Application of Classification Models for Predicting Shooting Performance in the NBA

A Case Study of Kobe Bryant

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Abstract

In a world with continuously increasing techological capabilities, the demand for answers increases alongside it. The domain of professional sports in particular is no exception to this trend. The very essence of competitive sports is rooted in a desire to optimize and gain every advantage over competitors. In this paper, we describe classification methodologies for predicting the performance of professional athletes through a scoped analysis of the long-time NBA allstar, Kobe Bryant. We detail three simulations modelling shooting accuracy over Bryant's 20 year career, using logistic regression and discriminant analyses to yield predictions about Bryant's theoretical future performance. We show that Bryant's potential to score is strongly dependent on his distance from the basket when shooting. We also show that Bryant's scoring performance in the post-season, as compared to that of the regular season, is consistent with his performance at any other point in the season.

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1 Introduction

With modern computers and the popularity of the budding disciple of data science, there are numerous predictive technologies readily available. In professionl sports alone, a host of disparate entities, players, ogranizations, and gamblers alike are hungry for new insights. Each bears an economic imperative to seek advantages and optimizations that will give them an edge over their peers. Technology, however, does not predicate useful and effective models. It is the rigorous application of sound statistical theory that yields actionable conclusions. Unfortunately, the appeal of novel algorithms and the sparkles of big data detract from the importance of a strong statistical foundation. Thus, we seek to right the ship of this rampant malpractice as it applies to this problem domain. In what follows, we explore insights we have garnered from the application of linear discriminant analysis and logistic regression, then leveraging those insights to appropriately tune the final predictive model.

Kobe Bryant marked his retirement from basketball by scoring 60 points in his final game as a member of the Los Angeles Lakers team on Wednesday, April 13, 2016. Starting to play professional basketball at the age of 17, Kobe earned the sport's highest accolades throughout his long career. Using 20 years of data on Kobe's shots made and shots missed, we wish to predict which shots will be successful.

2 Approach

2.1 Problem Definition

Sports analytics is, as many previously low-tech markets are, poised to boom as sports organizations are increasingly able to generate more data. Recent research

> "The Sports Analytics market is expected to grow from USD 123.7 Million in 2016 to USD 616.7 Million by 2021, at a Compound Annual Growth Rate (CAGR) of 37.9
>
> The increasing volume of on-field and off-field data generated among various sports organizations has led to an increase in managing these data to analyze them. This need is driving the adoption of sports analytics solutions. Analytics and big data technologies have found huge potential in various industries, including sports. The increasing demand of coaches, mentors, and other management officials for real-time access to the insights of relevant information presents huge potential for sports analytics market. The demand for cloud-based sports analytics solutions is also expected to increase due to the lack of budget allocation for hiring technical skills and experts to analyze data for sports organization. These are some of the major factors expected to augment the growth of the market. Moreover, in order to remain competitive, organizations are adopting sports analytics solutions."

[1]

This study was birthed out of a need to reliably quantify three key metrics specifically, each used in assessing a professional basketball player's shooting ability. Those metris are:

1. Odds of making a shot as distance from the basket increases.
2. Linearity of the decline rate of the probability of making a shot with respect to the distance the shot was taken from the basket.

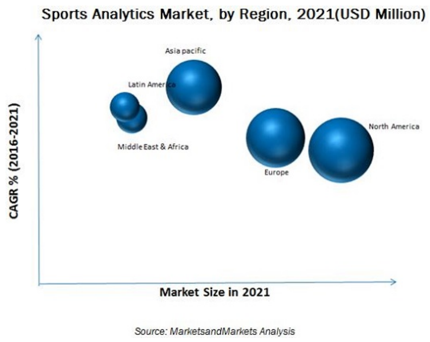


Figure 1: Market Analysis

3. The relationship between the distance from the shooter to the basket and the odds of the shot being made is different when in the regular season verses the post-season.

Rephrasing those metrics as questions helps clarify the focus of the analysis as it relates to Kobe Bryant. Those questions are as follows:

1. Do the odds of Kobe making a shot decrease with respect to distance he is from the hoop?
2. Does the probability of Kobe making a shot descrease linearly with respect to the distance he is from the hoop?
3. Is the relationship between the distance Kobe is from the basket and the odds of him making the shot different if they are in the playoffs.

To appropriately answer the questions of interest above, we must fit a series of classifier models to the training portion of our dataset, iteratively scoring and comparing the various models against one another so that we can tune their parameters and hone in on a final feature set.

The entirity of the analysis is implemented side-by-side in Python and SAS. Below, we set the stage for conducting our analysis through an exploratory analysis of the dataset.

