Do Better Batters Face Higher Quality Pitches? Group 45, Project 57

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Abstract

Even before the concept of "Moneyball" became prevalent, statistical analysis has always been at the core of baseball. With that head-start, baseball has maintained its position as a leader in sports in the development and usage of analytics. Currently, in Major League Baseball, "using analytics" is no longer a competitive advantage, but a bare minimum requirement for teams to stay competitive; the true edge lies within the depth of the analysis and the strength of the data.

The goal of this project is to develop models that quantify the quality of individual MLB pitches (commonly known as "Stuff+"), and to examine if the implemented results can be used to successfully answer the question of whether there is an observable relationship between how good a batter is and the difficulty of the pitches they face. This group hypothesizes that better batters perhaps are not facing better pitches, but are simply facing better pitchers.

There are currently multiple versions of Stuff+ models developed by different sources—including one from Driveline Baseball—that evaluate pitch quality against intrinsic run values through the calculation of simple linear weights. This group presents a state-of-the-art model to evaluate the quality of pitches against change in xwOBA instead. Rather than a measurement of batted ball results, xwOBA—developed by Statcast—measures the expected value of batted balls based on exit velocity, launch angle, and sprint speed. The contributions of this model are focused on evaluation based on quantifiable attributes of the pitch delivered, rather than the outcome of the event or the game state.

1 Introduction

When Boston Red Sox starting pitcher Nick Pivetta stands atop the pitcher's mound at Yankee Stadium and sees New York Yankees right fielder Aaron Judge dig into the batter's box, does he perform differently compared to when the person standing in the box is shortstop Isiah Kiner-Falefa? It is clear that the expected outcome of these two match-ups is very different—anyone with basic understanding of baseball and probability would expect Judge to perform better than Kiner-Falefa. Yet, this statement would likely be true regardless of who the pitcher on the mound is.

Better batters perform at a higher level than worse batters; that is precisely what makes them "better" batters. However, how does that affect—if at all—the performances of the pitchers they face?

Disregarding the fact that Pivetta may have different attack plans against the 6'7" Judge and the 5'10" Kiner-Falefa, would he throw his fastball differently? Would his curveball have more break against one than the other? This project aims to answer exactly these questions. Specifically, the intention is to understand if the presence of better batters makes the pitchers elevate their game and bring out their best "stuff" in order to compete with these elite opponents.

This group answers the above question by constructing and implementing models that quantify the quality of individual pitches from Major League Baseball games and studying the relationship between the skill level of the batters and the quality of the pitches they face. While the general idea of the Stuff+ model presented in this project is built on the concept of the Stuff+ model developed by Driveline Baseball, the target variable used in the models to reflect the value of each individual pitch is designed and produced originally by this group.

The observed results presented in this project suggest that better MLB batters do face higher-quality pitches compared to worse MLB batters. However, the hypothesis is not completely rejected, as there were also observed results that suggested better batters face better pitchers in general. Therefore, it is concluded that better batters do face better pitchers, but at the same time also face better pitches.

2 Related Work

The concept of the Stuff+ Model presented in this project is built on the Stuff+ model that Driveline Baseball has developed. Langin (2021) described the general concept of Driveline's Stuff+ model in his blog post and provided information such as input features and pitch type grouping. Although the specific model was not mentioned in the piece, it is to this group's knowledge that Driveline's implementation relies on the XGBoost model.

One feature that is included in Driveline's model but not in the models presented in this piece is Arm Angle because this variable is not publicly available and thus is not accessible by this group. The target variables used for the models are also different, as Driveline has constructed their model to predict run values, while this group presents a new variable named "Delta xwOBA." Lastly, although both Driveline and this group present the final Stuff+ numbers with 100 as the centered mean, the scaling of Driveline's metric is in terms of relative percentage to the mean, while this group utilized the concept of Z-scores.

3 Problem Definition and Algorithm

3.1 Task

To answer the proposed question—whether batter talent correlates positively with pitch quality—this paper starts with an overview of the modeling task, as well as an explanation of what the inputs and desired outputs look like.

