Maximizing Chances of Victory in Basketball

COMM 414 Final Report, December 2018

Annan (Aruba) Chen
49596521

Guo Guo (Vannie) Hong
19878157

Ziyi (Laura) Ma
39512371

TABLE OF CONTENTS

1. BUSINESS UNDERSTANDING

1.1 Background and Business Problem

Since its founding in 1946, NBA (National Basketball Association) has established itself as a global premier basketball league. Based in North America, the players from its 30 teams are also the best paid athletes by average annual salary in the world. Just like any average players, NBA players face the struggles of failing to score and losing an important game. Although, broadly speaking, ESPN has also been predicting champions of each season for some years now and sometimes they are very accurate (ESPN, 2018). But no predictions has been focused on the probability of a single shot and a single player. Therefore, it would be value adding to identify who the best NBA players are and how they can maximize their chances of scoring.

1.2 Project Objective

Our objective is to build a shot prediction model, whether the player will score or not score, based on the data analysis that we conduct after taking the shots and the circumstances under which they are made into consideration, to help all stakeholders develop more effective game strategies. In building our models, our data mining goal is to find the best model that has the highest accuracy and F1-score.

1.3 Relevant Reports

Data analytics in NBA can revolutionize how players play. They can identify, for instance, the best players at altering or discouraging the most efficient types of shots, like three-pointers and dunks(Kopf,D,2017). Data can tell us if it is appropriate to make a shot if a 7 feet Center standing 3 feet away from you (Anadiotis, 2018).

Moreover, picking a player for a team can also be a difficult job, like picking an employee for a company. A wrong choice in the first round can set a team back years. Teams look for whatever advantage they can when evaluating picks, and analytics play a key role (Merrimack College, 2018).

For a more business-pragmatic purpose, a game developer, like the famous NBA 2K series(Basketball games) produced by EA, is able to use the data to simulate the probability of a shot to determine whether under certain player's condition(parameter) a shot can be made or not, and build the algorithm based on it to make a more realistic game (Operations Port, 2018).

1.4 Impact on Stakeholders and Potential Benefits

Table 1: Our Model's Impact and Benefits

Stakeholders	**Potential Benefits**
Basketball management groups	They can better identify the best players and their strongest assets, and then hire accordingly.
Basketball coaches	They can develop more effective strategies prior to a game.
Basketball players	They can first follow the coaches' strategies. From their own statistics, they can better understand their own strengths and weaknesses.
Basketball fans	They can improve their own basketball skills after learning from the best players.
Basketball game bidders	They can identify the best players to bid on.
Business product managers	They can develop more realistic business products that involve basketball game simulations.

2. Data Understanding & Preparation

We will first explain our original dataset before explaining how it is prepared. Afterwards, we will explore our new, blended dataset using exploratory data visualization (EDA) methods.

2.1 The Original Kaggle Dataset

The dataset is a public Kaggle dataset that records all the shots attempted during the NBA 2014-2015 season. It is uploaded by a Kaggle data scientist named "DanB", and he derived the raw data from NBA's REST API. The target variable is the "Shot Result", whether the player made the shot

(“made”) or missed the shot (“missed”). The predictor variables include “Game_ID”, “Matchup”, “Location”, “W”, “Final_Margin”, “Shot Number”, “Period”, “Game_Clock”, “Shot_Clock”, “Dribbles”, “Touch_Time”, “Shot_Dist”, “PTS_Type”, “Closest_Defender”, “Closest_Defender_Player_ID”, “FGM”, “PTS”, “player_name”, and “player_ID”. There is a total of 128,069 data point (or shots attempted), each with 20 variables explaining the shot’s feature. The completeness of the dataset is quite high, but the depth of information on players is quite shallow. We thus decided to find another dataset on players’ personal information.

Link to the original dataset: https://www.kaggle.com/dansbecker/nba-shot-logs

2.2 Data Preparation Steps

We followed the 5 essential data preparation steps to create our ideal dataset. First, we gathered NBA players’ seasonal data from Kaggle1 and used Vlookup in Excel to link our original dataset’s variables “Closest Defender’s Name” and “Player” to their seasonal data. Second, we cleaned our dataset through deleting 70 variables that we deem unnecessary, such as offense variables in defenders and defend variables in offenders. We then renamed predictor variable fields so that we could conduct data blending, or matching the correct player data to the shots’ data. Lastly, we did data sampling by taking out data entries that we found to be outliers. Our finalized dataset has 127,951 observations with 46 variables.

2.3 Data Understanding Using Visualization

This session will illustrate relationship between pairs or small numbers of attributes using different visualization techniques.