2.2 Exploratory Analysis

2.2.1 Data Overview

The NBA has provided a comprehensive dataset of every shot Kobe Bryant took throughtout his career. Accompanying each shot record are a number of supplementary features that provide context to the positioning and environment in which a given shot was taken. Generally, the data was remarkably clean and readily manipulable. The majority of the wrangling effort was focused on synthesizing new predictors. A brief summary of the features is below.

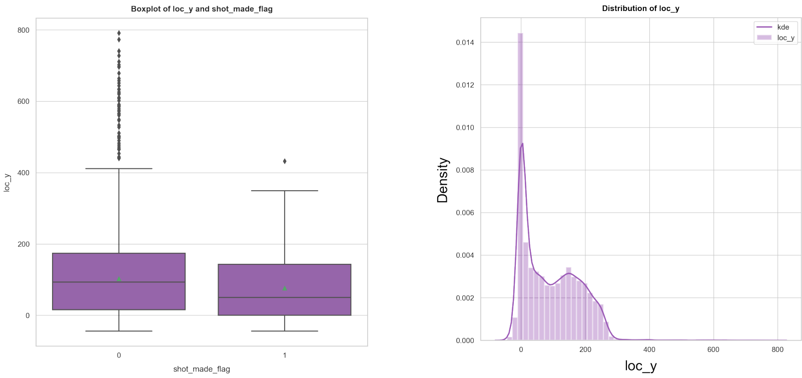
	count	mean	std	min	25%	50%	75%	max
game_event_id	25697	249	150	2	111	253	367	653
game_id	25697	24741091	7738108	20000012	20500064	20900337	29600270	49900088
lat	25697	34	0	33	34	34	34	34
loc_x	25697	7	110	-250	-67	0	94	248
loc_y	25697	91	88	-44	4	74	160	791
lon	25697	-118	0	-119	-118	-118	-118	-118
minutes_remaining	25697	5	3	0	2	5	8	11
period	25697	3	1	1	1	3	3	7
playoffs	25697	0	0	0	0	0	0	1
seconds_remaining	25697	28	18	0	13	28	43	59
shot_distance	25697	13	9	0	5	15	21	79
shot_made_flag	25697	0	0	0	0	0	1	1
team_id	25697	1610612747	0	1610612747	1610612747	1610612747	1610612747	1610612747
shot_id	25697	15328	8860	2	7646	15336	22976	30697
attendance	25697	15041	1076	11065	14314	15048	15738	20845
arena_temp	25697	70	2	64	69	70	71	79
avgnoisedb	25697	95	2	89	93	95	96	102

Table 1: Feature Summary

Table 2: Key Feature Descriptions

Game_event_id	Identification variable
Game_id	Identification variable
Lat and loc_y	Appear to be the same data (y-axis), based on location on the court. The tall bar indicates the frequency of shots taken at the location near the basket
Loc_x and lon	Appear to be the same data (x-axis), based on location on the court. The tall bar indicates the frequency of shots taken at the location near the basket
Minutes_remaining	Suggests that there is evidence that Kobe took more shots as the period progressed (higher shot counts closer to the end of the period)
Period	Indicates similar shot frequency across periods
Playoffs	Playoffs were a rare event in the season, hence the lower shot frequency overall
Season	Shot frequency was lower in 2 seasons
Seconds_remaining	Suggests that there is evidence that Kobe took more shots in the final seconds (higher shot counts closer to the end of the last minute in the period, correlates with shot frequency in the minutes_remaining variable above)
Shot_distance	High shot frequency at the basket, at the top of the key (field goals), and the three-point line. Shot frequency was comparatively rarer beyond the three-point line

From the available features, the variable "shot_made_flag" indicates whether a particular shot was made (1) or missed (0), and is the feature that acts as our endogenous variable. The remainder of the features are the potential predictors, or



(a) Boxplot of Shot Y Location **(b)** Distplot of Shot Y Location

Figure 2: Plots of y_loc

exogenous variables. Since there are a managable number of them, we can simply generate descriptive plots for each exogenous feature. Univariate distribution or frequency plots are ideal for vizualizing the underlying distristribution of each variable. In addition, boxplots for each exogenous feature against each level of the endogenous variable allowed us to develop our intuition about the variance within each level of the target feature.

Most of the features show no signs of skewness or severe departures from normality, however, there are some exceptions.

It's clear that outliers are prevalent in some of the features, particularly those representing the distance to the hoop and the time remaining, as represented in figures 2b and 2a. Several solutions were explored to mitigate the potential impact of the outliers, none of which yielded a model with better results. Thus, all outliers were included in the final models on their original scale.

The exploratory boxplot of shot_distance (figure 3) already hints at a potential relationship between a shot's likelyhood of being made verses the distance the shot was taken from the hoop.

