

Exploring MLB Batting Data Using Logistic Regression

Vivian Johnson

This project aims to study classification and its applications to Major League Baseball (MLB) batting data. The goal is to develop a model that is capable of classifying a hit based on various in-game metrics, including release speed, launch angle, bat speed, and swing length. The model development process incorporates different statistical techniques such as K-means cluster analysis and decision trees to understand the distributions of the data and how observations are being classified in the multinomial model. Additionally, specific balancing techniques are explored to address inherent bias and imbalance in the data for the purpose of making more accurate classifications.

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Introduction

Baseball is a competitive game that revolves around a defensive (fielding) team and an offensive (hitting) team. The field is shaped like a diamond, with each of the four corners representing first, second, third, and home respectively. The game lasts nine innings, where each inning is broken down into a top half (where one team hits and the other is on defense) and a bottom half, where they switch. Each half inning has three outs, and the objective of the hitting team is to score runs while the fielding team attempts to stop them by getting outs.

The game begins when the pitcher on the defensive team throws the baseball overhand from sixty feet to the batter, who tries to hit the ball with their wooden bat from home plate to somewhere out of reach of one of the eight other defensive players. Once the ball is hit, the batter tries to reach as many bases as possible without getting out. The winner at the end of the game is the team who scored the most runs.

For the purposes of this project, we look to analyze the different mechanics that go into an at bat, and how those swing mechanics differentiate based on what type of hit the batter gets. The diagram below shows the set up of a baseball field, where all the defensive players are positioned, as well as where the batter stands.

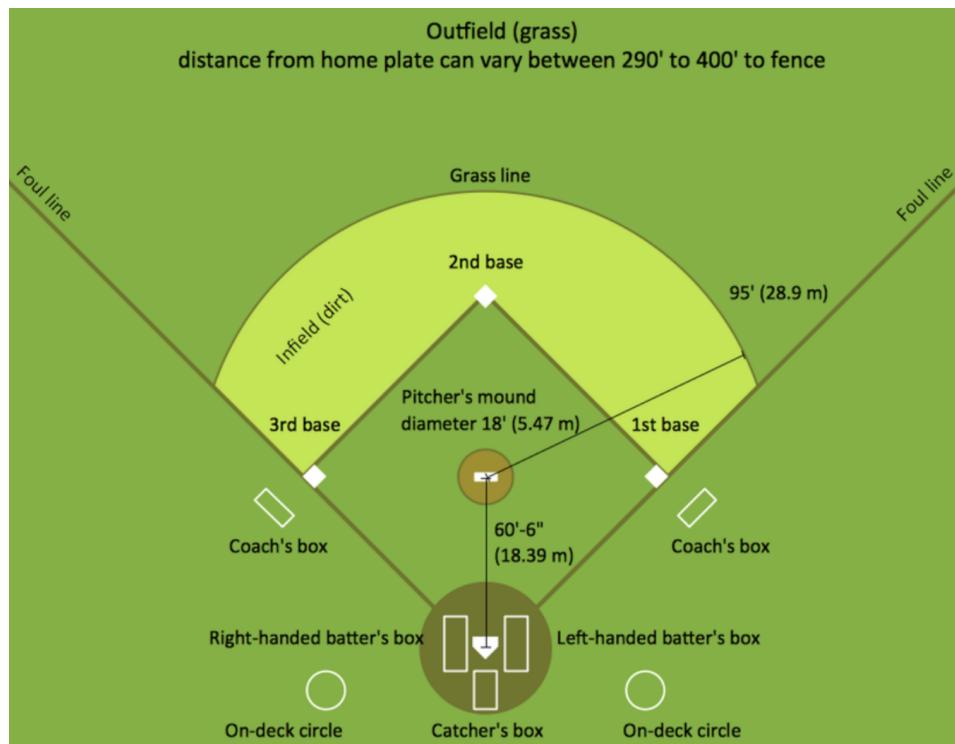


Figure 1: Diagram of baseball field (taken from <http://www.conceptdraw.com/solution-park/sport-baseball>)

Important Baseball Definitions

The terms below define key aspects of baseball that are relevant to this project.

- **Ground Out:** The batter hits the ball on the ground, and the defensive player is able to throw the ball to first base before the batter gets there.
- **Pop Fly/Out:** The batter hits the ball in the air, and a defensive player catches the ball without letting it touch the ground.
- **Single:** A hit where the batter is able to make it safely to first base without stopping.
- **Double:** A hit where the batter is able to make it safely to second base without stopping.
- **Triple:** A hit where the batter is able to make it safely to third base without stopping.
- **Homerun:** A hit where the batter is able to make it around every base and back to home without stopping, usually done by hitting the ball over the homerun fence, positioned about 350 feet, depending on the ballpark played at.

Theory

Binary and Multinomial Classification

Classifying and predicting the type of hit that results from an at bat can be described as a multinomial classification problem. Similar to binary classification, where the response variable, Y, has two binary categories, multinomial classification applies when there are multiple possible event outcomes for Y. In this case, the possible results of the hit are a single, double/triple (also referred to as an extra base hit), or a homerun, encoded as 1, 2, or 3 respectively.

Multinomial Logistic Regression

When predicting a response variable with more than two (binary) levels, the multinomial logistic regression model is effective. Similar to regular logistic regression, the multinomial logistic regression model predicts the probability of each level of Y.

In this case, for the dependent variable, `hit_outcome`, we're interested in looking at the probabilities of different hits occurring, which can be written as $P(Y = j)$. This includes singles, extra base hits, and homeruns. Using multinomial logistic regression, this can be modeled by the following equation:

$$P(Y = j | X_1 = x_1, X_2 = x_2, X_3 = x_3, X_4 = x_4, X_5 = x_5) \\ P(Y = j) = \frac{e^{\beta_0 j + \beta_1 j X_1 + \beta_2 j X_2 + \beta_3 j X_3 + \beta_4 j X_4 + \beta_5 j X_5}}{1 + \sum_{i=1}^{j-1} e^{\beta_0 i + \beta_1 i X_1 + \beta_2 i X_2 + \beta_3 i X_3 + \beta_4 i X_4 + \beta_5 i X_5}}$$

Where $X_1 \dots X_5$ indicate the various predictor variables for the multinomial logistic regression model. Since we're interested in the probability of each hit given the different values of the five predictor variables, we can transform the logit output from logistic regression to the probability of the event occurring with the equation above.

Accuracy, Precision, and Confusion Matrices

To evaluate the performance of the multinomial logistic regression model, a confusion matrix can be used and from that, the measures of accuracy and precision can be found. A confusion matrix is a table that shows for each value of the dependent variable, the number of true positives and negatives, as well as the false positives and negatives. In this case, as there are three levels of the dependent variable, the confusion matrix is a 3x3 table.

For each specific class of the dependent variable:

- **True Positives (TP):** The number of observations that are correctly identified as being a part of that class.
- **True Negatives (TN):** The number of observations that are correctly identified as not being a part of that class.
- **False Positives (FP):** The number observations that are incorrectly identified as being a part of that class.
- **False Negatives (FN):** The number of observations that are incorrectly identified as not being a part of that class.

From these metrics, accuracy (the accuracy in assigning the correct categories to the data) can be defined as:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

As there are some disadvantages of accuracy with the raw initial data set, precision can also be used to evaluate the model for each level of the response variable (i). Precision is the ratio of true positives to all observations that were identified as positives in the model.

$$Precision_i = \frac{TP_i}{TP_i + FP_i}$$

Methods

The data used in this project comes from Baseball Savant, the clearing house for the Statcast data provided by the Major League Baseball Association (MLB). The MLB employs advance statistical software and sports tracking in order to keep various statistics throughout the entirety of a major league game. Baseball Savant acts as the dashboard through which the public can view and access the data straight from the MLB (Statcast (2024)).

Initial Data Preparation

The data focuses on batting data from MLB games played from March 28, 2024 to October 30, 2024. The data was scraped from Baseball Savant using the `statcast_search()` function from the `baseballr` package in R¹. Once compiled, the data was saved to a CSV titled `full_batting_data_2024.csv`.

```
# loading in the data
batting_data_2024 <- read_csv("season_2024_batting_data.csv")
```

Data Cleaning

The following code describes removing certain columns where data was no longer collected and not useful to this project.

```
# renaming certain columns
batting_data_2024 <- batting_data_2024 %>%
  rename(bat_speed = newStat_1,
         swing_length = newStat_2)

# removing deprecated columns
batting_data_2024 <- batting_data_2024 %>%
  select(-spin_dir,
         -spin_rate_deprecated,
         -break_angle_deprecated,
         -break_length_deprecated,
         -tfs_deprecated,
         -tfs_zulu_deprecated,
         -umpire
  )
```

¹Petti and Gilani (2024)

Table 1: Description of Important Variables Used

Variable	Description
events	Records the event of the resulting plate appearance (single, double, triple, homerun)
release_speed	The speed of the pitch that was thrown to the batter
launch_angle	Vertical launch angle of the batted ball as tracked by Statcast. Refers to the angle at which the ball leaves the bat
bat_speed	Measurement of how fast the bat is moving when the player makes contact with the ball
swing_length	Total amount of feet the bat traveled during the swing (the total distance traveled by the barrel of the bat in x/y/z space)

Important Variables

Table 1 gives descriptions of the variables used to create a model and analyze hit types.