2.3.1 The Box Plot

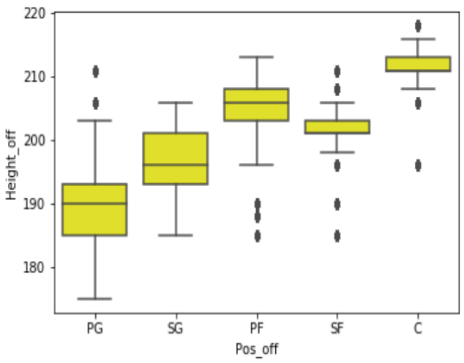
The Box Plot (Figure 1) illustrates the relationship between the height of players and their positions in teams. Intuitively, players with center positions, who are normally the last line of defense

in an offensive attempt, needs to be the tallest. Similarly, players who are point guards usually are ball-handler and requires a relatively smaller physique to agilely move around in the field.

Figure 1: Box Plot of Height and Team Position

```
sns.boxplot(x='Pos_off',y='Height_off',data=shot_data,color='Yellow')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x1027e89e8>
```



2.3.2 Distribution Plot

Figure 2 is a distribution plot of the shot-distance, from which a pattern can be clearly observed. Most of the shots made were concentrated to areas close to the basket or close to the three-point line (7.24 m). This makes intuitive sense because players either want to maximize probability of making the shot by being close to the basket or trying to maximize their points by trying outside the three-point line.

Figure 2: Distribution Plot of Shot Distance

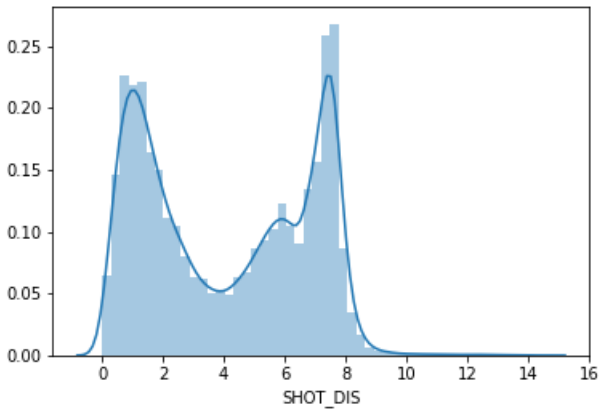
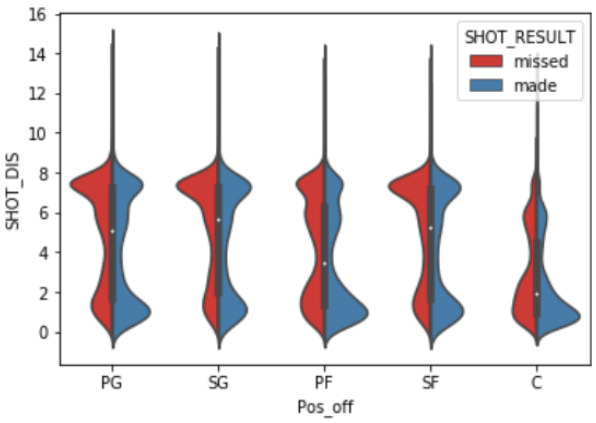


Figure 3: The Violin Plot of Shot Distance and Results



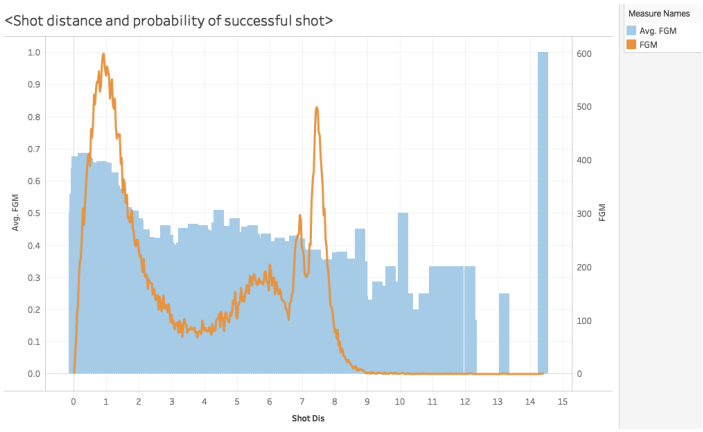
2.3.3 The Violin Plot

Above is the violin plot that illustrates the relationship between shot distance and shot results of different positions.

2.3.4 Tableau Visualization

In Tableau, both the sum of field goal made and its average were plotted against the shot distance. It can be observed that number of successful shots were concentrated at the two areas discussed above. Some interesting outliers can also be observed. For example, only one shot made at a distance of 14.39 meters was successful, which was made by John Wall. Generally, the shots with the biggest success rate is when you are closest to the basket.

Figure 4: Tableau Visualization



3. MODELING

In our analysis, **logistics regression, decision tree** and **random forest model** were employed because the target variable in this case is categorical, and we would like to predict whether the shot will be successful or not. Two different variable selection criteria were employed and their results will be compared. The first selection method is based on intuition, collinearity and p-value. The second one is based on feature selection method developed by William Koehrsen.