2.2.2 Multicollinearity

The base feature set was wrought with violations of independent variability. As noted in the table and it's accompanying correlation matrix, approximately half of the features showed a collinear relationship with other features in the data set. This caused our approach to feature selection vary from the normal methods. We chose to ignore the more nuanced stepwise / LASSO / LarsCV methods and

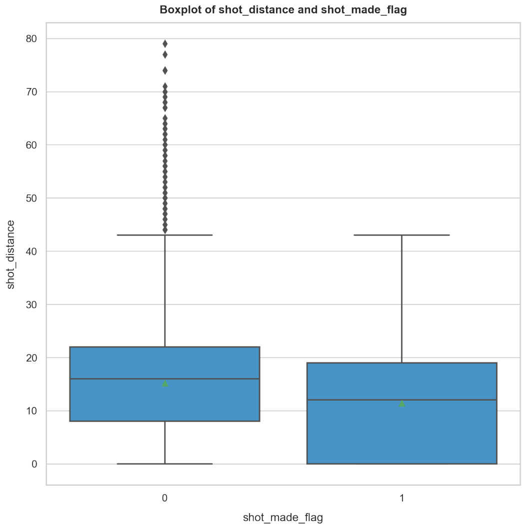


Figure 3: Boxplot of Shot Distance

instead implemented a procedure to recursively drop a feature with an exorbitant variance inflation factor on each iteration until reaching a feature set that showed no multicollinearity violations. We used an elimination cutoff of the initial median VIF + 2 standard deviations. Variance inflation factors for the original features can be seen in table 3. A correlation matrix of the same feature set is displayed in figure 4. [2]

	VIF Factor	features
0	0	Intercept
1	35	game_event_id
2	68	game_id
3	inf	lat
4	inf	loc_x
5	inf	loc_y
6	inf	lon
7	inf	minutes_remaining
8	inf	period
9	29	playoffs
10	inf	seconds_remaining
11	3	shot_distance
12	0	team_id
13	14	shot_id

Table 3: Variance Inflation Factors

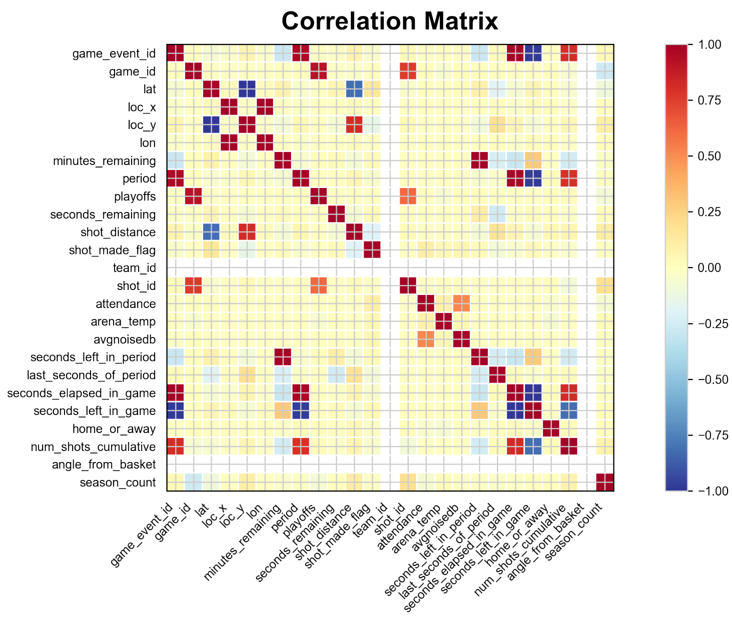


Figure 4: Correlation Matrix - All features

3 Methodoloy

3.1 Feature Selection

As mentioned in the previous section, the feature selection process was dominated by the prevalent mulicollinearity between many of the features. As example, collinearity was reduced to a tolerable range in the featureset of one candidate model pictured in figure 5.

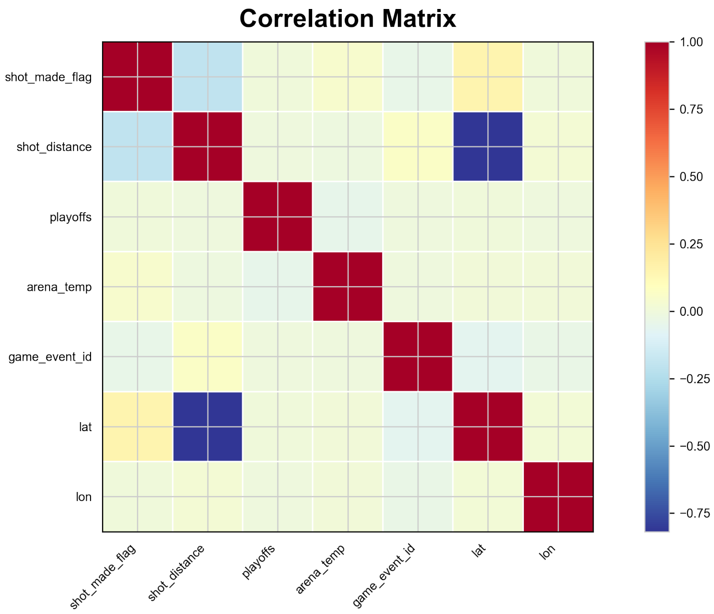


Figure 5: Correlation Matrix - Candidate Model

3.2 Model Selection

Our key observation during model selection arose in differentiating the preformance of Fisher's linear discriminant and binary logistic regression. While both procedures are common choices for two-level classification, and often yield simiar results, there aa