Indicator Variables

The indicator variable `hit_outcome` was created using the `events` variable in the data set and serves as the dependent variable for multinomial logistic regression. The table and code below describe the variable, as well as creating it using the data and storing it in an R object called `batting_with_indicators`.

```
# making the indicator variables
batting_with_indicators <- batting_data_2024 %>%
  filter(
    !is.na(bat_speed) &
    !is.na(swing_length) &
    !is.na(launch_angle) &
    !is.na(release_speed)
  ) %>%
  mutate(
    # homerun variable: 1 if homerun, 0 if double
    homerun = case_when(
```

Table 2: Description of Indicator Variables Used

Variable	Description
hit_outcome	Indicator for the type of hit recorded in the ‘events’ variable. 1 = single, 2 = extra base hit (double or triple), 3 = homerun

```

events == "home_run" ~ 1,
events == "double" ~ 0,
TRUE ~ NA_real_),
# hit_outcome corresponds to the type of hit
hit_outcome = case_when(
  events == "home_run" ~ 3,
  events == "triple" | events == "double" ~ 2,
  events == "single" ~ 1)
) %>% filter(
  !is.na(hit_outcome)
)

```

Standardizing Variables

The next step in cleaning the data was to standardize the `swing_length`, `bat_speed`, `launch_speed`, and `release_speed` variables.

Turning these variables into z-scores was done to normalize the data so that each variable has a mean of zero and a standard deviation of one. Therefore, an observation with a `swing_length_zscore` of 0.56 would indicate that that batter had a swing length 0.56 standard deviations longer than the average swing length for all batters. This process puts all observations for the variables on the same scale, and aids in the interpretation of the regression models and comparison across variables.

```

# standardizing swing length, bat speed, and launch speed.
batting_with_indicators <- batting_with_indicators %>%
  mutate(
    swing_length_zscore = scale(swing_length),
    bat_speed_zscore = scale(bat_speed),
    release_speed_zscore = scale(release_speed)
  )

```

Preliminary Data Analysis

Distributions of Independent Variables

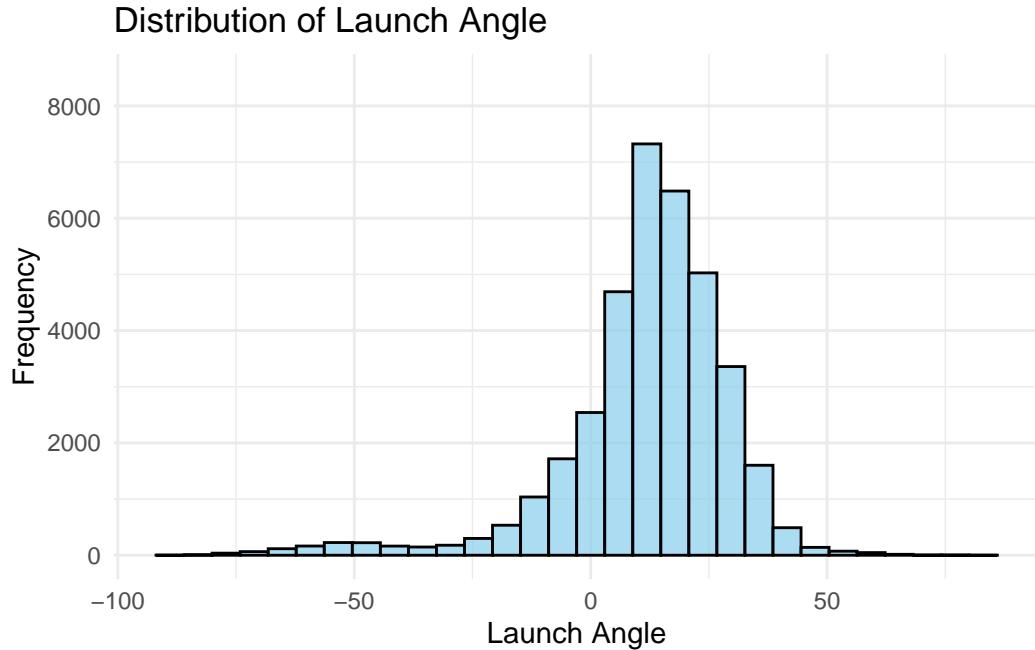


Figure 2: Distribution of Launch Angle

Figure 2 above, and Figure 3 below, show the distributions of the independent variables used during the model development process. From these figures, we can see that all follow an approximately normal distribution. Although multinomial logistic regression does not require normally distributed independent variables, this approximate normality could aid in interpretability. Additionally, this normality suggests that transformations to the independent variables such as log or polynomial terms might be unnecessary.

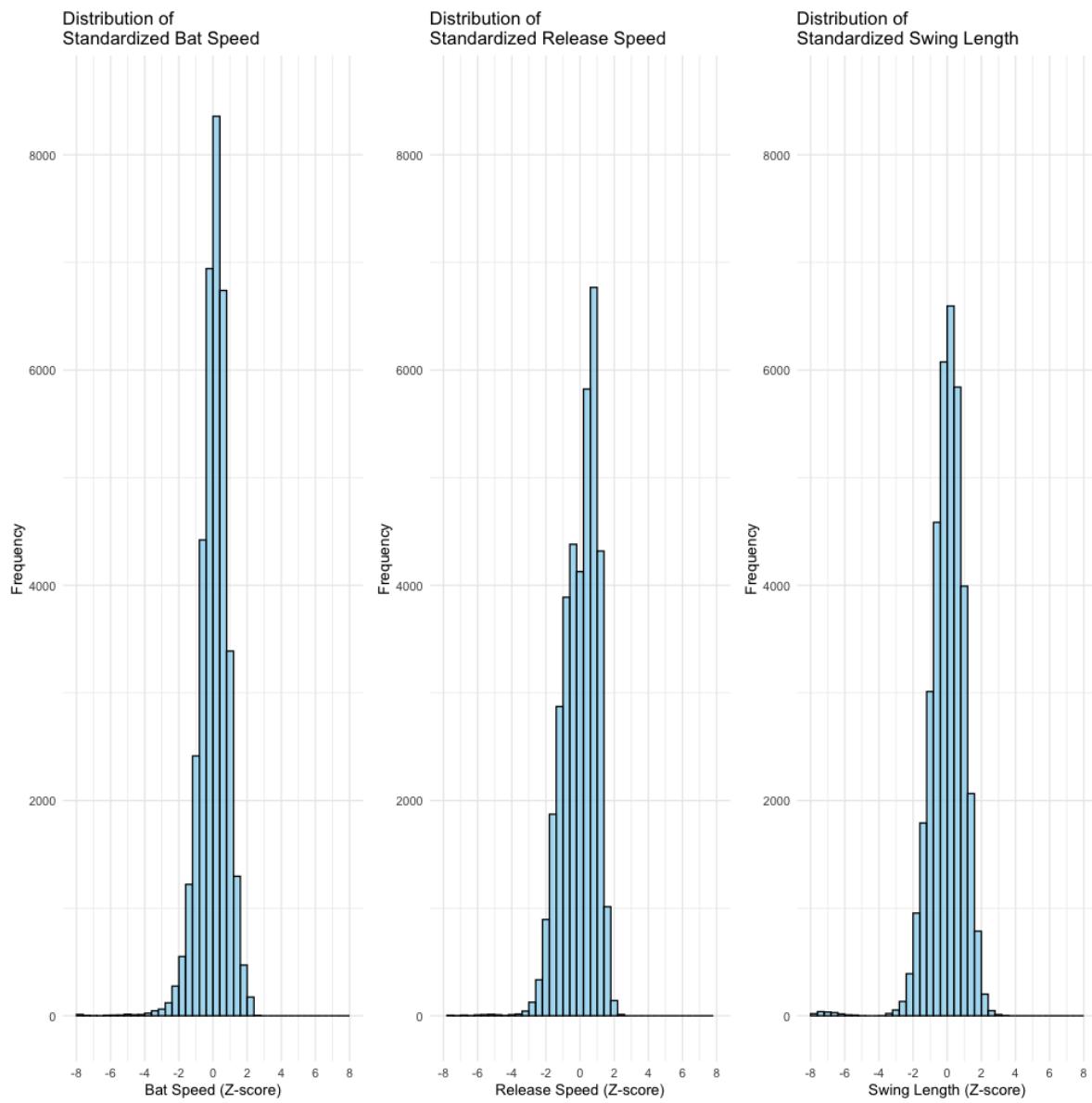


Figure 3: Distributions of Standardized Independent Variables

Table 3: Correlation Matrix For Independent Variables

	Bat Speed	Release Speed	Swing Length	Launch Angle
Bat Speed	1.000	0.011	0.589	0.174
Release Speed	0.011	1.000	-0.256	-0.045
Swing Length	0.589	-0.256	1.000	0.148
Launch Angle	0.174	-0.045	0.148	1.000

Correlations

Table 3 shows a correlation matrix for the independent variables. The table includes standardized bat speed, standardized release score, standardized swing length, and launch angle. The highest correlation is between `bat speed` and `swing length`, with a value of 0.589. This indicates a moderate positive correlation, which is logical, as higher bat speeds tend to be associated with longer swing lengths.

Since this is the highest correlation, and other correlations are low, multicollinearity does not appear to be a significant concern in the data, given that none of the correlations are excessively high (above 0.8, which is usually considered to be an indicator of multicollinearity).

