary among them is the relative ease of use since the API is quite similar to Numpy. It also supports automatic gradient calculation which allows for greater flexibility to create novel architectures. It is blessed with great GPU support.

This part details the creation and evaluation of a PyTorch neural network model. The dataset is loaded and split into training and testing sets. Features such as period, time remaining, shot distance, and location coordinates are standardized using StandardScaler to ensure uniformity and aid model convergence.

The core of our prediction system is a PyTorch neural network implemented as the ShotPredictor class. The architecture consists of fully connected layers with ReLU activation functions to introduce non-linearity. Dropout layers are incorporated to prevent overfitting during training. The final layer uses sigmoid activation for binary classification (successful or unsuccessful shot).

The model is trained using mini-batch gradient descent with the Adam optimizer and binary cross-entropy loss (BCELoss). The training loop runs for 50 epochs, with a batch size of 32. At each epoch, we compute the loss and update the model parameters based on backpropagation.

After training, the model's accuracy on the test set is evaluated. The accuracy metric gives us insights into how well the model generalizes to unseen data.

```
Epoch [10/50], Loss: 0.6679
Epoch [20/50], Loss: 0.6679
Epoch [30/50], Loss: 0.6679
Epoch [40/50], Loss: 0.6679
Epoch [50/50], Loss: 0.6679
Training duration: 33 min 45 sec
```

```
Accuracy on test set: 54.75%
```

```
Accuracy on train set: 54.84%
```