few critical assumptions that differ between them. The linear discriminant analysis (LDA) mandates the within-group covariance between each level of the endogenous variable be equal. Additionally, the LDA model is susceptible to the influence of extreme observations, and will potentially yield inconsistent results when outliers are not accounted for. Conversely, the logarithmic analysis has no exigence on the form of the model's predictors. The prevalence of outliers in the dataset, exposed during the exploratory analysis, was sufficient enough cause to move forward with the logistic regression as a conservative base on which we could build our predictions. Beta models using LDA can be found in the appendix (6.2).
Several iterations of model selection concluded on a final model that yielded a 0.615 AUC, with exceptional sensitivity (true positive rate) and moderate specificity (true negative rate). (table 4). Categorical predictors in the final model were substituted for dummied predictors for estimate. (See regression formula - 4)

	Model 5
Log Loss	0.6664
AUC	0.6155
Sensitivity	0.744
Specificity	0.425

Table 4: Logistic Model Summary

$$Logit(\frac{\pi}{1-\pi}) = \beta_0 + \beta_1 \text{shot\_distance} + \beta_2 \text{playoffs}_0 + \beta_3 \text{playoffs}_1 + \beta_4 \text{arena\_temp} + \beta_5 \text{game\_event\_id} + \beta_6 \text{lat} + \beta_7 \text{lon}$$

Regular Season (playoffs = 0)

$$= \beta_0 + \beta_1 \text{shot\_distance} + \beta_2(1) + \beta_3(0) + \beta_4 \text{arena\_temp} + \beta_5 \text{game\_event\_id} + \beta_6 \text{lat} + \beta_7 \text{lon}$$

$$= \beta_0 + \beta_1 \text{shot\_distance} + \beta_2 + \beta_4 \text{arena\_temp} + \beta_5 \text{game\_event\_id} + \beta_6 \text{lat} + \beta_7 \text{lon}$$

$$Logit(\frac{\pi}{1-\pi}) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + \beta_7 x_7 \tag{1}$$

Playoffs (playoffs = 1)

$$= \beta_0 + \beta_1 \text{shot\_distance} + \beta_2(0) + \beta_3(1) + \beta_4 \text{arena\_temp} + \beta_5 \text{game\_event\_id} + \beta_6 \text{lat} + \beta_7 \text{lon}$$

$$= \beta_0 + \beta_1 \text{shot\_distance} + \beta_3 + \beta_4 \text{arena\_temp} + \beta_5 \text{game\_event\_id} + \beta_6 \text{lat} + \beta_7 \text{lon}$$

$$Logit(\frac{\pi}{1-\pi}) = \beta_0 + \beta_1 x_1 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + \beta_7 x_7$$

A model composition chart, displayed in figure 6 shows the features selected in the champion model, along with the model's confusion matrix.