In order to quantify both pitch and batter talent, this section will break down the task into two models. The first model needs to be able to quantify pitch quality. Section 4.2.1 describes feeding in features to the model that capture the effectiveness of a pitch - speed and positional data. A target variable is then obtained: a statistic that needs to be able to define the value of a pitch. For this project, Delta xwOBA is used, differentiating it from past related work. Weighted On-Base Average (wOBA) is a statistic that assigns a value to a batted ball based on the outcome of the batted ball. xwOBA generates an expected value for wOBA based on metrics that define the quality of contact when the bat hits the ball. Finally, the difference in xwOBA between ball-strike counts is calculated to arrive at the delta.

For the second model, section 4.2.2 classifies batters using a k-Means clustering algorithm. Although the batting model (which we use to specify batter talent) is relatively simple, the results shown in section 4.3 show promising signs that support the notion that this model is not only sufficient, but actually a good classifier.

Putting the results of these two models together, section 4.3 then analyzes the performance of different clusters of batters against the pitches they receive. The pitches, whose values have been defined by the pitching model, should give readers insight into whether or not pitch quality is correlated with batter talent.

3.2 Algorithm

The first model architecture, the pitch model, is an XGBoost tree model. Defined are 6 different XGBoost models that are separately trained on 6 different pitch types, as outlined in section 4.2.1. The models take in granular pitch-level data, as well as a calculated target variable Delta xwOBA. To obtain the target variable, average xwOBAcon values by pitch count are calculated from our dataset. A 'Start xwOBA' and 'End xwOBA' are then defined, which are the average xwOBAcon values at the start and end of the pitch. Finally, the start and end values are used to calculate the Delta, which is then used as the dependent variable in training the XGBoost models.

To illustrate this process, an example is given. Say the initial pitch count is 0-1. The mean xwOBAcon for a 0-1 count is .357, which will be our Start xwOBA value. The pitcher delivers a strike and the ending count is now 0-2, and the end xwOBA is the average xwOBAcon for a 0-2 count: .328. (If the ball had been a batted ball, then the actual xwOBAcon would be used since actual values are calculated for batted balls. Alternatively, for strikeouts, walks, and hit-by-pitches, wOBA would be used). The Delta xwOBA would therefore be .357 - .328 = .029. For every pitch, these values are calculated, then the resulting values are fed into the XGBoost models as the dependent variable. Then, for every pitch, a predicted Delta xwOBA value is calculated based on its speed and positional features.

The second model, the batter model, is a k-Means clustering algorithm. Batting Runs and Projected wRC+ (a weighted projection before the season starts of how many runs a batter will produce) are used as the two dimensions.

The final part of the algorithm involves analyzing the two model outputs for every pitch. For example, analyzing a pitch a star player (as determined by k-Means) faces, and its given value. Every pitch this star player faced in a given season would be analyzed, then compared against every pitch a role player (as determined by k-Means) faced.

4 Experimental Evaluation

4.1 Data

Data used for this project consists of two major parts: pitching data and batting data. All data are directly related to Major League Baseball and its players. Since the source and formatting of each data set are different, they will be discussed in detail in the two following sub-sections.

4.1.1 Pitching Data

All pitching data was downloaded from Baseball Savant, the official website of MLB's Statcast, using the PyBaseball package in Python. The data set used for training and testing the model included 972,840 pitches from the 2020 and 2021 MLB seasons after the initial cleaning. Of which, 80 percent was randomly assigned to the training set and the remaining 20 percent was assigned to the testing set. As further cleaning was necessary, the eventual training and testing sets used for the models consists of 776,619 and 194,186 pitches, respectively. The trained models are then applied on 706,553 pitches from the 2022 MLB season.

4.1.2 Batting Data

Batting data used for this project included 2022 Pre-Season projections by the Steamer Projections provided by Alex Caravan of Driveline Baseball and non-pitcher seasonal batting data from the 2022 MLB season downloaded from the FanGraphs Major League Leaderboards.