K Means Cluster Analysis

Relationship Between Standardized Bat Speed and Swing Length

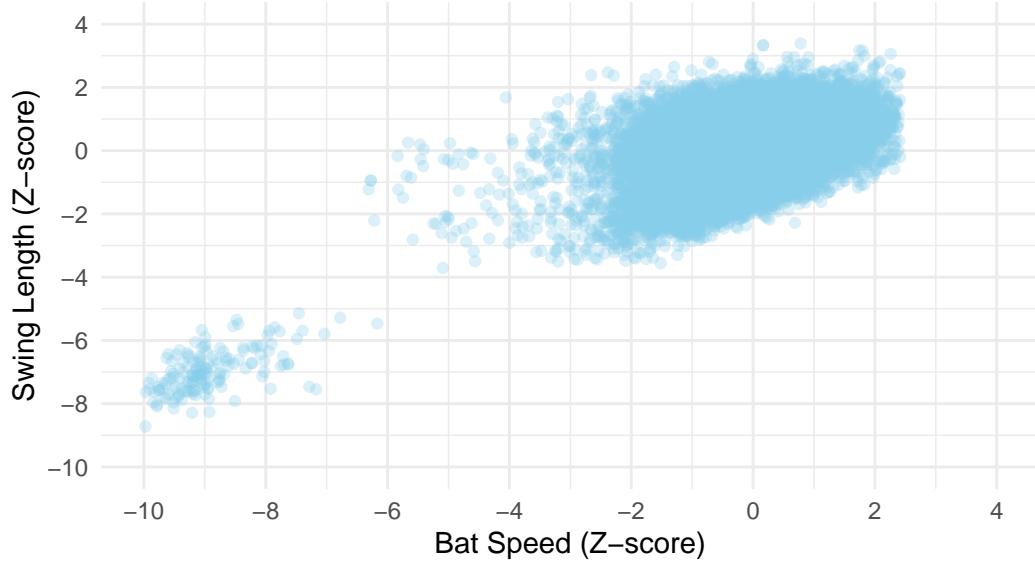


Figure 4: Scatterplot of Bat Speed and Swing Length

Figure 4 shows a moderately positive linear relationship between the standardized swing length of a batter and the standardized bat speed of the batter. From this, it can be understood that longer swings tend to produce higher bat speeds. A reasoning for this could be because with a longer bat path, the batter has more time to generate speed in their swing. Due to this, it was decided to add an interaction between bat speed and swing length, as the effect of bat speed on hit outcome could also be affected by the batter's swing length.

The scatterplot in Figure 4 also shows distinct grouping within the data. There is a grouping of hits, most likely bunts² or soft ground balls, where the batters had much lower swing lengths and bat speeds compared to the other observed hits. To analyze this further, K-means cluster analysis was performed to look at the specific groupings in the data.

K-Means Cluster Analysis is the process of grouping each observation in the data based on distinct characteristics. Upon completion, groups will be formed ideally with similar characteristics. The goal is to extract relationships, in this case, between the swing length of the batter and the bat speed. The algorithm begins by first determining how many groups will be formed ($K = 3$ for this scenario). Then, 3 observations are randomly chosen from

²A bunt is a strategic hit where the batter lightly taps the ball with the bat, usually to advance a runner already on base, or get on base quickly.

the data, and assigned to a group. These rows act as the preliminary centers (means) of the groups. The remaining observations are individually assigned to the group that minimizes the Euclidean distance³ between the observation and the group mean. Following this, a new average for the groups are calculated, and each observation is re-examined to see if it is closer to a different groups average. This process repeats until no observation changes groups. (Wu and Wu (2012))

The following code was used to perform the cluster analysis, while Figure 5 shows the corresponding groups that were created.

```
# selecting only the two columns needed
batting_cluster <- batting_with_indicators %>%
  select(swing_length_zscore,
         bat_speed_zscore)

set.seed(12) # so it is reproducible
cluster_analysis <- kmeans(batting_cluster,
                            centers = 3,
                            nstart = 25)
```

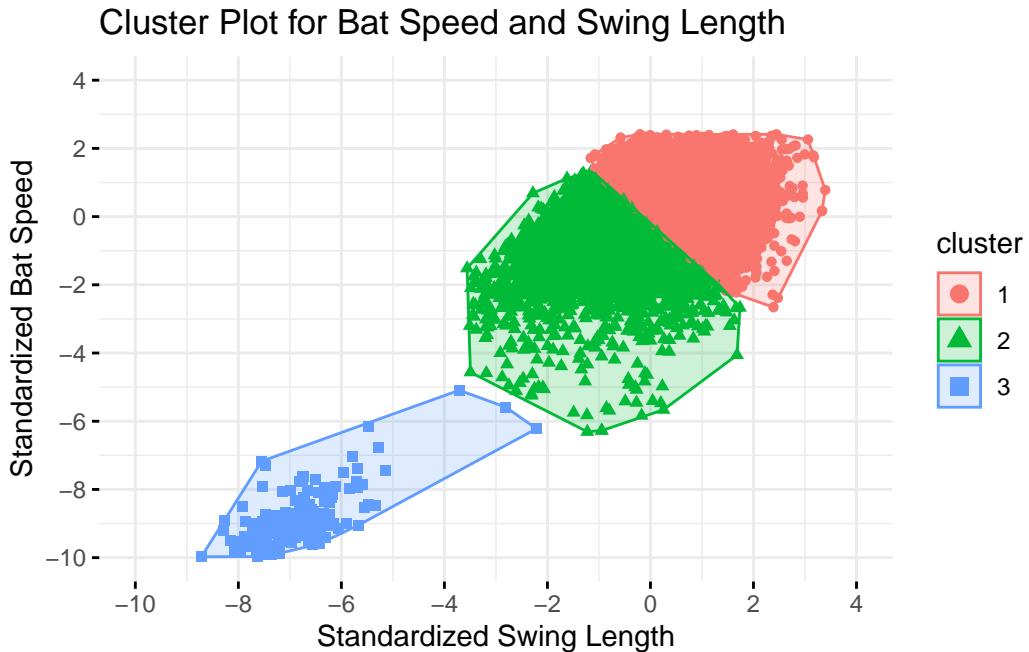


Figure 5: Scatterplot showing clustered groups

³Euclidean distance is the straight line distance between two points in space.

Table 4: K-Means Summary Statistics

Cluster	Cluster Size	Centers (swing length, bat speed)	WSS
1	21986	(0.559, 0.429)	15027
2	14567	(-0.767, -0.549)	13916
3	162	(-6.891, -8.857)	236

Figure 5 shows the results from performing K=3 Means Cluster Analysis. It is evident that the third cluster has significantly different bat speeds and swing lengths. Because the goal of this project is to examine the difference in hitting mechanics between true singles, extra base hits, and homeruns, it was determined that these hits, which are most likely check swings or bunts, don't accurately represent the data and that this cluster should be removed.

Table 4 describes the cluster size, center, and within cluster sum of squares for each group. The within cluster sum of squares, also known as the intra-cluster variation, is the sum of the squared Euclidean distances between each observation and the center of the cluster (Wu and Wu (2012)). A smaller WSS indicates that the observations are grouped closer together, thus forming a more specific group. Since the WSS of group 3 is significantly lower than the other two groups and relatively small, removing the observations in this group is not of high concern.

Bat Speed (Z-Score) vs. Swing Length (Z-Score) With Cluster Removed

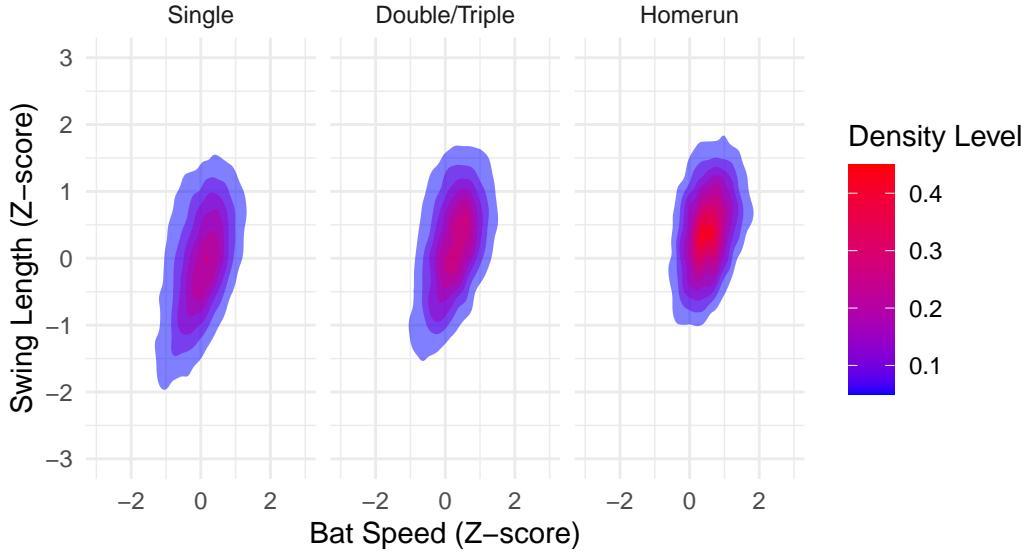


Figure 6: The relationship between bat speed and swing length for each hit outcome

Figure 6 shows the relationships between standardized bat speed and standardized swing length for each level of `hit_outcome` after removing the cluster of hits. For each hit outcome, there is a clear positive relationship between the bat speed and the length of the swing. The density level represents how closely packed the points are, (i.e. where data points are more concentrated). From Figure 6, we can see that the direction of the relationship between the hit types are similar, but the densities and variance differ. Homeruns vary the least, as the majority of the observations that are homeruns are tightly concentrated. Singles tend to vary the most, as there is not an extremely high density level anywhere on the graph. This is somewhat logical, as there is more opportunity / ways in which a batter could hit a potential single compared to a homerun.