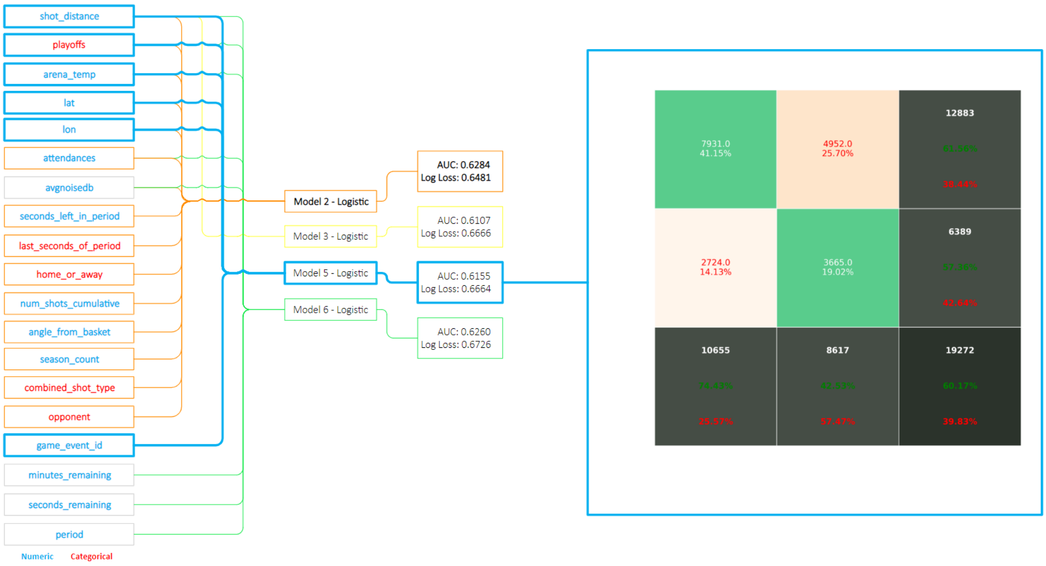


Figure 6: Model Composition Chart

[2]
A full listing of candidate models can be seen in the appendix (6.2).

3.3 Evaluation

Goodness of fit measured by logarithmic loss function, where:

$$LogLoss = -(y\,log(p) + (1 - y)log(1 - p))$$

Logarithmic loss (related to cross-entropy) measures the performance of a classification model where the prediction input is a probability value between 0 and 1. Log Loss takes into account the uncertainty of a prediction based on how much it varies from the actual label, insead of simply counting if the predicted value exactly equals the true value, as is the case with accuracy. This gave us a more nuanced view into the performance of our model.

4 Conclusion

Finally, now that we've demonstrated the process of applying binary classification techniques to NBA shooting data, we can return to the original questions of interest. Our findings show a $-1.87\% \pm 0.85\%$ $(-2.72\%, -1.01\%)$ step change in Kobe Bryant's shot making ability, measured with a p-value of < 0.001 at $\alpha = 0.05$ (figure 7). That is to say, for every additional foot between Bryant and the basket, his accuracy is reduced by just under 2%. Another, perhaps more familiar way to put it is in terms of odds. Kobe's odds of making a basket are

$$0.9813 \pm 0.0084 \ (0.9728, 0.9899)$$

with respect to his distance from the basket.

Additionally, the model indicates a $4.25\% \pm 9.9\%$ $(-4.77\%, 14.15\%)$increase in shooting ability during the playoffs, however, the result was not statistically significant, with a p-value of 0.3671 at an α level of 0.05 on the χ^2 distribution. There is not sufficient evidence to reject the null hypothesis that Kobe's performance shows no notable difference between regular and post season. (table 8)

Figure tables of Log-odds, odds, and percentage change in shooting ability with respect to distance:

		Coef.	Std.Err.	z	P>|z|	[0.025	0.975]
Log-Odds:	lat	0	0	-2	0	0	0
	lon	0	0	-0	1	0	153130194710622
	playoffs	71	0	1	0	0	1400174
	seconds_remaining	1	0	2	0	1	1
	shot_distance	0	0	-4	0	0	0
	attendance	1	0	10	0	1	1
	arena_temp	28	0	4	0	6	133
	avgnoisedb	1	0	0	1	0	6
	seconds_left_in_period	1	0	1	0	1	1
	last_seconds_of_period	0	0	-7	0	0	0
	seconds_left_in_game	1	0	2	0	1	1
	home_or_away	0	0	-1	0	0	32
	num_shots_cumulative	1	0	0	1	0	2
	angle_from_basket	1	0	0	1	1	1
	season_count	3	0	3	0	1	5