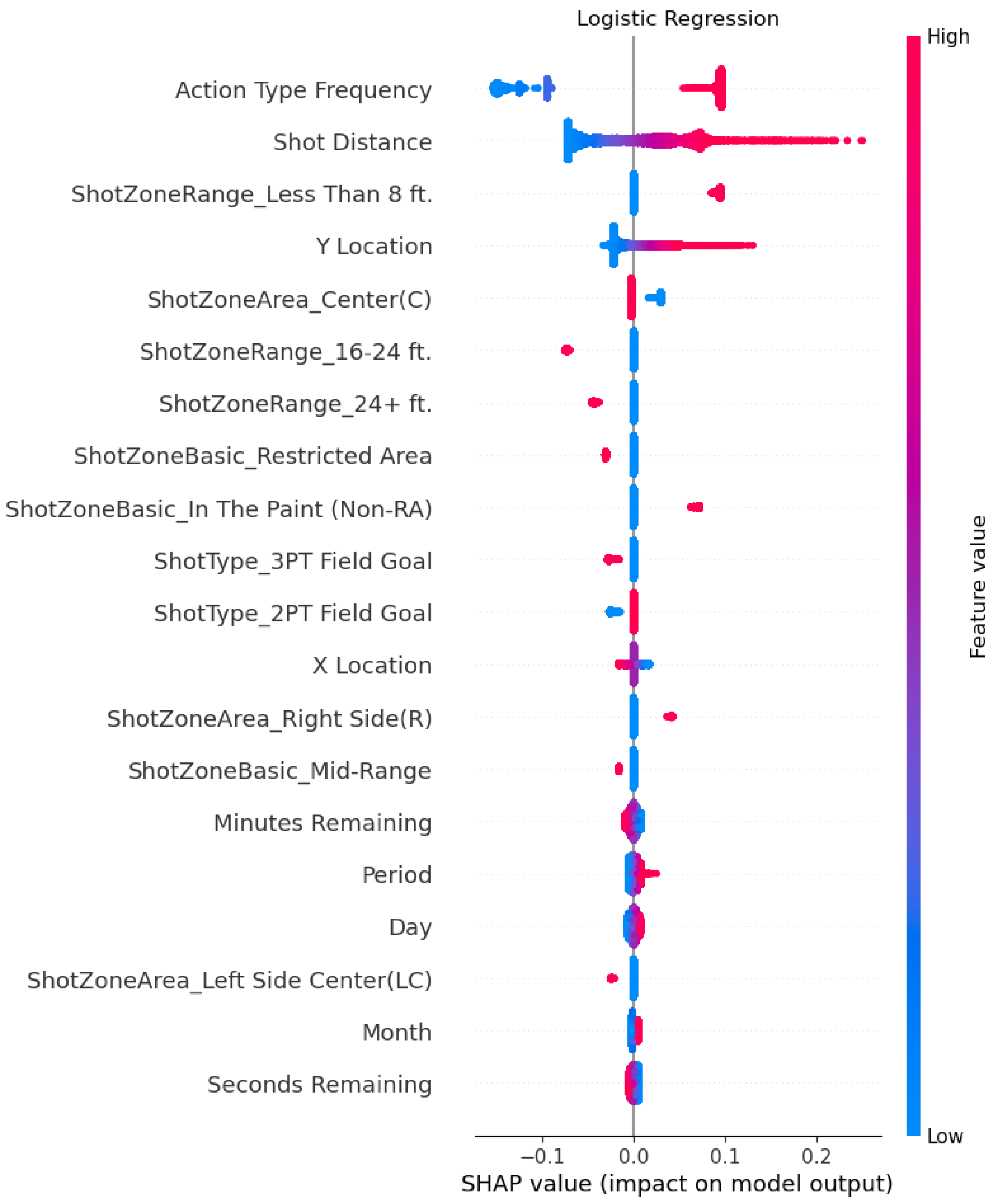
13.1 Conclusion for PyTorch framework

This outcome serves as an initial demonstration of PyTorch's capabilities in our machine learning application. To achieve better results, further investigations such as hyperparameter tuning using techniques like grid search are warranted. This iterative process of experimentation and refinement is crucial in enhancing the model's accuracy and ensuring its practical utility in real-world basketball analytics and decision support systems.