Distributions Incorporating Ground Outs and Fly Outs

The data allows us to differentiate between fly outs and ground outs, meaning that we can also observe the difference in the independent variables between these types of outs, as well as hits. This is important as it aids in understanding how these factors differ between outs and hits.

Distribution of Launch Angle for Different Hit Outcomes

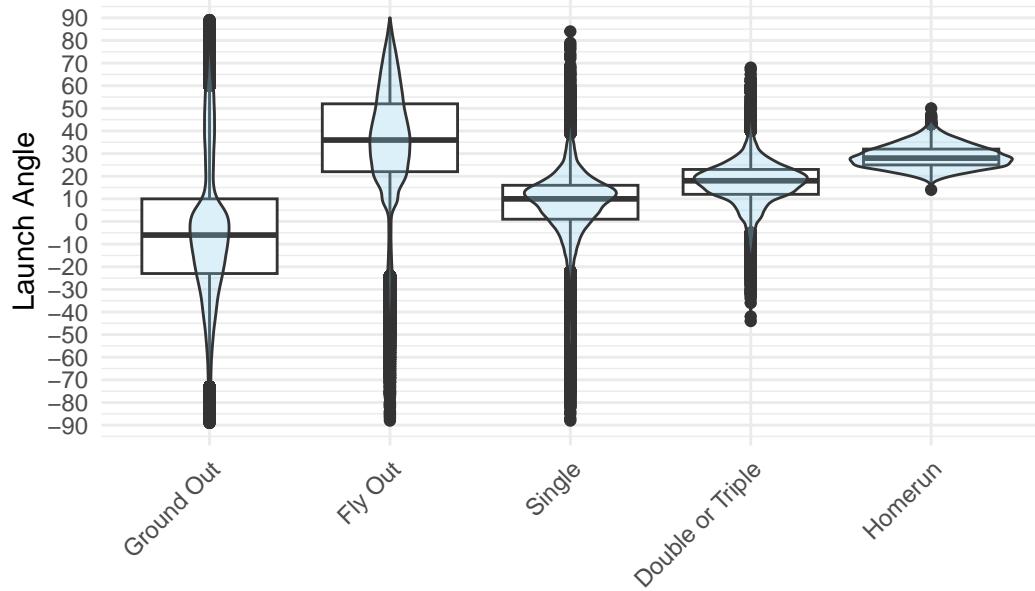


Figure 7: Distribution and mean launch angle by hit outcome

Figure 7 shows the distribution of launch angle for different hit outcomes. For each at bat that resulted in an actual hit (a single, double/triple, or a homerun), it is evident that the launch angles follow a relatively normal distribution, being unimodal and centered around the mean.

There are no drastic changes in the spread of the data, and no discernible U-shaped pattern. Using this, the decision to square launch angle and use a quadratic term was not made, as it is probable that it wouldn't add much explanatory power to the model.

The side by side box plots in Figure 7 also indicate that there does seem to be a difference in average launch angle for each hit type. This supports including `launch_angle` in the model, and that it would be possible to have a model solely using it to predict `hit_outcome`, but it wouldn't explain everything. By bringing in fly outs and ground outs, we can see how launch angle varies between the two as well. It makes sense that the launch angle for ground outs would tend to be lower, as it is likely that the ball was hit low on the ground to a fielder, and the same goes for fly balls. Eventually, the launch angle on the ball is too high and results in an out rather than a hit. While this is the overall trend of these two specific results, the variation and spread of the data is much larger.

It is important to note that it doesn't make sense for `launch_angle` to be negative for fly outs. As it is not one of the variables that is standardized, a fly ball should have a positive launch angle, as that would indicate that the ball went up in the air. After examining these instances where the hit was recorded as a fly out and the launch angle was negative, the conclusion was drawn that it was an error in recording the data. This serves as another layer that makes modeling this data more difficult.

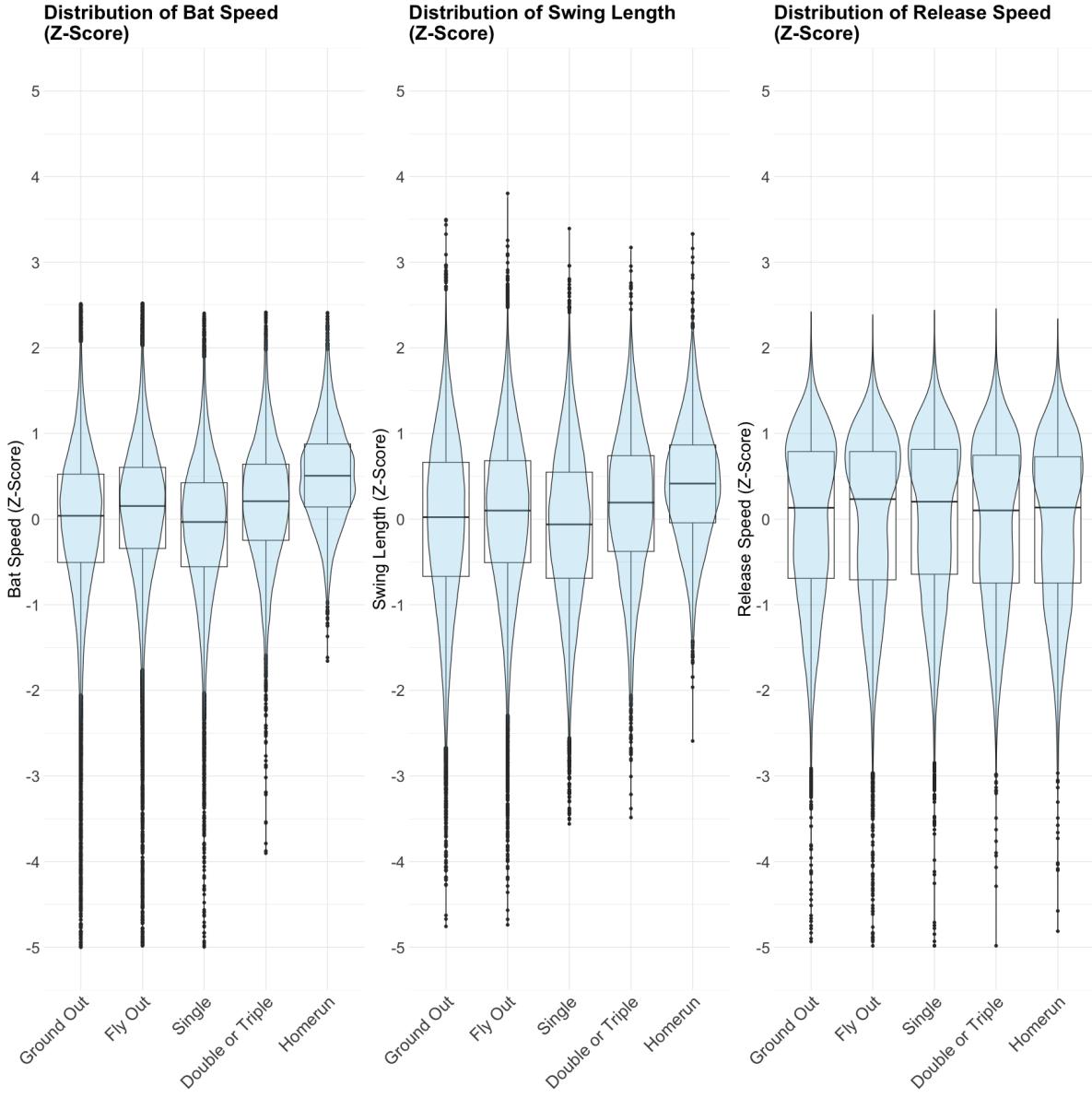


Figure 8: Distributions of Dependent Variables by Hit Outcome

Similar to Figure 7, Figure 8 shows the distribution of each standardized variable for each hit type, but also includes fly outs and ground outs.

From these, there does seem to be differences in each variable depending on the type of out, as well as differences in the variables depending on the type of hit. The variable that seems the most constant is release speed, and from that it can be drawn that the speed at which the pitch is thrown matters less. However, release speed was still included in the model because it

Table 5: Stage 1 Multinomial Logistic Regression Output for Initial Model

Term	Double/Triple		Homerun	
	Estimate	Std. Error	Estimate	Std. Error
Constant	-1.995	0.026	-6.086	0.072
Swing Length Z-Score	0.158	0.019	0.394	0.031
Bat Speed Z-Score	0.482	0.022	1.609	0.038
Release Speed Z-Score	-0.010	0.015	0.086	0.022
Launch Angle	0.065	0.001	0.208	0.003
Swing Length/Bat Speed Interaction	0.090	0.019	-0.243	0.037

aids in explaining information pertaining to the pitcher during the at bat, and is not correlated with other variables pertaining to the batter's mechanics.

Model Development

Stage 1

The first stage of model development looks at simply creating logistic regression models based on the available data. The first step of stage one is to develop an initial model that will form the basis for the rest of the analysis.

Initial Model

The following code describes how to make the initial multinomial regression model, where our goal is to predict `hit_outcome` from `swing_length_zscore`, `bat_speed_zscore`, `release_speed_zscore`, `launch_angle`, and an interaction between `bat_speed_zscore` and `swing_length_zscore`.

```
reg_model_1 <- multinom(hit_outcome ~
                         swing_length_zscore +
                         bat_speed_zscore +
                         release_speed_zscore +
                         launch_angle +
                         bat_speed_zscore:swing_length_zscore,
                         data = batting_without_g3)
```

Table 6: Stage 1 emmeans Summary for Initial Model

hit_outcome	prob	SE	df	lower.CL	upper.CL
1	0.7521163	0.0028169	12	0.7459789	0.7582538
2	0.2264192	0.0027123	12	0.2205097	0.2323288
3	0.0214645	0.0008994	12	0.0195049	0.0234240

Table 5 shows the multinomial regression output for the initial model. The bold coefficients represent those that have a p-value that is significant at the 0.01 level. Using this table, we can view the coefficients for the model and understand how each contribute to the hit outcome. There are two columns for the regression table, and the coefficients in each column represent the difference in log-odds resulting from a one unit change in the predictor between the base group, (hitting a single) and the corresponding hit column, which can be transformed into a probability.