3.1 First-level variable selection-Intuition, correlation and P-value

Among 45 explanatory variables in total, one who watches NBA games for a while could discover some irrelevant features when player makes a shot. For example, when considering the ability

of the offender, the blocking and rebound rate of the offender seems to be of little importance on the shot results. On the other hand, the three-point shooting percentage might be insignificant to determine whether the defender could successfully hinder the shot. Therefore, we firstly deleted 23 variables that are perceived to be trivial and kept 22 independent variables in the models. Among them: 9 variables were about the offender (shooting percentage, height, etc), 9 variables were about the defender (the distance between Off and Def, rebound rate, etc), and 4 variables were about other attributes of a shot (shot clock, shot distance, etc). The details of variables are shown in the tables below.

Table 2.1: Variables About the Offenders

Variable	Touch_Time	Dribbles	Height_off	Age_off	OWS_off	OBPM_off	FG%_off	USG%_off	TOV%_off
Coef	-0.0732	0.0350	-0.0005	0.0069	-0.0016	0.0257	0.0038	0.0038	-0.0073
P_Value	0.000	0.000	-0.002	0.004	-0.014	0.012	0.000	0.021	0.001

Table 2.2: Variables About the Defenders

Variable	Height_def	Age_def	DWS_def	BLK&_def	TRB%_def	STL%_def	USG%_def	TOV%_DEF	Close_def_dist
Coef	-0.0017	-0.0014	-0.0231	-0.0540	-0.0034	-0.0019	0.0004	-0.0011	0.3886
P-Value	0.028	0.369	0.003	0.000	0.043	0.980	0.922	0.680	0.000

Table 2.3: Variables about shot attributes

	Home	Period	Shot_Clock	Shot_Dis
Coef	0.0235	-0.0049	0.0137	-0.2152
P_Value	0.090	0.429	0.000	0.000

We then run the three models for the first time, but we discovered that the result for logistics regression is not optimal because some of the P-Value for certain variables were too high to be significant. Also, for decision tree and random forest, the accuracy scores were low. To further narrow down our variable selection, we plotted the heat map of both the defender variables and the offender's variable to see which have more correlation. With the heat map, we deleted more variables and only

kept the correlated ones, which are: “Dribbles”, “Shot-Dis”, “Shot-Clock”, “Close_Def_Dist”, “Height_def”, “BLK%_def”, “Age_off” , “OBMP_off”, and “FG%_off”

Table 2.4: Variables Selected after Deleting High-p-value Features

Variables	Dribbles	Shot_Dis	Shot_Clock	Close_Def_Dist	Height_def	BLK%_def	Age_off	OBMPoff	FG%_off
Coef	-0.0236	-0.2139	0.0154	0.3985	-0.0029	-0.0667	0.0069	0.0303	1.2046
P_Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

With the variables at hand, we perform the decision tree and random forest model separately with all the variables above. The results are shown before, where one could observe a significant increase in accuracy and F1-score for random forest than the decision tree. For the decision tree, we identified the importance of each variables. For random forest, we run both 100, 200, 300, and 400 and found out that 400 gives us the highest accuracy and F1 scores.

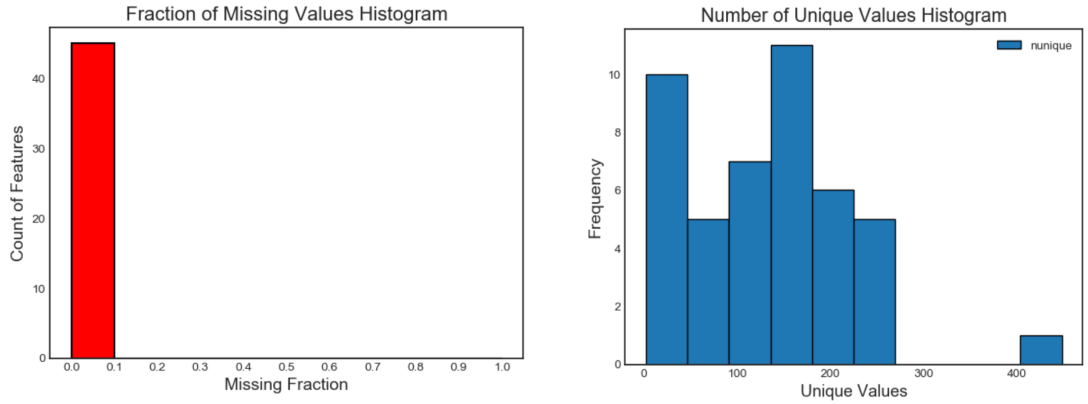
3.2 Feature Selection Model

To test whether the variables selected by intuition is on the right track, we find another model posted in Github whose goals is also to select the best-fitting features to the model, except for sklearn, another statistical package imported to this model is “LightGBM”, in which gradient boosting machine is used (See Appendix 2). The detail mechanism of this model is shown in the Jupiter Notebook files named “Feature Selector Development” and “Feature Selector Usage”.