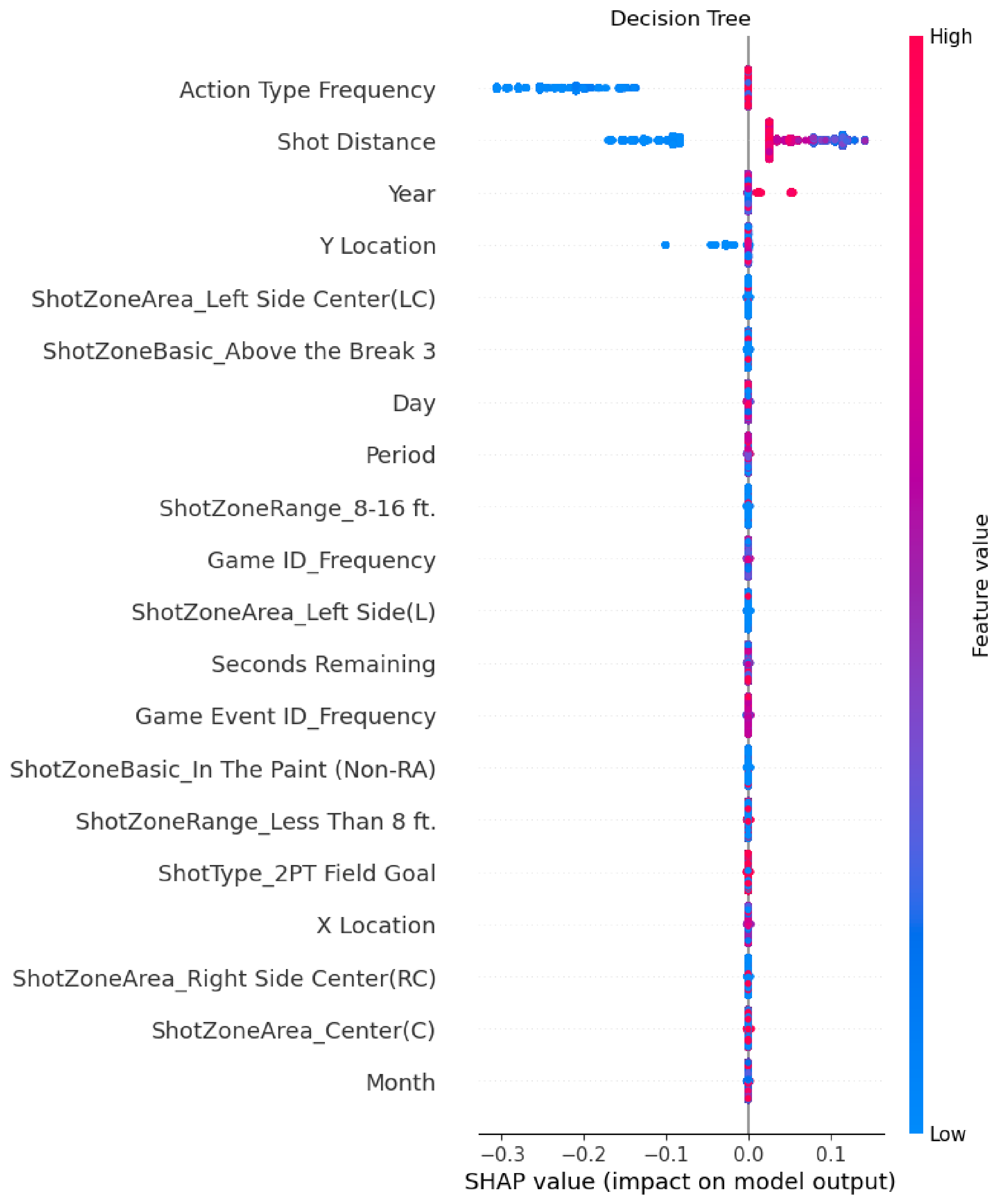
14 Interpretation of results

We have finished all our models. Let's have a comparative analysis of feature interpretation using SHAP (SHapley Additive exPlanations) values across multiple machine learning models.

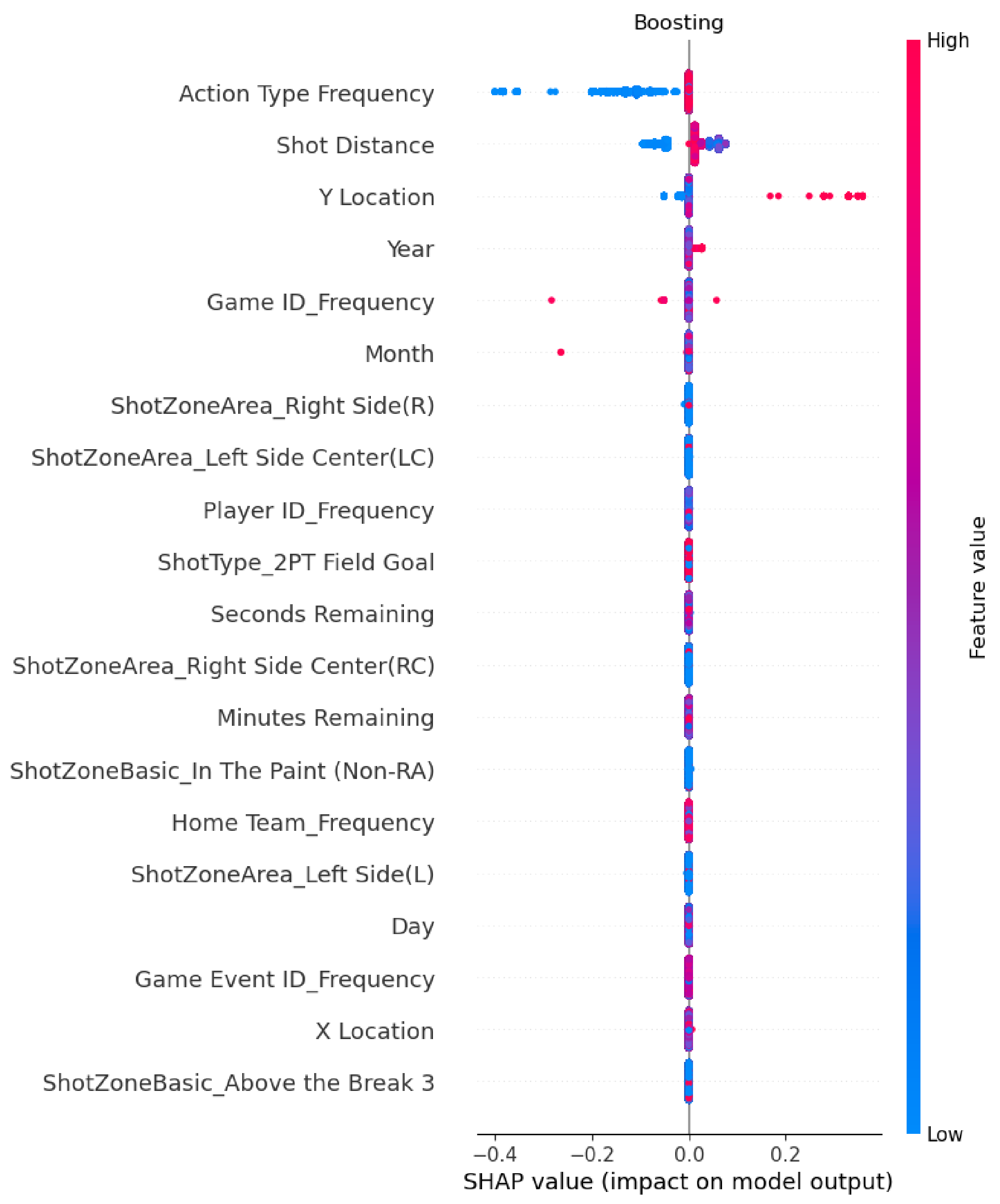
```
  0%|          | 0/37836 [00:00<?, ?it/s]
```