The Steamer Projections data set has 19,956 rows and 76 columns and was used to calculate the pre-season wRC+ projections for all batters. The seasonal batting data set from FanGraphs has 690 rows and 25 columns; two rows were removed because the two players did not record any plate appearance in the 2022 season; Christian Bethancourt was also removed because he lacks Steamer projections. As such, the eventual data set that went into the classification model included 687 batters.

4.2 Methodology

The process of this project includes the construction and application of Stuff+ models that assign values to each pitch used to compute the results, as well as a classification model that buckets all the batters by their skill level. The following subsections will provide detailed descriptions of the methods used to build, evaluate, and implement these models.

4.2.1 Pitching Model

Six separate XGBoost models were trained, tested, and implemented in this project. Pitches in the training set were separated based on the classified pitch types provided in the data set. The six pitch types are Four-Seam Fastball (FF), Sinker (SI), Cutter (FC), Slider (SL), Curveball (CU), and Changeup (CH). Pitches that are classified as Knuckle Curve (KC) were grouped together with Curveballs, and pitches that are classified as Splitter (FS) were grouped together with Changeups.

The models have the same four input features—Pitch Velocity, Vertical Movement, Horizontal Movement, and Release Extension—and aim to predict our own calculated metric called Delta xwOBA. The calculation of Delta xwOBA is as follows:

Using the training set, the average xwOBAcon by each of the twelve possible ball-strike counts prior to the pitch being delivered was calculated; this variable is named “Start xwOBA.” The values and the corresponding counts are presented below:

Count	xwOBAcon
0-2	.328
1-2	.344
2-2	.357
0-1	.357
1-1	.376
3-2	.383
0-0	.384
2-1	.389
1-0	.394
2-0	.421
3-1	.423
3-0	.463

Table 1: Average xwOBAcon of initial ball-strike count

The corresponding value to every single pitch was assigned based on the starting count.

Then an “End xwOBA” value was assigned based on the result of each pitch, which could be classified into three different occasions. If the pitch was struck by the batter and produced a batted ball, the actual xwOBAcon was used as the value; if the pitch resulted in a strikeout, walk, hit by pitch, or catcher’s interference, the corresponding wOBA for these events was used as the value; if the pitch did not result in the end of the plate appearance and simply took the plate appearance from one ball-strike count to another (or in the case of a two-strike foul ball, remained in the same ball-strike count), the average xwOBAcon presented above based on the new ball-strike count was used as the value.

$$Delta\ xwOBA = End\ xwOBA - Start\ xwOBA$$

The input variables and target variables are used to train and test the XGBoost models. As mentioned, each of the six pitch types is trained and tested separately. The models were trained each with a maximum depth of six and five estimators, with the objective to minimize the squared loss of the regression function. It is worth noting that while the cross-validation function generally recommended having fourteen estimators for each model, the decision of going with five estimators was made after studying the results and observing strong indications of overfitting. It must be acknowledged that Delta xwOBA is an inexact valuation of pitch value on a single-pitch basis, and thus an accurate prediction would produce over-fitted results.

The XGBoost models with the input features, target variable, and parameters described above produced the following results:

Pitch Type	Training RMSE	Training COD (R^2)	Testing RMSE	Testing COD (R^2)
FF	0.215	0.006	0.215	0.001
SI	0.294	0.012	0.206	0.0004
FC	0.209	0.020	0.205	0.001
SL	0.206	0.009	0.211	0.001
CU	0.192	0.018	0.194	0.002
CH	0.207	0.014	0.206	0.0004

Table 2: Training and Testing Errors and COD of Models

RMSE is the metric used to measure the accuracy of the predictions, and R^2 is used to determine the directionality of the predictions. As mentioned, the target variable Delta xwOBA is very noisy by nature (as the majority of the pitches do not lead to PA-ending events), and the low R^2 observed is deemed to be reasonable. After all, the metric is neither linear nor normally distributed.