For example, `launch_angle` has a value of 0.065 in the double/triple column. We can interpret this as follows:

On average, a one degree increase in a batter's launch angle is associated with an increase in the probability of hitting a double or a triple by about 1.07%

We can also interpret the interaction between swing length and bat speed. With a logit coefficient of 0.09, we can turn it into a probability and understand it as:

The interaction between bat speed and swing length suggests that as both increase, the likelihood of hitting a double or triple increases compared to a single. This is reflected in the positive interaction term, indicating that the effect of swing length on the hit outcome is enhanced as bat speed increases.

The package `emmeans` in r compares the estimated marginal means. In this model, it allows us to see the differences in the mean predicted probabilities for each hit outcome.

Table 6 shows the estimated probabilities for each hit outcome in this model. Singles are estimated to occur the most, about 75.2% of the time, followed by doubles and triples (22.6%), and the least likely to occur are home runs (2.1%). While hitting a single in a baseball game is more common than other types of hits, there is still a stark difference in the probability of each hit occurring, this is likely due to the imbalance in the data set, with the model being more tailored to predicting singles because they are much more prevalent in the data.

Decision Tree Initial Model

```

initial_decision_tree <- rpart(hit_outcome ~
                                swing_length_zscore +
                                bat_speed_zscore +
                                release_speed_zscore +
                                launch_angle,
                                data = batting_without_g3,
                                method = "class")

```

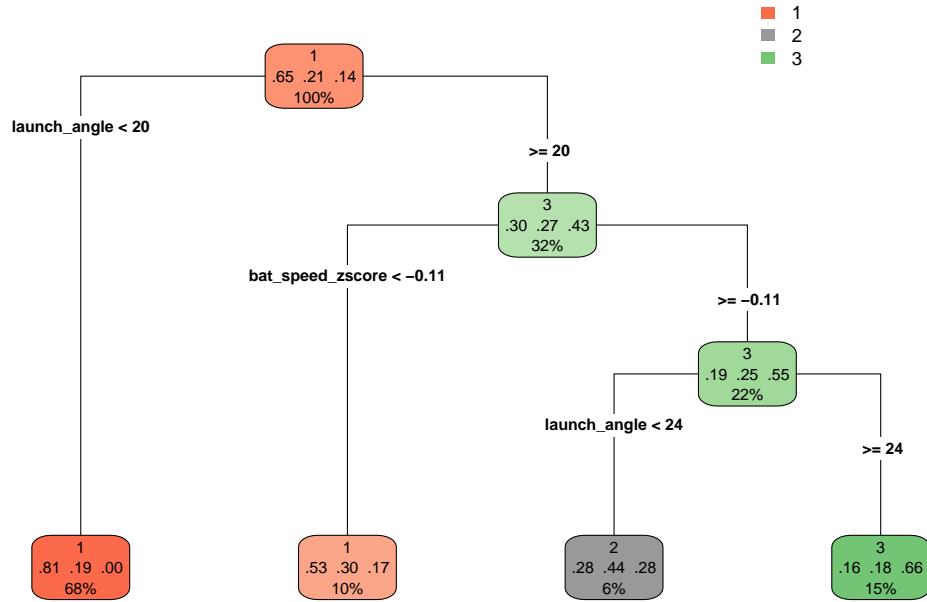


Figure 9: Decision Tree for Initial Model

Figure 9 shows a decision tree of the initial model. The decision tree is a classification model that visualizes the steps that the model goes through when attempting to classify each observation. The nodes of the tree correspond to the decisions made based on certain thresholds or levels of the predictor variables. The branches represent the outcome of the decision, or the comparison that was made, and the leaves represent the final predicted outcome of the response variable.

From Figure 9, we can see that classifying the type of hit mostly relies on a hit's launch angle and bat speed. The model starts with all of the observations, and if the launch angle is less than 20, the hit is automatically classified as a single. Of those hits, it represents 68% of the data, and of that, 81% were actually singles, 19% were actually doubles/triples, and 0% were actually homeruns. The model continues to make similar comparisons until all terminal nodes are reached.

Table 7: Results of stage 1 decision tree classification for the initial model

Hit Outcome	% Observations	% Singles	% Double Triple	% Homerun
1	68	81	19	0
1	10	53	30	17
2	6	28	44	28
3	15	16	18	66

Table 8: Summary of Sample Sizes for Each Class

Hit Outcome	Sample Size
Single	23696
Double/Triple (Extra Base Hit)	7772
Homerun	5085

Figure 9 has four terminal nodes. Table 7 shows the breakdown of each terminal node. It shows the outcome the model predicted, the percentage of the overall observations it makes up, as well as the percent of those observations that were actually of other classes.

It is evident that the model over classifies singles out of the data and doesn't classify doubles/triples very well (only 6% are being classified as doubles/triples). Among the terminal nodes for doubles/triples and homeruns, there is still a large percentage of those that are being incorrectly classified as singles.

Balancing

While this model has some explanatory power, the coefficient estimators are biased and inconsistent. This is due to the inherent class imbalance among the different hit outcomes. Biased and inconsistent estimators are those that skewed away from the true population average. Table 8 is a table corresponding to the relative sample sizes of each hit outcome (single, extra base, or homerun).

Due to the fact that the sample size within the observed data for a single is 23696, while doubles/triples and homeruns have 7772 and 5085 observations respectively, singles are going to contribute much more to the overall model, thus causing the imbalance and bias towards predicting the singles hit.

The singles hit in the data set are referred to as the majority class, meaning they have the higher sample size and at this moment contribute more to the model than the minority classes, the extra bases and the homeruns. Intervention is necessary at this point to combat the imbalance class size problem.

Existing Literature About Balancing

A part of this project revolves around the issue of an imbalanced data set, the implications of it, and possible solutions. The purpose of this section is to examine literature related to the class imbalance problem and apply it to the model predicting `hit_outcome`.

As seen with the current batting data, a dataset is imbalanced if different categories are not represented equally in the data. This can lead to bias in the prediction model and flawed performance measures (Chawla et al. (2002)). To combat this, multiple studies have been done with the goal to develop various ways of balancing the data. Random under sampling is the process of using random examples from the majority class and taking them out of the dataset without replacement. This is done until the dataset is roughly balanced. Random over sampling, on the other hand, is the process of randomly sampling with replacement from the category with less observations. This is also done until the data set is somewhat balanced. (Thammasiri et al. (2014))

The effectiveness and performance of these processes are measured by the accuracy, the error rate, sensitivity, and specificity generated from each model's respective confusion matrix. The confusion matrix displays the true positives (TP) identified, false positives (FP), true negatives (TN), and false negatives (FN) (Thammasiri et al. (2014)). These performance measures are reliable for balanced data sets, but their reliability decreases as more imbalance is introduced in the data set. Thus, representing another reason as to why it's important to have balance. With the purpose of creating a more effective method to balancing data rather than random under or over sampling, Chawla, Bowyer, Hall, and Kegelmeyer created the Synthetic Minority Over - Sampling (SMOTE) algorithm, which is a combination of under sampling of the majority class and creating synthetic observations from the minority class (Chawla et al. (2002)). SMOTE is another way to balance the dataset so that one class doesn't have a much larger impact on the data. SMOTE is the process of adding artificially generated data to the minority class, following the same distribution. This method of oversampling takes its k nearest neighbor of the same minority class and generates a new data observation between the k neighbors and the observed observation. The `over_ratio` is a parameter that specifies when SMOTE is terminated and represents the ratio of minority class sample size to the majority class sample size. In this case, an `over_ratio` of one means that now the data set is exactly balanced, all classes have the same sample size (Chawla et al. (2002)).

SMOTE is important in improving the performance of the predictive model because it offers more examples from the underrepresented group that follow the distribution of the data, as opposed to random over sampling, that takes already existing data points with no extra room for the model to learn.

In their study comparing various types of prediction techniques for dealing with imbalanced data, Thammasiri et al. (2014), was able to rank the performance measures of logistic regression with oversampling, logistic regression with under sampling, logistic regression with SMOTE, and logistic regression with the original data. After performing 10-fold cross validation on these different models, they found that logistic regression using SMOTE performed better than

random under sampling and oversampling. While the original data model had high accuracy it's important to note that it could be biased and inconsistent because of the imbalanced class sizes.

In conclusion, this literature provides useful evidence as to why the current batting data is flawed, and a detailed approach on how to employ the SMOTE algorithm to balance the data with the aim of creating a model that can better predict the `hit_outcome` of an at bat.