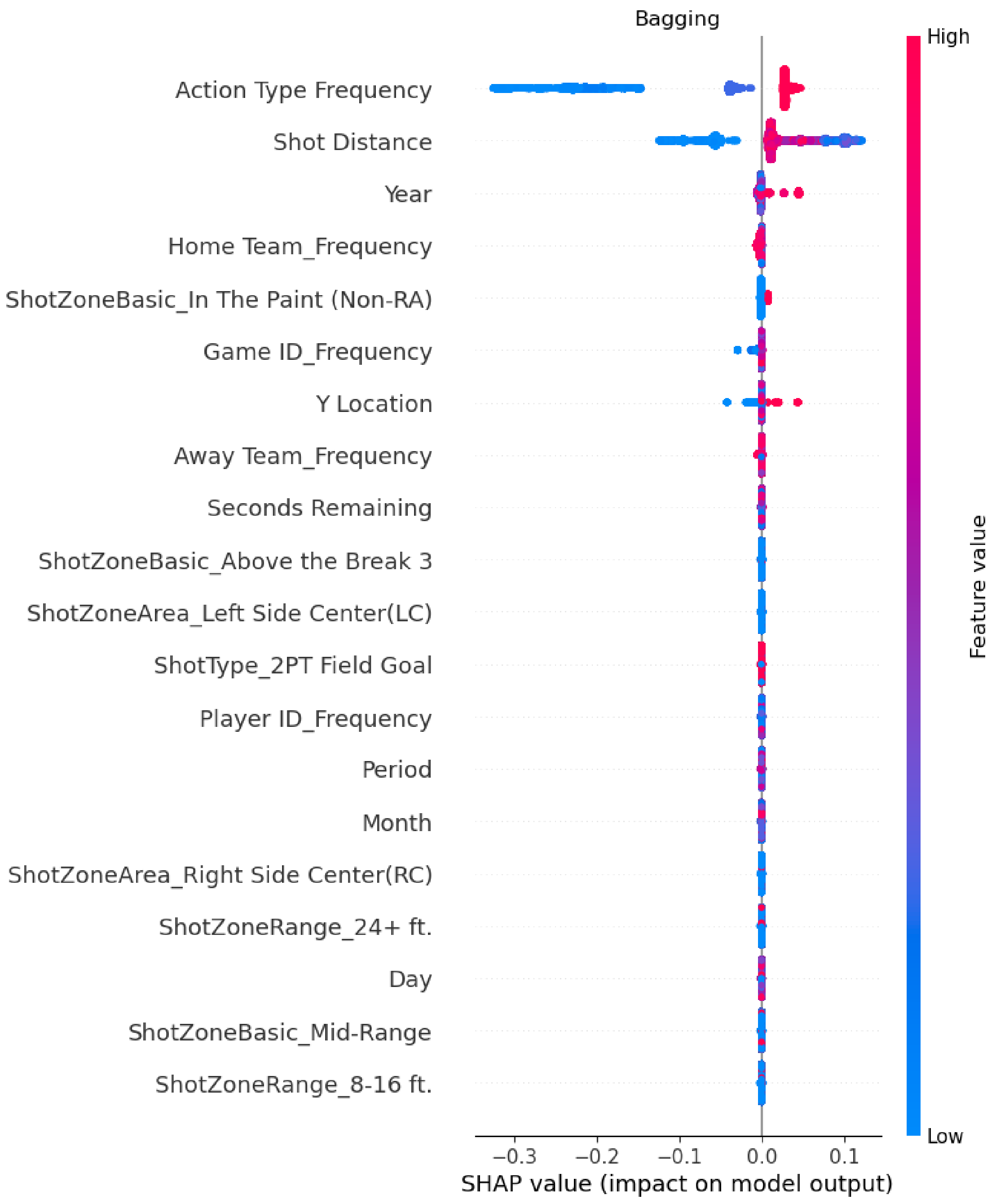
```
0%|          | 0/37836 [00:00<?, ?it/s]
```