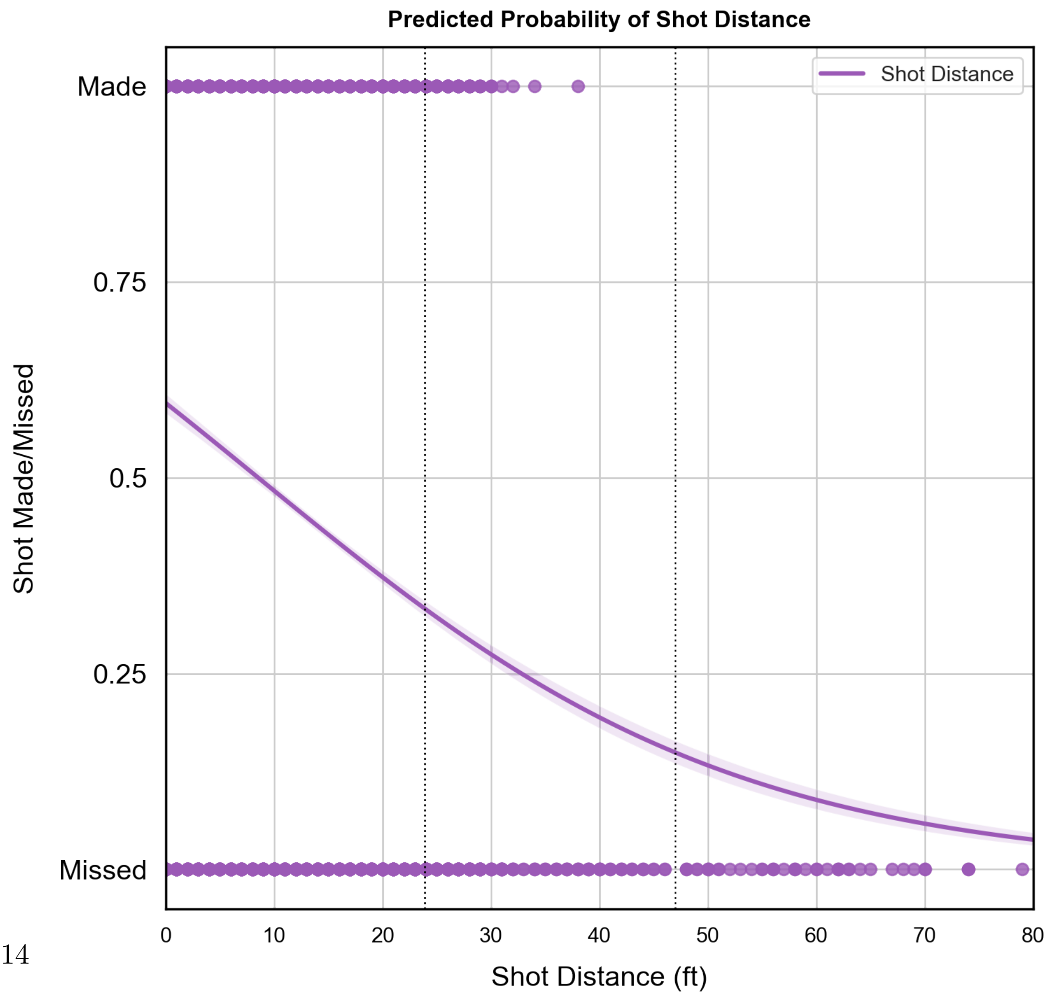


Figure 7: Predicted Shot Probability over Distance to Hoop

Table 5: Log-odds with Respect to Distance

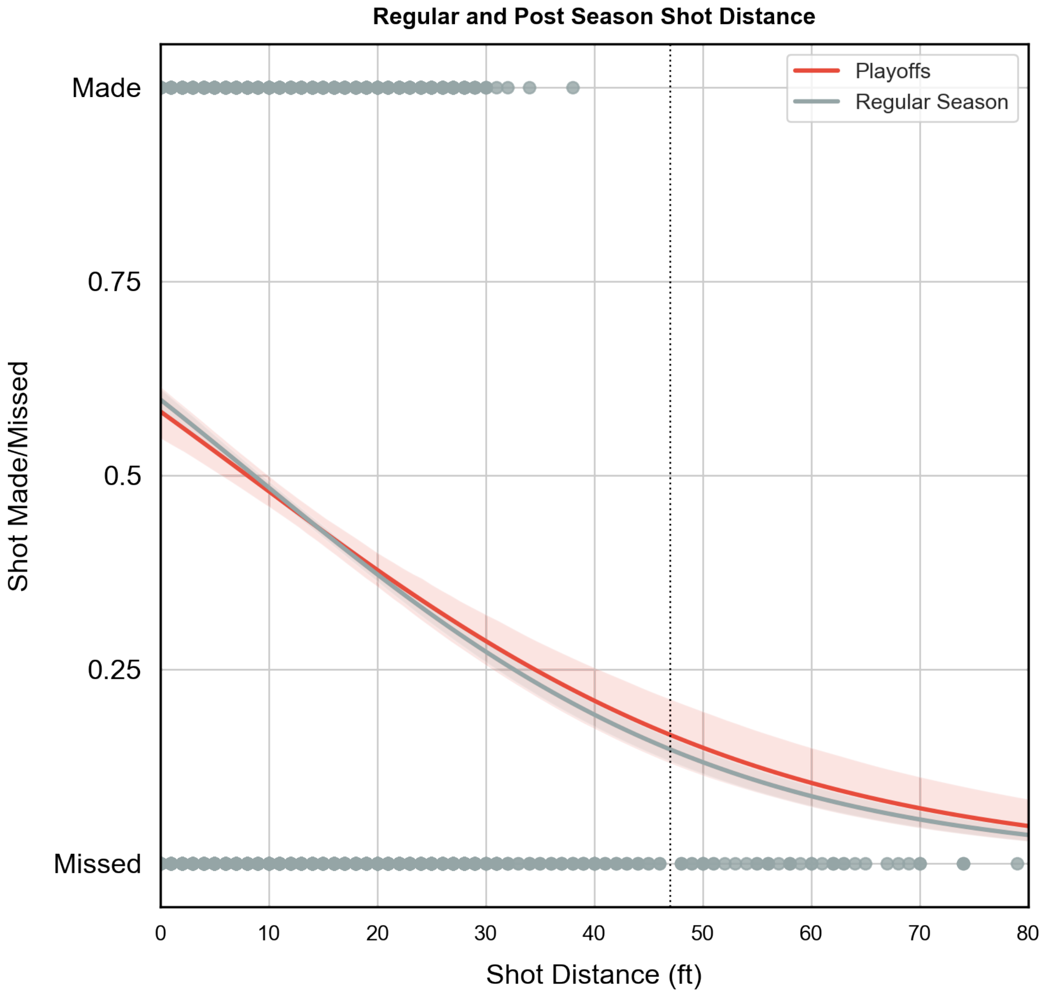


Figure 8: Performance in Regular and Post Season

Odds:

	Coef.	Std.Err.	z	P>|z|	[0.025	0.975]
lat	0	0	-2	0	0	0
lon	0	0	-0	1	0	153130194710622
playoffs	71	0	1	0	0	1400174
seconds_remaining	1	0	2	0	1	1
shot_distance	0	0	-4	0	0	0
attendance	1	0	10	0	1	1
arena_temp	28	0	4	0	6	133
avgnoisedb	1	0	0	1	0	6
seconds_left_in_period	1	0	1	0	1	1
last_seconds_of_period	0	0	-7	0	0	0
seconds_left_in_game	1	0	2	0	1	1
home_or_away	0	0	-1	0	0	32
num_shots_cumulative	1	0	0	1	0	2
angle_from_basket	1	0	0	1	1	1
season_count	3	0	3	0	1	5

Table 6: Odds with Respect to Distance

Percent Change:

	Coef.	[0.025	0.975]
lat	-100	-100	-99
lon	-99	-100	15313019471062054
playoffs	6978	-99	140017285
seconds_remaining	15	-3	37
shot_distance	-85	-93	-64
attendance	2	1	2
arena_temp	2699	505	13151
avgnoisedb	28	-72	499
seconds_left_in_period	1	-1	2
last_seconds_of_period	-100	-100	-100
seconds_left_in_game	1	0	1
home_or_away	-92	-100	3078
num_shots_cumulative	5	-53	140
angle_from_basket	2	-6	10
season_count	154	31	394

Table 7: Percent Change over Distance

5 Limitations and Future Directions

The primary (and obvious) limitation to this study is the narrow subject pool from which the data was gathered. The data, being observational in nature and from a single athlete's history, allows us no ability to draw conclusions that accurately reflect a causal relationship between the predictors and the outcome variable. Additionaly, the absence of a random sampling mechanism would make any inferrening our conclusions to any population, other than Kobe Bryant himself, highly suspect. Even with such a limited scope, the conclusions produced from our study serves an important purpose.