SMOTE Model

In order to use the SMOTE algorithm, the data needs to be cleaned further. The code below describes this cleaning and formatting process, and stores the data in an object called `smote_data`.

```
# Cleaning the data for SMOTE function
smote_data <- batting_without_g3 %>%
  mutate(
    hit_outcome_factor = as.factor(hit_outcome)
  ) %>%
  select(swing_length_zscore,
         bat_speed_zscore,
         release_speed_zscore,
         launch_angle,
         hit_outcome_factor)
```

After the data is in the correct format, the SMOTE algorithm can be used with the following code. The `over_ratio` of 0.8 indicates a roughly balanced data set.

```
# running the SMOTE algorithm
balanced_batting_data <-
  smote(
    smote_data,
    "hit_outcome_factor",
    k = 5,
    over_ratio = 0.8 # a roughly balanced data set
  )
```

After balancing the data set, we can now run multinomial logistic regression the same was as the initial model, except using the SMOTE dataset.

Table 9: Stage 1 Multinomial Logistic Regression Output for SMOTE Model

Term	Double/Triple		Homerun	
	Estimate	Std. Error	Estimate	Std. Error
Constant	-1.140	0.019	-6.147	0.055
Swing Length Z-Score	0.163	0.015	0.420	0.022
Bat Speed Z-Score	0.506	0.017	1.794	0.028
Release Speed Z-Score	-0.010	0.011	0.088	0.015
Launch Angle	0.067	0.001	0.262	0.002
Swing Length/Bat Speed Interaction	0.107	0.015	-0.305	0.028

```
# logistic regression with the balanced data set
reg_model_smote<- multinom(hit_outcome_factor ~
                           swing_length_zscore +
                           bat_speed_zscore +
                           release_speed_zscore +
                           launch_angle +
                           bat_speed_zscore:swing_length_zscore,
                           data = balanced_batting_data)
```

Table 9 shows the multinomial regression output for the balanced smote model. We can interpret the coefficients of the launch angle and interaction term similarly to the interpretation for the initial model.

`launch_angle` has a value of 0.067 in the double/triple column. We can interpret this as follows:

On average, a one degree increase in a batter's launch angle is associated with an increase in the probability of hitting a double or a triple by about 1.95%

With a logit coefficient of 0.107, we can turn it into a probability and understand the interaction between swing length and bat speed as:

The interaction between bat speed and swing length suggests that as both increase, the likelihood of hitting a double or triple increases compared to a single. This is reflected in the positive interaction term, indicating that the effect of swing length on the hit outcome is enhanced as bat speed increases.

Table 10 shows the summary output for estimated probabilities of each hit type for the SMOTE model using a balanced data set. After balancing the data, it can be noted now that there is less of a difference in what hit type would be predicted, which should be the case if there are the same amounts of observations in each class. While the odds of predicting a single decreased, it is better for the overall model, as a lot of singles were being incorrectly identified.

Table 10: Stage 1 emmeans Summary Output for SMOTE Model

hit_outcome_factor	prob	SE
1	0.4308485	0.0027574
2	0.4677700	0.0027754
3	0.1013815	0.0019387

Decision Tree for SMOTE Model

The code below generates the decision tree for the multinomial logistic regression using the balanced SMOTE data, which is displayed in Figure 10.

```
smote_decision_tree <- rpart(hit_outcome_factor ~
                           swing_length_zscore +
                           bat_speed_zscore +
                           release_speed_zscore +
                           launch_angle,
                           method = "class",
                           data = balanced_batting_data)
```

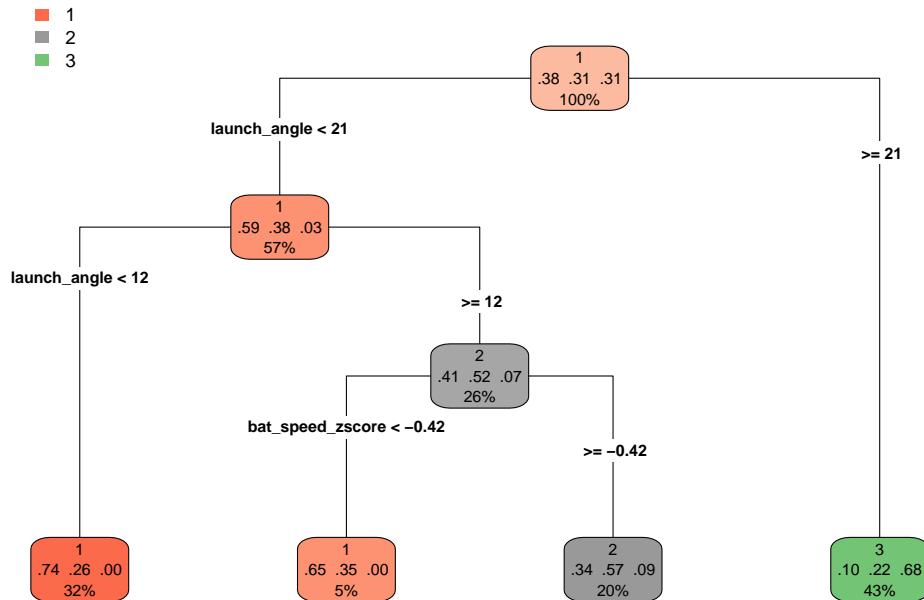


Figure 10: Decision Tree for SMOTE Model

Table 11: Results of stage 1 decision tree classification for the SMOTE model

Hit Outcome	% Observations	% Singles	% Double Triple	% Homerun
1	32	74	26	0
1	5	65	35	0
2	20	34	57	9
3	43	10	22	68

Similar to the initial decision tree model, from Figure 10, we can see that classifying the type of hit mostly relies on a hit's launch angle and bat speed. There are four terminal nodes. Table 11 below shows the breakdown of each terminal node. It shows the outcome the model predicted, the percentage of the overall observations it makes up, as well as the percent of those observations that were actually of other classes.

After balancing the data, the decision tree does a better job at classifying doubles/triples and homeruns. In this model, 57% of the correctly identified doubles/triples were classified correctly, opposed to 44% in the initial model, and the same is true for the homerun category.

Stage 2

The second stage of this project examines the predicted probabilities from the multinomial logistic regression models by feeding them into a decision tree. In a multinomial model, the predicted probabilities represent the likelihood that an observation belongs to a certain class. In this case, the predicted probabilities correspond to the likelihood that each hit is a single, double/triple, or homerun. By feeding these predicted probabilities into a decision tree model, we're able to identify patterns in how the probabilities map to certain classes, and better understand the models.

Initial Model

Below are the steps taken to feed predicted probabilities from a training set of the initial model into a decision tree model.

1. Getting how many rows are in the data and splitting into 2 parts

```
# so it is reproducible
set.seed(11)

# number of rows in dataset
n_batting_initial = nrow(batting_without_g3)
```

```

# randomly take 80% of the rows for the training object
train_initial = sample(1:n_batting_initial,
                      0.8*n_batting_initial,
                      replace=FALSE)

# split data into two parts - training
batting_train_initial = batting_without_g3[train_initial,]
# part that isn't the training part
batting_test_initial = batting_without_g3[-train_initial,]

```

2. Getting predicted probabilities from initial model on training data

```

# fitting the model on the training data
reg_train_initial<- multinom(hit_outcome ~
                                swing_length_zscore +
                                bat_speed_zscore +
                                release_speed_zscore +
                                launch_angle +
                                bat_speed_zscore:swing_length_zscore,
                                data = batting_train_initial)

# getting predicted probabilities
predicted_probs_initial <- predict(reg_train_initial,
                                      newdata = batting_test_initial,
                                      type = "probs")

# getting predicted classes
predicted_class_initial <- predict(reg_train_initial,
                                      newdata = batting_test_initial,
                                      type = "class")

```

3. Feeding the predicted probabilities into a decision tree

```

stage_2_tree_initial <- rpart(hit_outcome ~
                               predicted_probs_initial,
                               method = "class",
                               data = batting_test_initial)

```

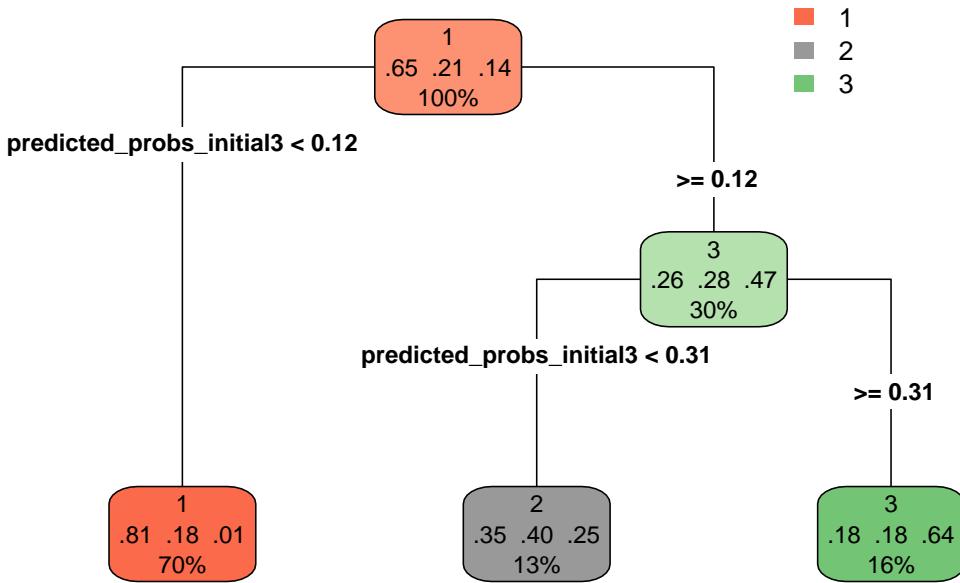


Figure 11: Stage 2 Decision Tree from Predicted Probabilities (Initial Model)

Figure 11 Shows the how the predicted probabilities affect the overall classification of the observation. `predicted_probs_initial_tree3` represents the predicted probability that the observation is a homerun. We can see that the model is only using that predicted probability to classify the hits. If that probability is less than 0.12, it is automatically classified as a single. If it's more than 0.12, it is compared again, this time to 0.31. Any hit with a predicted probability less than 0.31 is classified as a double/triple, and a probability greater than that is classified as a homerun. The summary table below shows the percentages for each terminal node.