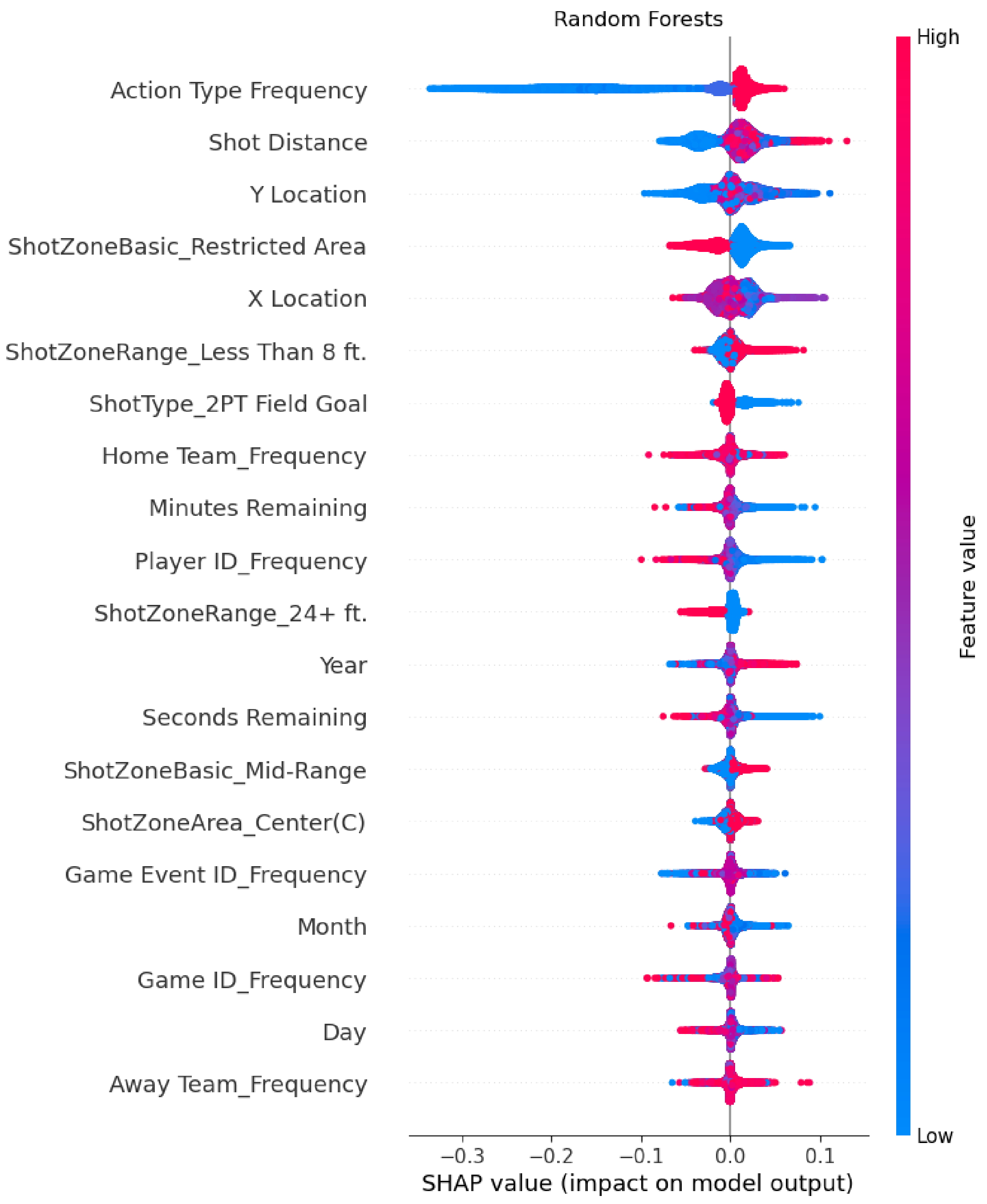
```
/Users/mihrandovlatyan/anaconda3/lib/python3.11/site-
packages/sklearn/ensemble/_weight_boosting.py:519: FutureWarning: The SAMME.R
algorithm (the default) is deprecated and will be removed in 1.6. Use the SAMME
algorithm to circumvent this warning.
  warnings.warn(

  0%|          | 0/37836 [00:00<?, ?it/s]
```



```
0%|          | 0/37836 [00:00<?, ?it/s]
```



```
0%|          | 0/37836 [00:00<?, ?it/s]
0%|          | 0/37836 [00:00<?, ?it/s]
```