The feature selection model developed by William is based on five selection standards: 1. Excluding the variables that have the missing fraction greater than a specified threshold. 2. Excluding variables that only have a single unique value. 3. Excluding variables that have correlation coefficient larger than a given value. 4. Excluding the variables that with 0 importance based on gradient boosting machine. 5. Excluding features that do not contribute to a specified cumulative feature importance from the gradient boosting machine.

We already performed the data cleaning process by replacing the missing value with league's average data. Also, as each shot's attribute is quite different, we do not have variables that only have single unique value. These two features is shown in Figure 5. Thus we have 0 variable being excluded by the first and second standard.

Figure 5: Histogram of Missing Value and Unique Value in the Dataset



As two highly correlated variables would overshadow the effect of the other one, therefore we only need to keep one of them and deleting the others. Similar to the heat map used in the previous selection method, but William's model provides the threshold of correlation and could exclude the variables whose correlation is above the set threshold. Here we set the correlation upper limit to be 0.6, which means we delete the features whose correlation is higher than 0.6. Figure 6 demonstrates the correlation of all variables included and those whose correlation is higher than 0.6. In this step, we delete all 24 variables (Table 3) that have the correlation above the threshold. Figure 7 is an example of the correlation value and which variable to keep or remove.

Table 3: Excluded Variables Based on Collinearity

3PAr_off	FG_off	Height_off	DRB%_def	DRIBBLES	FG%_off
3P%_off	SHOT_NUMBER	DWS_def	TS%_off	Weight_def	OBPM_off
TOV_off	USG%_off	2P_off	BLK%_def	Height_def	2PA_off
FGA_off	WS_off	TRB%_def	ORB%_def	OWS_off	3P_off

Figure 6: Correlation Heat Map with all Variables and Upper Limit of 0.6

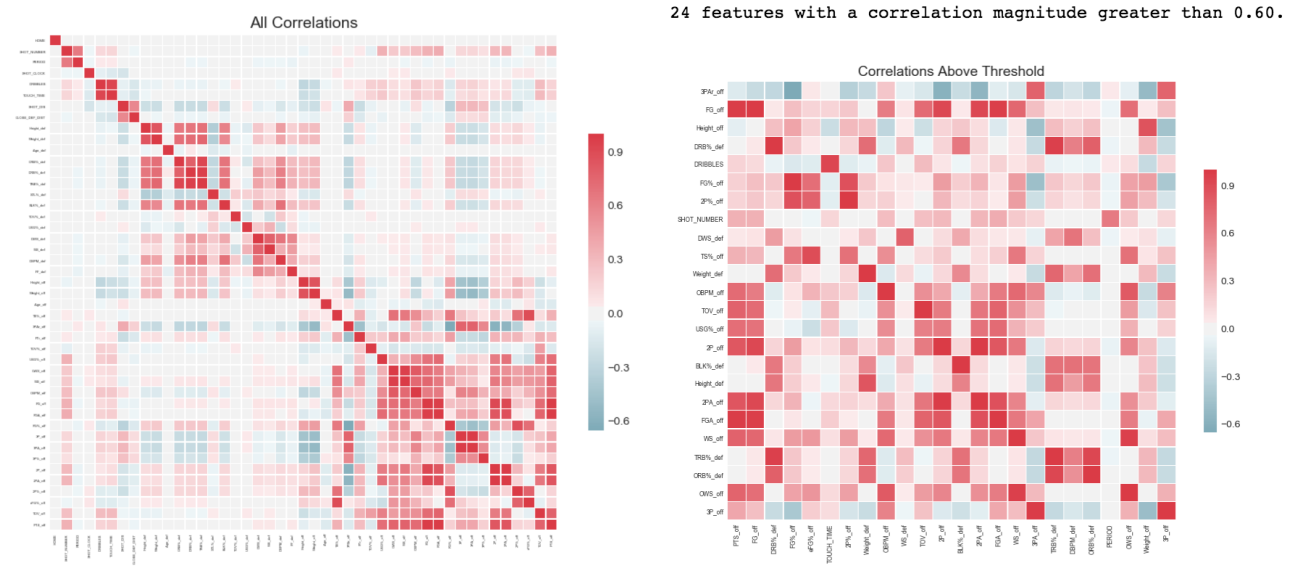


Figure 7: Example of Correlation Value and Variables Selected

	drop_feature	corr_feature	corr_value
0	TOUCH_TIME	DRIBBLES	0.931226
1	Weight_def	Height_def	0.847111
2	TRB%_def	ORB%_def	0.920680
3	TRB%_def	DRB%_def	0.967089
4	Weight_off	Height_off	0.860958

The fourth and fifth selection criteria are built on a supervised machine learning model, which remove the variables according to their estimated importance level using a gradient boosting machine in the LightGBM library. In these two steps, we remove features with zero importance and those variables that do not account for 95% of accumulative importance. The gradient boosting training process is shown below in Figure 8. After the modeling we find out that all variables are with positive importance level, and 36 variables required for 0.95 of cumulative importance. Table 4 demonstrates the 12 variables with highest importance, as well as how do those 36 variables accumulate to account for 0.95 importance. The remaining variables are '3P_off', 'PERIOD', 'TOV_off', 'Height_off',

'2PA_off', 'FGA_off', 'PTS_off', '3PA_off', ‘HOME’ and they are excluded — they only have relatively little contribution to predict the shot result.