In addition to understanding the accuracy of the model, it is also important to understand the reliability of the numbers produced by the models. For this, Cronbach's Alpha—which is a coefficient that measures the "internal consistency" of a metric—was the chosen metric of measurement. It is common industry practice to aim for the threshold of 0.7 in Cronbach's Alpha, as it implies that α^2 would be close to or above the 0.5 thresholds, and therefore the first-half sample would have the ability to explain at least 50-percent of the second-half sample.

The following plot shows Cronbach's Alpha by the number of pitches by the six different models:

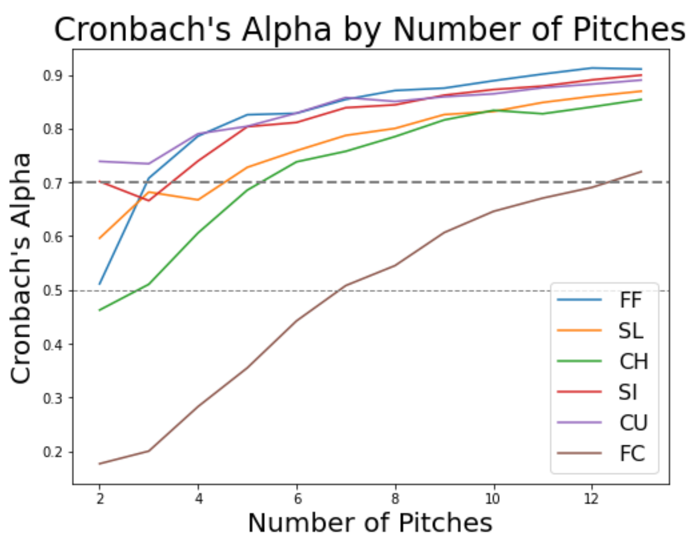

Figure 1: Cronbach's Alpha by Number of Piteches

The results show that five of our six models were able to produce predictions that are consistent immediately. The Curveball, Fastball, and Sinker models achieved desired reliability at or before four pitches; and the Slider and Changeup models achieved desired reliability at or before six pitches. However, the Cutter model clearly lagged behind, requiring thirteen pitches to achieve the desired reliability threshold.

The fact that the Cutter model takes more than double the number of pitches to stabilize compared to the other pitch types is interesting, given that the errors were pretty inline with other models. It is worth noting that the Cutter model also produced the highest training R^2. It is possible that it may be more difficult for pitchers to replicate their cutters in terms of pitch characteristics, although that is unlikely given that other Stuff+ models have not reported similar findings.

4.2.2 Batting Model

Batter classification was produced by a simple two-dimensional k-Means clustering model with five clusters. To properly assess the skill level of batters, both projected performance and actual performance of the 2022 MLB season were taken into account. The two features selected were projected wRC+ by Steamer, and Batting Runs by FanGraphs. Actual wRC+ from 2022 was avoided to prevent small-sample outliers, and Batting Runs were used instead of other metrics such as wRAA and wRC for the consideration of the added layers of park and league adjustments.

The initial idea of classifying batters was to only use projected wRC+ as the indicator. However, by incorporating actual performance on top of projected performance, the model is able to identify players who 1) were believed to be good and 2) were actually good. This method successfully filters out players who had strong projections but underperformed—thus no longer posed clear threats to the pitcher. The addition of Batting Runs as an indicator of actual performance also allows the model to identify breakout players who became threats to the pitchers, despite projections suggesting otherwise. The batter clusters are presented below:

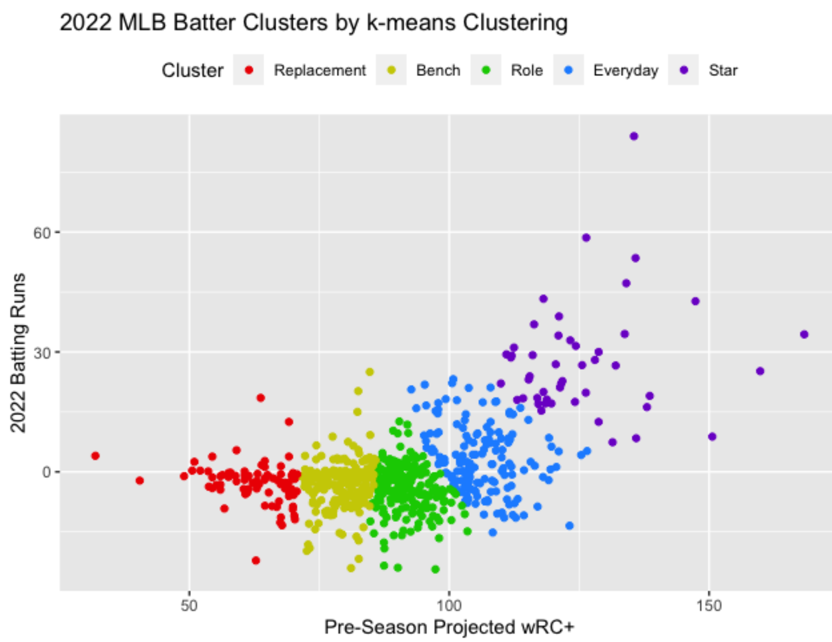

Figure 2: Batter Clusters produced by k-Means Clustering Model

The decision to use $k = 5$ as the number of clusters was purely from visualization; the Silhouette method—which suggested seven clusters—was attempted but decided against because the presented clusters did not make as much sense. The five clusters produced by the models were named accordingly as **Star** players ($n = 47$), **Everyday** players ($n = 153$), **Role** players ($n = 211$), **Bench** players ($n = 197$), and **Replacement**-level players ($n = 79$). It can be clearly observed that Star players are the group that truly stands out from the rest of the field, and they are exactly the group of "better batters" that this project is most concerned with.

4.3 Results

To make the produced predictions from the pitching models easily interpretable, the numbers were converted to Z-scores, then scaled and centered around 100 with $\pm$ 100 being one standard deviation. In the remainder of this piece, all Stuff+ numbers, unless otherwise stated, will be represented in the same scale: 100 is average, 200 is one standard deviation better than the average, -100 is two standard deviations worse than the average...etc.

In the following page, six tables are presented, each consisting of the top ten pitchers in average Stuff+ of the given pitch type, with a minimum threshold of 200 pitches of that pitch type thrown.

Four-Seam Fastball		
Rank	Pitcher	Stuff+
1	Pete Fairbanks	393
2	Ryan Helsley	392
3	Jhoan Duran	386
4	Félix Bautista	373
5	Andrés Muñoz	315
6	Hunter Greene	273
7	Gerrit Cole	256
8	Jacob deGrom	253
9	Spencer Strider	253
10	Matt Bush	252

Sinker		
Rank	Pitcher	Stuff+
1	Zack Wheeler	211
2	Jonathan Hernández	200
3	John Schreiber	194
4	José Alvarado	193
5	Tanner Houck	192
6	Clay Holmes	183
7	Garrett Whitlock	183
8	Nick Lodolo	182
9	Jake Bird	178
10	Ryan Borucki	176

Cutter		
Rank	Pitcher	Stuff+
1	Corbin Burnes	227
2	Emmanuel Clase	219
3	José Alvarado	184
4	Bryan Baker	170
5	Paul Blackburn	154
6	Yu Darvish	154
7	A.J. Minter	144
8	Shawn Armstrong	144
9	Aaron Civale	144
10	Chris Flexen	139

Slider		
Rank	Pitcher	Stuff+
1	Emmanuel Clase	272
2	Matt Bush	270
3	Evan Phillips	233
4	Michael King	226
5	Rich Hill	210
6	Bryan Abreu	208
7	Jacob deGrom	206
8	Shohei Ohtani	204
9	Yohan Ramirez	204
10	Brooks Raley	201

Curveball		
Rank	Pitcher	Stuff+
1	Trevor Megill	280
2	Jhoan Duran	259
3	Germán Márquez	238
4	José Ruiz	230
5	Matt Brash	227
6	Tommy Nance	219
7	David Robertson	218
8	José Berríos	210
9	Craig Kimbrel	200
10	Alex Lange	194