The plots reveal that across all models, the most critical features include "Action Type Frequency," "Shot Distance," "Y Location," and "ShotZoneRange_Less Than 8 ft.," which is intuitive given their relevance in basketball dynamics. Certain actions significantly increase the probability of a successful shot, while proximity to the basket strongly influences shot outcomes.

In the Boosting model, "Y Location" emerges as the third crucial feature, with a substantial impact when considered, despite being overshadowed by the first two features. "Action Type Frequency" and “Shot Distance” consistently influence many predictions, albeit with varying degrees, while “Y Location” has not so much impact on a lot of predictions, but when it has it has a huge impact.

In contrast, the “Random Forests” model shows relatively equal importance among all features in predicting shot outcomes.

SHAP plots help us to understand the importance of features in making predictions and provided insights into which features were most influential for each model.

15 Conclusion drawn

15.1 Difficulties encountered during the project

During our project, we encountered several challenges that affected the progress and timeline:

Dataset Size: Our dataset, consisting of approximately 5 million rows, posed challenges during model training and hyperparameter tuning. Training models, such as CNNs with hyperparameters, required several days due to the sheer volume of data. Additionally, working on a personal computer with limitations contributed to longer processing times during model training. For instance, attempting to run an SVM model led to system crashes on our MacBook due to the dataset’s size.

Learning Curve: Learning new ML techniques, frameworks, or tools during the project slowed down our progress. Becoming proficient in these areas and effectively applying them took considerable time and effort.

Advanced Techniques: Certain advanced techniques, like SHAP interpretation, were not covered in our initial training. Acquiring the necessary knowledge for these methodologies involved additional self-learning and seeking external resources, which added to our project timeline.

Relevance and Performance: Ensuring the relevance of our approach required iterative work on model architectures, feature engineering techniques, and evaluation metrics. This iterative process was crucial for improving the relevance and performance of our models.