Figure 8: Gradient Boosting Training

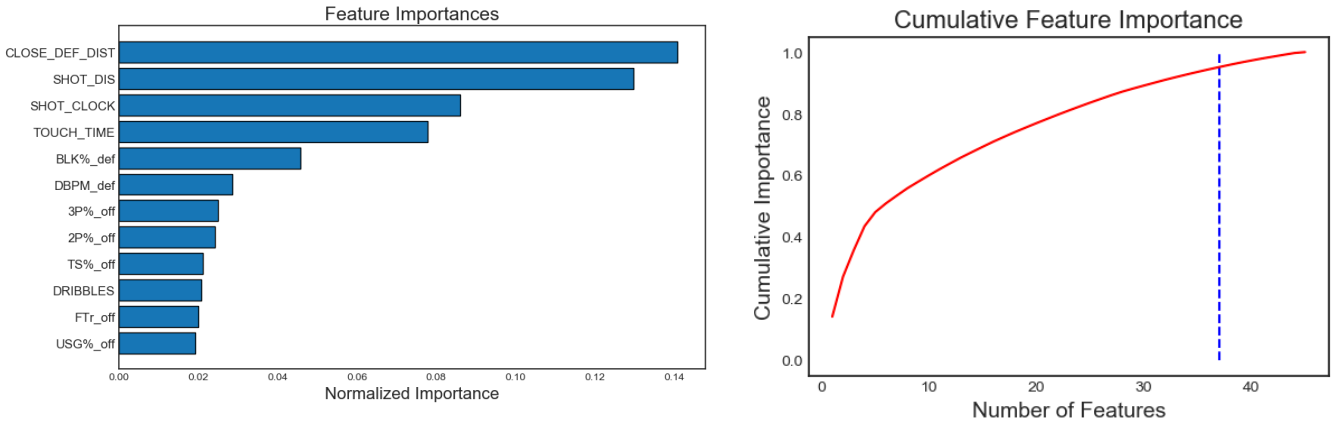


Table 4: Twelve Variables with the Highest Importance

Feature	Importance	Normalized_importance	Cumulative_importance	Feature	Importance	Normalized_importance	Cumulative_importance
CLOSE_DEF_DIST	**475.9**	0.140882	0.140882	**3P%_off**	**84.3**	0.024956	0.533807
SHOT_DIS	**438.2**	0.129722	0.270604	**2P%_off**	**81.8**	0.024216	0.558022
SHOT_CLOCK	**290.6**	0.086027	0.356631	**TS%_off**	**71.2**	0.021078	0.579100
TOUCH_TIME	**262.9**	0.077827	0.434458	**DRIBBLES**	**70.2**	0.020782	0.599882
BLK%_def	**154.8**	0.045826	0.480284	**FTr_off**	**67.8**	0.020071	0.619953
DBPM_def	**96.5**	0.028567	0.508851	**USG%_off**	**64.7**	0.019153	0.639106

These low importance variables might have overlaps with high correlation variables, therefore the Feature Selection model totally removes 26 variables which are 'HOME', ‘FG_off’, ‘Height_off', 'DRB%_def', ‘FG%_off', 'eFG%_off', 'TOUCH_TIME', '2P%_off', 'Weight_def', 'OBPM_off', 'WS_def', 'TOV_off', '2P_off', 'BLK%_def', '2PA_off', 'FGA_off', 'WS_off', '3PA_off', ‘TRB%_def', 'DBPM_def', 'ORB%_def', 'PERIOD', 'OWS_off', ‘Weight_off', and ‘3P_off'. With the remaining features, we apply logistic regression, decision tree, and random forest to further analyze whether our intuitive variable selection and modeling variable selection produce distinguished results.

3.3 Further Variable Selection Method

Except for variable selections based on their importance level, collinearity, and p-value as shown in previous sections. We could also use recursive feature elimination to examine whether our model include the variables that might still could be removed for improvement. Our RFE model shows that all variables' label is "TRUE", which means it is unnecessary to remove any of them.

Figure 9: Results of Recursive Feature Elimination for Feature Selection Model

```
rfe = RFE(model,19)
rfe = rfe.fit(X_train,y_train.ravel())
print(rfe.support_)
print(rfe.ranking_)
```

```
[ True  True  True  True  True  True  True  True  True  True  True  True
  True  True  True  True  True  True  True]
[1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1]
```

Stepwise regression is another way to find the most suitable features to include in our model by using the backward elimination (deleting variables from full-feature model) or forward elimination (adding variables from empty model). However, owing to the word limit, our report would not include this method. If length permitted, researchers could take a look into the stepwise regression to find out whether there would be a better models containing different variables.