Changeup / Splitter		
Rank	Pitcher	Stuff+
1	Shohei Ohtani	299
2	Logan Webb	273
3	Hirokazu Sawamura	243
4	Kyle Wright	212
5	Jason Adam	208
6	Joely Rodríguez	193
7	Alex Lange	191
8	Carlos Carrasco	191
9	Nathan Eovaldi	184
10	Buck Farmer	184

Table 3: Top Ten Average Stuff+ Pitcher Ranking for each Pitch Type

With Stuff+ applied to every pitch from the 2022 MLB season and all the batters classified into five separate categories, it can now be examined if there is any observable relationship between the quality of the pitch and the general ability of the batter. Simply looking at the average Stuff+ across all pitch types that batters in each category faced, there is a clear relationship: the better the batter, the tougher the pitches he sees:

Cluster	Stuff+
Star	103.0
Everyday	101.0
Role	98.7
Bench	98.1
Replacement	97.1

Table 4: Average Stuff+ by Batter Cluster

However, it is suspected that there may be sampling bias in this case. It is possible that better players see better pitches on average because they face better pitchers more often. If opposing teams want to have success against these elite hitters, they should use their best pitchers to face them. To adjust for pitcher strength, the Stuff+ for each pitch is further centered around the average Stuff+ of that given pitcher for that given pitch type. For instance, if a pitcher threw a slider that is graded as 120 Stuff+, but his personal average slider Stuff+ is 140, that pitch now has an adjusted Stuff+ of 80 instead of 120 because the figure is 20 below his personal average. A 100 adjusted Stuff+ in this case means the pitcher threw a pitch that is in line with his personal average, and not necessarily in line with the average of the entire population. Interestingly, even after adjusting for pitcher strength, we see no difference in Stuff+ at the top end. Star players still face the toughest pitches:

Cluster	Adjusted Stuff+
Star	103.0
Everyday	101.0
Role	98.8
Bench	98.4
Replacement	98.9

Table 5: Adjusted Stuff+ by Batter Cluster

The results seem to suggest that while better batters indeed face better pitches, it is not because of what was hypothesized, where it is mostly due to the strength of the pitchers they face, at least not on a per-pitch basis. However, in theory, better pitchers could be throwing fewer pitches because they are relatively better at fulfilling their task and putting away the batters, without having to waste many pitches. Throwing more pitches does not mean a pitcher is deployed more often.

To verify the deployment of pitchers against the different batter clusters, it is necessary to observe the pitcher by their personal Stuff+ average and group them together on a per-PA basis rather than on a per-pitch basis. Essentially, this will reflect the average strength of pitchers used against batters from each cluster. A relationship, albeit small, is observed in this case: the better the batter, the better the pitcher they face. However, the differences among clusters are smaller, particularly at the top end, where there is barely any discrepancy observed between the star players and the everyday players.

Cluster	Pitcher Stuff+
Star	100.0
Everyday	99.6
Role	99.1
Bench	98.6
Replacement	97.3

Table 6: Pitcher Stuff+ by Batter Cluster

In summary, while there is an observed difference, it is clearly not large enough to offset the previously observed relationship between the batter cluster and the pitcher-adjusted Stuff+. It is likely that both cases are true: star players face better pitchers, but also face better pitches from all the pitchers.

4.4 Discussion

This group initially hypothesized that better batters may be facing better quality pitches because they are facing better pitchers. Through the construction and implementation of the Stuff+ model and the observation of the different batter clusters, the hypothesis is rejected. It is observed that better batters do face better pitchers but also face better pitches. In other words, pitchers perform better when they are tasked to face better opponents. However, since "better" is a relative term, it could also be suggested that pitchers have the tendency to relax and do not necessarily bring out their best stuff—perhaps as an attempt to conserve energy—when facing worse hitters. Thus, the results can be interpreted from different perspectives.