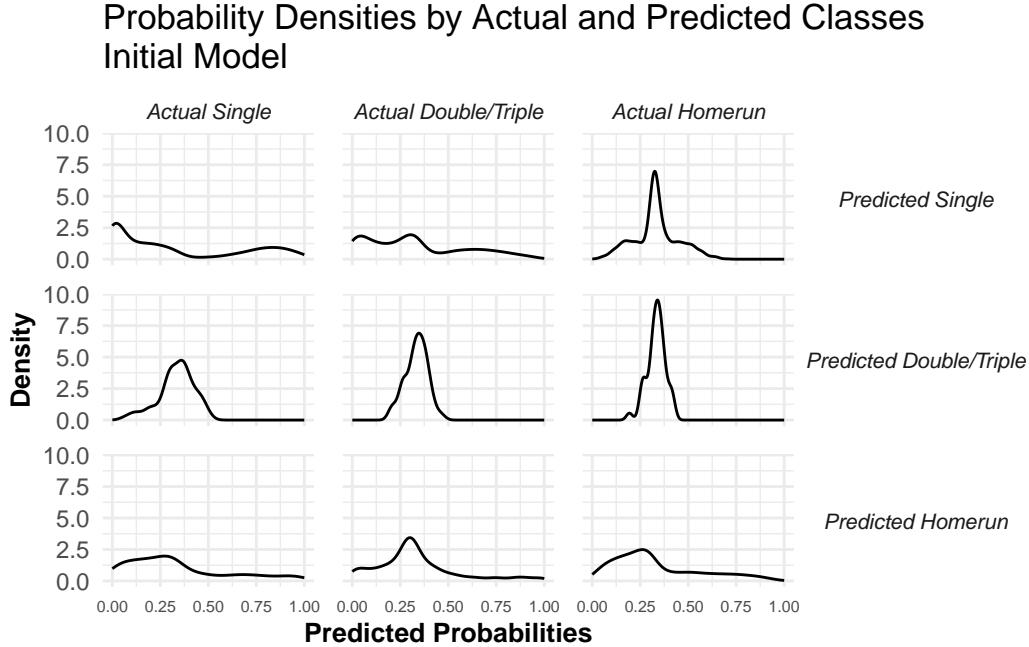


Figure 12: Comparing the probability distributions across combinations of actual vs. predicted hits for the initial model

Figure 12 shows each of the density distributions for the observations based on their predicted and actual class. By following a specific column and row of the graph, you can look at combinations of hits and the different predicted probabilities that were generated by the model. The diagonal line of three graphs going through the center correspond to hits that were correctly classified, while the distributions around the diagonal line were incorrectly classified.

We can see from Figure 12 that for hits that were actually doubles/triples and were correctly classified as doubles/triples, there is a high concentration of predicted probabilities ranging from 0.25-0.5, with a peak being around 0.35. This means that for hits that were correctly classified as doubles/triples in the initial model were all done so with less than 50% certainty. This graph can be used to understand the ability of the model to be confident in certain classifications.

SMOTE Model

A similar process was done to the data used for the SMOTE model in order to create a decision tree from the predicted probabilities based on that data.

1. Getting how many rows are in the data and splitting into 2 parts

```

# reproducibility
set.seed(11)

# number of rows
n_batting_smote = nrow(balanced_batting_data)

# randomly take 80% of the rows for the training object
train_smote = sample(1:n_batting_smote,
                     0.8*n_batting_smote,
                     replace=FALSE)

# split data into two parts
batting_train_smote = balanced_batting_data[train_smote,]
# part that isn't the training part
batting_test_smote = balanced_batting_data[-train_smote,]

```

2. Getting Predicted Probabilities from SMOTE Model on training data

```

# fitting the model on the training data
reg_train_smote <- multinom(hit_outcome_factor ~
                            swing_length_zscore +
                            bat_speed_zscore +
                            release_speed_zscore +
                            launch_angle +
                            bat_speed_zscore:swing_length_zscore,
                            data = batting_train_smote)

# getting predicted probabilities
predicted_probs_smote <- predict(reg_train_smote,
                                    newdata = batting_test_smote,
                                    type = "probs")

# getting predicted classes
predicted_class_smote <- predict(reg_train_smote,
                                    newdata = batting_test_smote,
                                    type = "class")

```

3. Feeding into decision tree the predicted probabilities

```

stage_2_tree_smote <- rpart(hit_outcome_factor ~
                           predicted_probs_smote,

```

```

method = "class",
data = batting_test_smote)

```

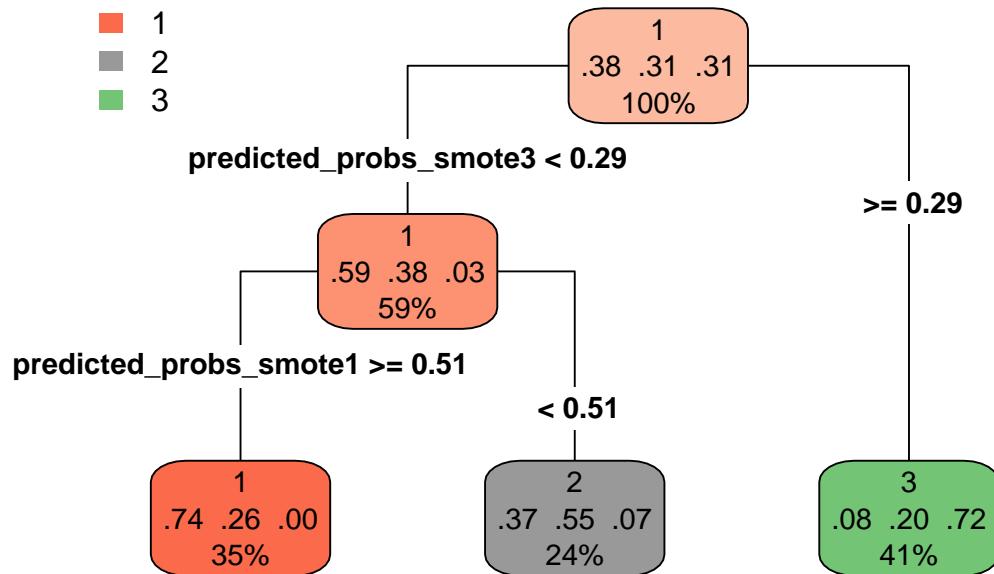


Figure 13: Decision Tree from Predicted Probabilities (SMOTE Model)

Figure 13 shows the decision tree trained from the predicted probabilities of the balanced SMOTE model. The model begins by looking at if the predicted probability of the hit being a homerun ($\text{predicted_probs_smote3} < 0.29$). If that probability is greater than or equal to 0.29, it is classified as a homerun. If it is less than 0.29, the model looks at the predicted probability being a single. If that predicted probability is greater than 0.51 the observation is classified as a single, if not, a double/triple. This model first attempts to determine if a hit is a homerun or not, and then tries to separate the singles from the doubles/triples. This strategy differs from the initial model, which first decided if a hit was a single and then compared the other types.

Probability Densities by Actual and Predicted Classes SMOTE Model

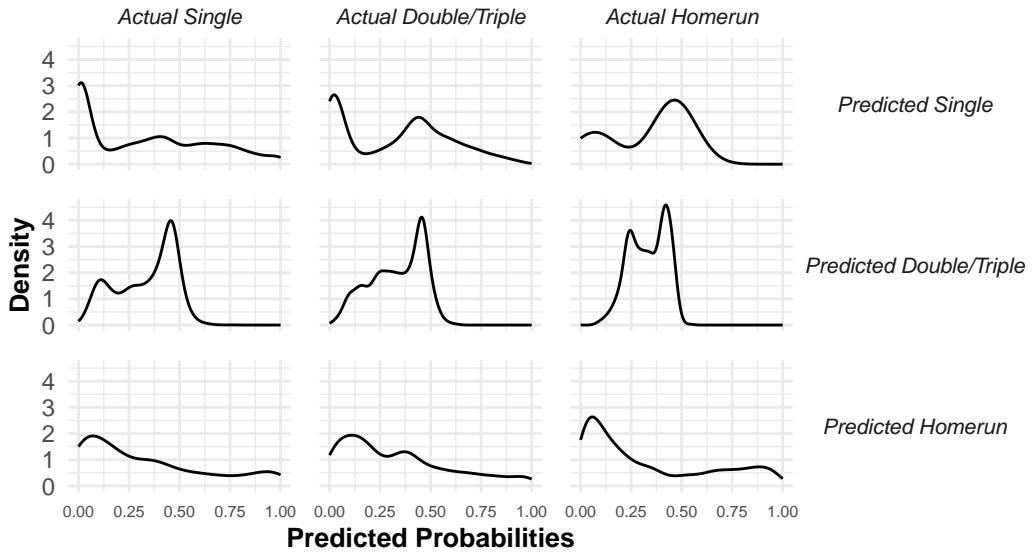


Figure 14: Comparing the probability distributions across combinations of actual vs. predicted hits for the smote model

Figure 14 shows the density graphs of the predicted probabilities for the SMOTE model. The density distributions of hits that were incorrectly classified tended to smooth out. However there are still some instances where the model is consistently wrong. The model does a poor job at distinguishing between a single and doubles/triples. This is evident by the graphs where singles and doubles/triples were misclassified as the other. For example, the observations that were actually singles but were classified as doubles/triples has a high density of predicted probabilities around 0.5, meaning that the model was getting a high probability of the hit being a double/triple when it was actually a single for the majority of hits that fall in that category.