4. RESULTS & EVALUATIONS

4.1 Result from First variable selection - Intuition, correlation and P-value

Our business objective is to predict as accurately as possible whether a shot will be made or not, so the accuracy of the models is important and should be ranked and compared. To compare the results and accuracy of each models, we calculated the accuracy score and F1 score of logistics regression, decision tree, and random forest models. We compared the different precision, F1 score between the three models. We found that the accuracy for logistics regression was bigger than decision tree, but it was similar to the random forest model. Logistics regression also has the largest F-1 score. Therefore, logistics regression is the most accurate model to employ in this case.

Figure 9: Confusion Matrix for Logistic Regression & Decision Tree

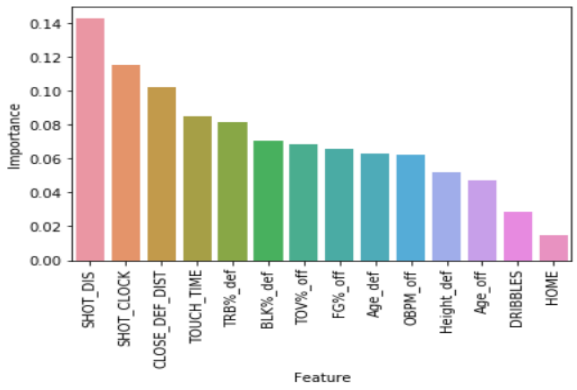
```
confusion matrix:
 [[15556  5412]
 [ 9419  7999]]
--------------------------------------------
Model: Logistic Regression
Accuracy: 0.6136351794925233
Precision: 0.5964506748191782
Recall: 0.45923757032954415
F1-score: 0.5189269843329333
--------------------------------------------
```

```
confusion matrix:
 [[12061  8918]
 [ 8783  8624]]
--------------------------------------------
Model: Decision Tree
Accuracy: 0.5388683374146824
Precision: 0.49162011173184356
Recall: 0.4954328718331706
F1-score: 0.4935191278720421
--------------------------------------------
```

Figure 10: Confusion matrix for Random Forest

Figure 11: Importance in Decision Tree

```
confusion matrix:
 [[16723  4256]
 [10541  6866]]
--------------------------------------------
Model: Random Forest
Accuracy: 0.6145209190850831
Precision: 0.6173350116885452
Recall: 0.39443901878554605
F1-score: 0.481334782151495
--------------------------------------------
```



In decision tree analysis, the variable with the highest importance level is Shot Distance (0.14), the next one is Shot Clock (0.11), followed by Closest Defender Distance (0.1). It is shown that deciding variables are not the player's own attributes. The reason may be that we used the whole NBA data to base our model on, which likely will measure an average player's capabilities. Therefore, in the average area, player's skills do not matter that much. What is important is the circumstances under which the offense was taken. This insight is important for coaches, and basketball players in finding the best strategy in a game and fully utilizing each person's potential.

4.2 Results from Feature Selection Model

We later perform logistic regression, decision tree and random forest model to the variables selected based on 5 standards from Feature Selection Model, and the results are shown as follows.

Figure 12: Confusion Matrix for Logistic Regression & Decision Tree

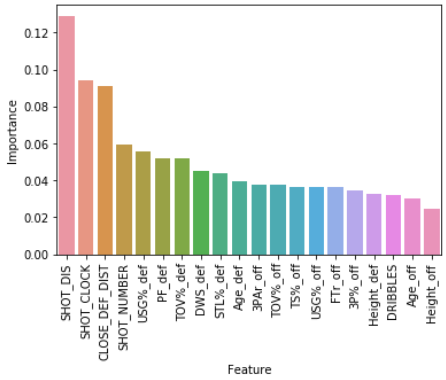
```
confusion matrix:
 [[15493  5475]
 [ 9301  8117]]
--------------------------------
Model: Logistic Regression
Accuracy: 0.6150679935393112
Precision: 0.59718952324897
Recall: 0.4660121713170284
F1-score: 0.5235085456304418
--------------------------------
```

Figure 13: Confusion matrix for Random Forest

```
confusion matrix:
 [[12229  8750]
 [ 8799  8608]]
--------------------------------
Model: Decision Tree
Accuracy: 0.5428281144167144
Precision: 0.49590966701232864
Recall: 0.4945137013845005
F1-score: 0.49521070041708626
--------------------------------
```

Figure 14: Importance in Decision Tree

```
confusion matrix:
 [[16147  4832]
 [10281  7126]]
--------------------------------
Model: Random Forest
Accuracy: 0.6062887511071745
Precision: 0.5959190500083626
Recall: 0.40937553857643477
F1-score: 0.48533969010727057
--------------------------------
```



As can bee seen from the results above, the accuracy and F-1 score of logistics regression model is the highest among the three models. The results based on feature selection also are highly similar to that based variable selected by intuition and correlation.