5 Conclusions

This project has successfully demonstrated that batter MLB batters—specifically the very elite star hitters—do face better quality pitches. At the same time, they also face better pitchers in general. Through the pitch quality model that was built and implemented in this project, this group found that MLB pitchers bring out their best "stuff" and elevate their game when they are tasked to battle against the best of the best in the batter's box. However, since there were no clear differences observed within specific pitch types, it is likely that pitchers choose to use their best pitches more, rather than truly throw their pitch better when facing the best hitters.

It is worth noting that the concept of this pitch quality model is similar to most others, where the purpose is to quantify the raw "stuff" of any given pitch. Additional factors such as pitch location and pitch sequencing were not taken into account, even though these are clearly variables that have impacts on the outcome of pitches. Future studies could aim to incorporate pitch location or into consideration isolate pitch location as the sole variable to find out if pitchers locate their pitches more carefully when they face the best hitters.

Some additional adjustments to this study can also be made. Platoon splits and times-through-order penalties are some examples of factors that this study did not include given various constraints. It would be interesting to see how pitchers perform facing batters of different handedness, but the effect of the potential difference in pitch type usage would have to first be adjusted for. For instance, the slider is a pitch that is much more commonly used against same-handed pitchers, while the changeup is a pitch that is more commonly used against opposite-handed hitters.

6 Lessons Learned

Baseball domain knowledge is central to this project and large amounts of research needed to be done in order to answer the project question. When constructing models, advanced stat metrics required a full understanding in order to build models with the proper variables for learning. Additionally, a lot of difficulty was encountered in the model selection phase for the pitching model. A variety of different models were tested, including simple linear regression, k-nearest neighbors, random forests...etc. Model performance was poor at first, and a deeper understanding of each model's pros and cons, as well as scenarios for model applications was needed to complete the project.

Being able to interpret the results to an audience that was not familiar with baseball also presented itself as a challenge. A glossary that was too lengthy or too brief might have scared off readers, or left them still confused. But the glossary at the end of the poster and report clearly communicated the knowledge necessary in a succinct manner that provided the audience a better understanding of the project's problem formulation and model construction/application.

Moving forward, the communication skills learned in the process of undergoing this project will be hugely applicable. Be it sports or other industries, the ability to convey key technical terminology and processes to stakeholders that lack the proper domain knowledge will be critical. In addition, the research skills gained from this undertaking will be broadly applicable to many future projects. More specifically, the process of researching an unfamiliar field and balancing between learning and deferring to domain experts for problem formulation was an important part of this process that lead to some good takeaways on domain exploration.

7 References

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8 Student contributions

All members of the group contributed to each aspect of this project. The tasks included researching on the topic, gathering data, writing code, building models, coordinating meetings, making the poster, and writing the report.

A Glossary

This section provides definitions of various baseball terms and metrics used throughout this piece.

- **wOBA**: Weighted On-Base Average, a metric developed by Tom Tango that uses Linear Weights to assign values to different outcome events in baseball and quantify the production a player produces with his bat. Adjusted to match the OBP scale; not adjusted for ballpark or league.
- **xwOBA(con)**: Expected Weighted On-Base Average (on Contact), a metric developed by Statcast that uses Exit Velocity, Launch Angle, and in certain cases Sprint Speed to predict the wOBA of a given batted ball. Uses a k-NN model plus a GAM model to incorporate Sprint Speed.
- **wRC+**: Weighted Runs Created Plus, a metric developed by FanGraphs that aims to quantify the production a player produces with his bat. Adjusted for ballpark and league average, which is set at 100. A 110 wRC+ means a player's production is 10% better than the average; a 80 wRC+ means a player's production is 20% worse than the average…etc.
- **HBP**: Hit By Pitch, when a batter is struck by the pitch thrown by the pitcher, he is awarded first base.
- **PA**: Plate Appearance, representing each turn a batter comes to bat at the plate.
- **Pitch Types**:
  - **FF**: Four-Seam Fastball
  - **SI**: Sinker (aka. Two-Seam Fastball)
  - **FC**: Cutter (aka. Cut Fastball)
  - **SL**: Slider
  - **CU**: Curveball
  - **CH**: Changeup