Model Evaluation

The initial model attempts to classify the hit type using the standardized swing length, standardized bat speed, standardized release speed, launch angle, and an interaction between standardized bat speed and standardized swing length. All predictors in the model are significant and bat speed and swing length seem to contribute the most to model.

The SMOTE model takes all of the same predictors, but uses different data. The new balanced data has roughly the same amount of observations among classes to prevent one class from

creating bias. All predictors in this model are significant and bat speed and swing length both contribute the most to the model as well.

Confusion Matrix Initial Model

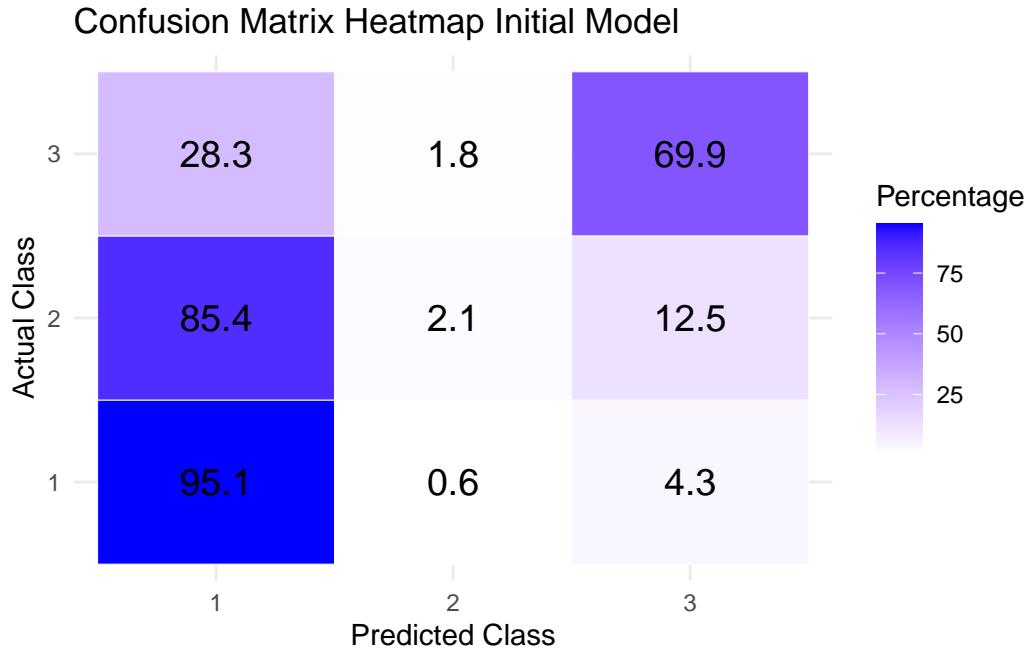


Figure 15: Confusion Matrix for Initial Model showing the percentage of the actual class that was classified to the corresponding category

Figure 15 shows the confusion matrix for the initial multinomial logistic regression model. The percentages in each box indicate the percent of the total number of hits in that class the prediction makes up. For example, 95.1% of the observed singles were correctly identified as singles, while 2.1% of the observed doubles/triples were correctly identified as doubles/triples and 69.9% of homeruns were correctly classified as homerun. We can also use this confusion matrix to find weak spots in the model. For example, 85.4% of all hits that were actually doubles/triples were classified as singles, and 28.3% of homeruns were classified as singles.

Figure 15 provides evidence for the fact that because the initial data set is so imbalanced, the model incorrectly identifies singles at higher rates than any other hit. This is seen as the darkest colors, indicating high percentages, and more concentrated in the predicted singles column, and the percentages get lower everywhere else.

From the numbers behind the percentages of Figure 15, we can find the accuracy as:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} = \frac{22536 + 166 + 3552}{36553} = 0.7182$$

While accuracy is a respected metric for evaluating model performance, it should not be the only one evaluated in a multinomial classification model. This is because accuracy fails to take into account the number of correctly identified observations of the other classes. It also fails to account for class balance. For these reasons, it is also important to look at precision for a certain level, i

$$Precision_{singles} = \frac{22536}{22536 + 6635 + 1441} = 0.736$$

$$Precision_{extraBH} = \frac{166}{166 + 139 + 92} = 0.418$$

$$Precision_{HomeRuns} = \frac{3552}{3552 + 971 + 1021} = 0.641$$

As the precision measures indicate, the model is not precise at all in predicting extra base hits and homeruns, and that the majority of the accuracy comes from predicting singles.

Confusion Matrix SMOTE Model

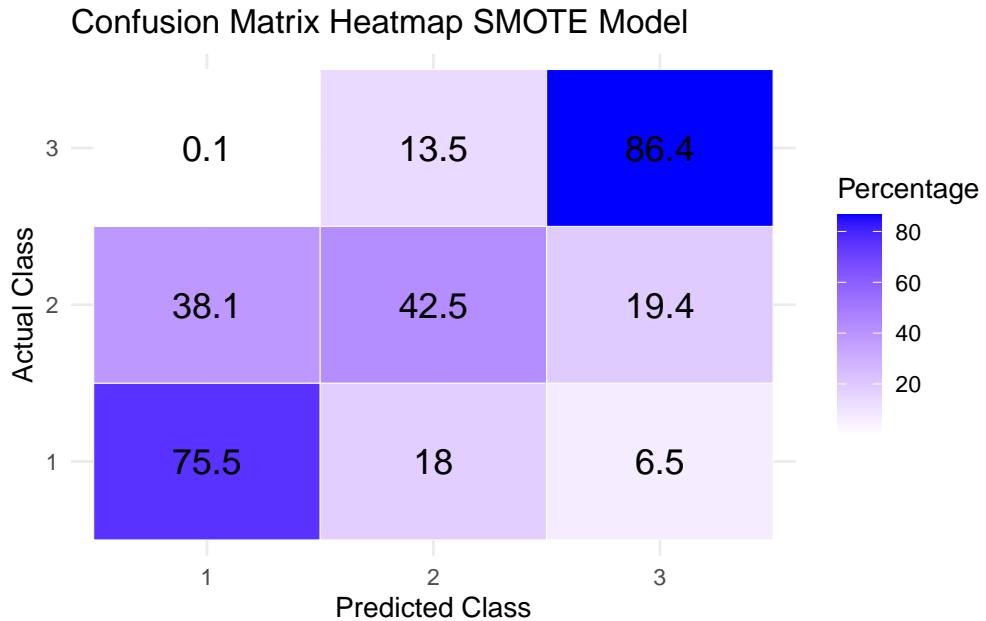


Figure 16: Confusion matrix for SMOTE model showing the percentage of the actual class that was classified in that category

Table 12: Accuracy and Precision Comparison

Model	Accuracy	Precision S	Precision Extra BH	Precision HR
Initial	0.7182	0.736	0.418	0.641
SMOTE	0.6871	0.713	0.542	0.758

$$Accuracy = \frac{17899 + 8082 + 16350}{61608} = 0.6871$$

$$Precision_{singles} = \frac{17899}{17899 + 7196 + 21} = 0.713$$

$$Precision_{extraBH} = \frac{8082}{8082 + 4249 + 2585} = 0.542$$

$$Precision_{HomeRuns} = \frac{16350}{16350 + 3678 + 1548} = 0.758$$

Figure 16 shows how with the balanced data set, the model does a better job at predicting hits that aren't singles. While the percent of singles that were correctly predicted declines, the trade off is a much higher rate of doubles/triples that were correctly predicted, as well as home runs. This is also evident in the precision calculations for each level of the hit outcome. While the overall accuracy of the model declines, we can see that the precision for the extra base hits and homeruns are significantly higher compared to the initial model.

Discussion and Implications

Table 12 shows side by side comparisons of accuracy and precision for each model. While the models aren't perfect and there are inherent issues with class balance, bias, accuracy, and precision, the SMOTE model using synthetic data does a better job than the initial model according to these metrics. There are still issues with classification, as seen in the predicted probabilities. The SMOTE model is not extremely accurate in distinguishing singles from doubles/triples, but does a better job than the initial one. This inability could simply be from the wide variation in ways a batter can hit a single, double/triple, which makes modeling difficult.

References

- Chawla, Nitesh V, Kevin W Bowyer, Lawrence O Hall, and W Philip Kegelmeyer. 2002. “SMOTE: Synthetic Minority over-Sampling Technique.” *Journal of Artificial Intelligence Research* 16: 321–57.
- Petti, Bill, and Saiem Gilani. 2024. *Baseballr: Acquiring and Analyzing Baseball Data*. <https://github.com/mlascaleia/baseballr>.
- Statcast, MLB. 2024. “Statcast Bat Tracking Leaderboard.” Major League Baseball. <https://baseballsavant.mlb.com/leaderboard/bat-tracking>.
- Thammasiri, Dech, Dursun Delen, Phayung Meesad, and Nihat Kasap. 2014. “A Critical Assessment of Imbalanced Class Distribution Problem: The Case of Predicting Freshmen Student Attrition.” *Expert Systems with Applications* 41 (2): 321–30.
- Wu, Junjie, and Junjie Wu. 2012. “Cluster Analysis and k-Means Clustering: An Introduction.” *Advances in K-Means Clustering: A Data Mining Thinking*, 1–16.