4.3 Evaluation of Results

Six of our predicted results above show that the both decision tree models perform worse than the other two models, which could probably because our models include too many variables and thus introduce the overfitting problem. This situation, reflected by the accuracy and F1-Score, has improved in the random forest model when we set many trees to jointly predict our results. Nevertheless, the logistic regression produces the similar output confusion matrix with the random forest (a little bit higher in F1-score even). And it is easier for interpret the result in the NBA's context. For example, if

we use the average data for the 9 variables chosen in first selection method, we could predict the player's chance of making that shot is 44.08%.

However, no matter which variable selection model we use, our best prediction results is limited to around 0.61 accuracy and 0.52. There is little difference between our intuitive variable selection model and William's feature selection model. The possible explanation for the similarity is that, despite the difference in the number of variables included, both models include those variables with highest importance value like "SHOT_DIS" (shot distance), "CLOSE_DEF_DIST"(distance between defender and player) and so on, and those are the determined factor to the prediction.

Under both variable selection models, our prediction performance is also far from satisfaction. We believe the data constrain is one important limitation to our model. We only have one-dimensional data — distance of the shot, however the shot's condition is measured by the three-dimensional data with location of the shot and height of the shot. Also, we try to use seasonal data to predict player's specific game's performance. While the player's performance are not always constant and variability is common among all NBA players. Finally, we ignore the team-level influence which is the most important thing on the court. Basketball is never a one-on-one game, but the team cohesive, team morale, and team strategy are something hard be measured by the data.

5. RECOMMENDATIONS, CHALLENGES AND MITIGATIONS

5.1 Team Strategy Development

Despite having individual strengths and weaknesses, all the NBA players are highly skilled, thus making their skills not highly correlated to their success or failure. Instead of focusing on refining and improving individual skills, it is more critical to develop cohesive team strategies.

The actions that the coaches could employ would be developing these strategies using our model prior to the games, and ensure that the teams have the time to practice following these strategies. This will be value-adding for teams to increase their chances of winning. The challenge with this recommendation comes from the tradeoffs in training time that basketball players and the coaches have to sacrifice. The coach may not have the time to use the model to develop game strategies amongst many other matters that he/she will need to prioritize. These benefits of focusing on team strategies are impossible to prove, thus they may not see the need and advantages of doing so. It is also hard for players to follow a specific strategy when they are moving because it is natural to follow one's instincts than processing information in sports. The players' performance is also affected by a wide range of factors, making our model less accurate and effective.

To further convince these stakeholders, we can prove the validity of our model. In the future, it would be also worthy to include data from the most recent seasons and more detailed player information, such as the players' left or right handedness and personal state into our model.