Our conclusions, presented in the previous section, yielded strong evidence of Kobe's ability to make shots dwindling as his distance from the basket grew. The general principle behind this conclusion seems obvious, and it is. Of course an athlete is going to see diminished shooting accuracy as they take longer shots. What is significant about our results is not even the quantification of that relationship between accuracy and distance directly, but it is the proof that such a relationship is reliably quantifiable and, holding all other variables constant, interpretable in a 2-dimensional space. These findings build a foundation on which future studies will be able to design experiments and investiagte broader populations. Future directions for our work may be investigating similar trends across NBA players of different vintages, skill levels, positions, and team compositions. Such an experiment, with the appropriate design, would provide definitive insight into the extensibility of our findings in this analysis.

6 Appendix

6.1 Github Repository

We are on Github! (`https://github.com/la-mar/Applied-Stats-Project-2`) All code used in our analysis is included in the appendix below, but we recommend viewing it in its original form in our github repository.

6.2 Appendix A

6.2.1 Model Comparison - Continued

	Model 2	Model 3	Model 4A	Model 4B	Model 5	Model 6
	LOGIT w/PCA	LOGIT w/shot_distance	LOGIT w/shot_distance, (playoffs)	LOGIT w/shot_distance, (no playoffs)	LOGIT w/selected varsA	LOGIT w/selected varsB
R-Square	0.0498	0.0393	0.0328	0.0405	0.042	0.05
Max-rescaled R-Square	0.0666	0.0526	0.0439	0.0542	0.0562	0.0669
AIC	34035.67	34298.864	5042.4	29258.947	34237.279	34024.718
SC	34125.365	34315.172	5054.863	29274.939	34294.358	34098.106
-2 Log L	34013.67	34294.864	5038.4	29254.947	34223.279	34006.718
Area Under ROC Curve	0.6262	0.6107	0.6008	0.6124	0.6155	0.626
Log Loss		0.66666			0.6664	0.67267