Team Coordination and Changes: Challenges in team coordination and unexpected changes within the team also impacted our project’s timeline and workflow.

By addressing these challenges in our final report, we aim to provide insights into the complexities faced during the project and how we navigated them to achieve our results.

15.2 Report

Our main contribution lies in achieving a 64% accuracy in predicting NBA shot success, surpassing existing benchmarks for similar datasets. Using SHAP values, we identified action type, player position, and shot distance as the most influential features, enhancing model interpretability. This consistent accuracy performance, especially in the stochastic domain of basketball shot attempts, underscores the effectiveness of our models.

Our achievements include not only high accuracy prediction but also insightful feature identification, aligning with our project goals of accurate prediction and feature importance understanding. These capabilities make our models suitable for real-time decision-making in basketball analytics, historical data analysis for player performance trends, and enhancing fan engagement through data-driven insights, such as fantasy basketball platforms or interactive sports analytics dashboards.

15.2.1 Model Experiments and Results

Our experiments with different models produced similar results. Our random forests model was able to achieve 63.64% accuracy.

15.2.2 Experiment 1

We attempted to identify the most influential factors for predicting shot success in our analysis. Even after excluding player names from the dataset, the model still achieved an accuracy of 63.77%. This suggests that the model considered the 'player name' feature to be relatively insignificant.

However, it's widely acknowledged that different players exhibit significant variations in their shot-making abilities. Therefore, it would seem logical that the player's name should be a crucial factor. We propose utilizing a larger dataset, allowing the model more exposure to each player's historical shot-making performance. This extended data exposure would enable the model to better incorporate the player's name into its predictive capabilities.

```
Accuracy on test set after removing 'Player ID_Frequency': 0.6377
```

15.2.3 Experiment 2

Additionally, when we removed the 'Shot Distance' factor, the model still achieved an accuracy of 63.95%. This suggests that the network could effectively compensate for the absence of 'Shot Distance' by leveraging the XY coordinates factor.

```
Accuracy on test set after removing 'Shot Distance': 0.6395
```

15.2.4 Experiment 3

The 'Action Type' emerged as the most critical factor for the network, as its removal resulted in a drop in accuracy to 62.07%. This finding underscores the importance of players and coaches focusing on the specific category of shots taken to significantly enhance shot success rates.

```
Accuracy on test set after removing 'Action Type': 0.6207
```

15.3 Continuation of the project

Achieving an accuracy of around 64% in NBA shot prediction analysis is typical and aligns with similar reports around 65%. This level of accuracy can be influenced by several factors: the complexity of basketball as a sport with numerous variables affecting shot outcomes, potential limitations in data quality or quantity leading to noise or biases, the crucial role of feature engineering and model choice in capturing relevant information, challenges in adapting to temporal dynamics and evolving game trends, the impact of sample size and variability on model robustness, the choice of evaluation metrics beyond accuracy to provide a nuanced view of performance, and the inherent human and random factors in basketball games that statistical models may struggle to fully account for. Overall, these factors collectively contribute to the observed accuracy levels in NBA shot prediction analyses.

For further improvement, we suggest exploring more advanced hyperparameters for random forests and deep learning models. Enhanced hyperparameter tuning, especially with access to more powerful computers and a wider range of hyperparameters, could potentially improve our prediction accuracy. For instance, increasing the training epochs for CNN models to 500 resulted in a slight improvement in accuracy, indicating that deeper exploration of hyperparameter spaces may lead to better model performance. Investing in computational resources that allow for extensive experimentation and optimization can be a key factor in achieving higher accuracy levels and refining our predictive models in sports analytics.

Furthermore, the increased data points will allow the network to train for longer and further improve its accuracy.

15.4 Bibliography

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[4] Evaluating the effectiveness of machine learning models for performance forecasting in basketball: https://link.springer.com/article/10.1007/s10115-024-02092-9

The code used throughout this paper can be found here: https://github.com/DataScientest-Studio/feb24_bds_int_nba