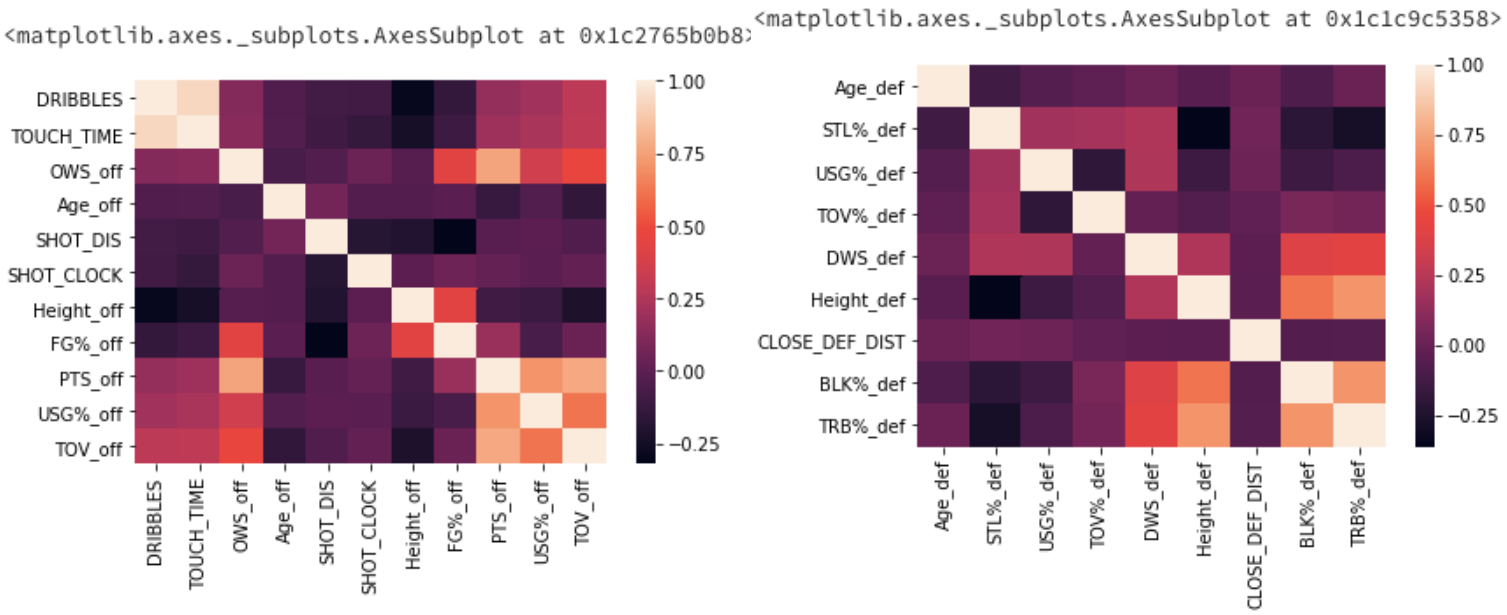
5.2 Emphasis on Team Morale

To maximize players' performance, it is also important to ensure that everyone is in their best physical and mental being to increase their chances of outperforming their regular state. Balancing training and leisurely activities that boost team morale prior to the game is another strategy that can employed.

A key initiative that the coaches can take would be scheduling more team building or social activities prior to the game, again increasing their chances of winning. The challenge with this recommendation again lies in the tradeoffs of losing training time and the unforeseeable benefits of these tradeoffs. Another challenge is that the charm of sportsmanship lies in the possibility of creating the impossibility. If there are no miracles in sports competitions, then we will lose all the joy that we derive from chasing miracles.

Appendix

1. Heat Map of correlation



2. Training Gradient Boosting Model

```
Training Gradient Boosting Model

Training until validation scores don't improve for 100 rounds.
Early stopping, best iteration is:
[104]   valid_0's auc: 0.651058 valid_0's binary_logloss: 0.644349
Training until validation scores don't improve for 100 rounds.
Early stopping, best iteration is:
[148]   valid_0's auc: 0.655783 valid_0's binary_logloss: 0.640883
Training until validation scores don't improve for 100 rounds.
Early stopping, best iteration is:
[123]   valid_0's auc: 0.645724 valid_0's binary_logloss: 0.645258
Training until validation scores don't improve for 100 rounds.
Early stopping, best iteration is:
[95]    valid_0's auc: 0.65085  valid_0's binary_logloss: 0.645417
Training until validation scores don't improve for 100 rounds.
Early stopping, best iteration is:
[127]   valid_0's auc: 0.647792 valid_0's binary_logloss: 0.644913
Training until validation scores don't improve for 100 rounds.
Early stopping, best iteration is:
[81]    valid_0's auc: 0.648173 valid_0's binary_logloss: 0.643775
Training until validation scores don't improve for 100 rounds.
Early stopping, best iteration is:
[98]    valid_0's auc: 0.645094 valid_0's binary_logloss: 0.644643
Training until validation scores don't improve for 100 rounds.
Early stopping, best iteration is:
[99]    valid_0's auc: 0.642448 valid_0's binary_logloss: 0.646671
Training until validation scores don't improve for 100 rounds.
Early stopping, best iteration is:
[154]   valid_0's auc: 0.649535 valid_0's binary_logloss: 0.643623
Training until validation scores don't improve for 100 rounds.
Early stopping, best iteration is:
[97]    valid_0's auc: 0.642805 valid_0's binary_logloss: 0.646462

0 features with zero importance after one-hot encoding.
```

3. Bibliography

Anadiotis, G. (2018, October 29). NBA analytics and RDF graphs: Game, data, and metadata evolution, and Occam's razor. Retrieved from https://www.zdnet.com/article/nba-analytics-and-rdf-graphs-game-data-and-metadata-evolution-and-occams-razor/

Comprehensive Simulations Stat Mechanics Guide - ALL ... (n.d.). Retrieved from https://forums.operationsports.com/forums/nba-2k-last-gen-rosters/530243-comprehensive-simulations-stat-mechanics-guide-all-roster-makers-should-read.html

Goldstein, O. (2018, April 27). NBA Players stats since 1950. Retrieved October, 2018, from https://www.kaggle.com/drgilermo/nba-players-stats#Seasons_Stats.csv

How NBA Analytics is Changing Basketball | Merrimack College. (2018, February 20). Retrieved 2018, from http://onlinedsa.merrimack.edu/nba-analytics-changing-basketball/

Kopf, D. (2017, October 18). Data analytics have made the NBA unrecognizable. Retrieved from https://qz.com/1104922/data-analytics-have-revolutionized-the-nba/

Summer Forecast: East, West and NBA champs in 2018-19. (2018, August 13). Retrieved December, 2018, from http://www.espn.com/nba/story/_/id/24349948/nba-champs-predictions-espn-summer-forecast

WillKoehrsen. (2018, August 07). WillKoehrsen/feature-selector. Retrieved from https://github.com/WillKoehrsen/feature-selector