6.2.2 Data Dictionary

6.3 SAS Code

```
MSDS 6371 - Applied Statistics  */
Allen Crane and Brock Friedrich */
Kobe Bryant Shot Selection      */
November 2018                   */

```

```
 import data */
oc import datafile="c:\users\allen\documents\smu data science\MSDS 6372 - Applied Statistics\project 2\project2Data.csv"
        dbms=dlm out=train replace;
   delimiter=',';
   getnames=yes;
```

	Model 1
	GLM w/PCA
Root MSE	0.48463
Dependent Mean	0.44616
R-Square	0.0498
Adj R-Sq	0.0495
AIC	-11521
AICC	-11521
SBC	-37155
CV PRESS	6037.80515

```
n;

 print data */
oc print data=train (obs=10);
n;

 investigate data for variable types*/
oc contents data=train;
n;

 look for missing numeric data - may need to impute */
oc means data = train n nmiss;
var _numeric_;
n;

 investigate means of training data and any missing values */
oc means data = train n nmiss;
n;

 univariate data analysis */
oc univariate data = train;
r season;
n;

```

	Model 7
	LDA
Sensitivity (classified 1 when really 1)	0.4298
Specificity (classified 0 when really 0)	0.744
Type I Error (classified 1 when really 0)	0.256
Type II Error (classified 0 when really 1)	0.5702
Total Error	0.3962
Accuracy (1-Total Error)	0.6038

```
 note that certain "season" fields are missing */
ta _season;
  set train;
  where missing (season);
n;

 print "season" data, where "season" is missing */
oc print data=_season (obs=200);
n;


 more univariate data analysis */
s graphics on;
oc univariate data = train plot;
r recId
me_event_id
me_id
t
c_x
c_y
n
nutes_remaining
riod
ayoffs
ason
conds_remaining
ot_distance
ot_made_flag
am_id
me_date
ot_id
tendance
ena_temp
gnoisedb

n;
```

```
s graphics off;

 create a time-based variable, concatenating Period, minutes remaining, and seconds remaining, in descending order. This one is for Periods remaining... */
ta train2;
set train;
    if period = 1 then periods_remaining2 = "14";
    else if period = 2 then periods_remaining2 = "28";
 else if period = 3 then periods_remaining2 = "42";
 else if period = 4 then periods_remaining2 = "57";
 else if period = 5 then periods_remaining2 = "71";
 else if period = 6 then periods_remaining2 = "85";
 else if period = 7 then periods_remaining2 = "99";
 else periods_remaining2 = period;
n;

 print data */
oc print data=train2 (obs=10);
n;

 Minutes remaining... */
ta train2;
set train2;
    if minutes_remaining = 11 then minutes_remaining2 = "99";
    else if minutes_remaining = 10 then minutes_remaining2 = "90";
 else if minutes_remaining = 9 then minutes_remaining2 = "81";
 else if minutes_remaining = 8 then minutes_remaining2 = "72";
 else if minutes_remaining = 7 then minutes_remaining2 = "63";
 else if minutes_remaining = 6 then minutes_remaining2 = "54";
 else if minutes_remaining = 5 then minutes_remaining2 = "45";
 else if minutes_remaining = 4 then minutes_remaining2 = "36";
 else if minutes_remaining = 3 then minutes_remaining2 = "27";
 else if minutes_remaining = 2 then minutes_remaining2 = "18";
 else if minutes_remaining = 1 then minutes_remaining2 = "09";
 else if minutes_remaining = 0 then minutes_remaining2 = "00";
```

```
else minutes_remaining2 = minutes_remaining;
n;

print data */
oc print data=train2 (obs=10);
n;

Seconds remaining... */
ta train2;
set train2;
    if seconds_remaining = 59 then seconds_remaining2 = "99";
    else if seconds_remaining = 58 then seconds_remaining2 = "97.3";
else if seconds_remaining = 57 then seconds_remaining2 = "95.6";
else if seconds_remaining = 56 then seconds_remaining2 = "94";
else if seconds_remaining = 55 then seconds_remaining2 = "92.3";
else if seconds_remaining = 54 then seconds_remaining2 = "90.6";
else if seconds_remaining = 53 then seconds_remaining2 = "88.9";
else if seconds_remaining = 52 then seconds_remaining2 = "87.3";
else if seconds_remaining = 51 then seconds_remaining2 = "85.6";
else if seconds_remaining = 50 then seconds_remaining2 = "83.9";
else if seconds_remaining = 49 then seconds_remaining2 = "82.2";
else if seconds_remaining = 48 then seconds_remaining2 = "80.5";
    else if seconds_remaining = 47 then seconds_remaining2 = "78.9";
else if seconds_remaining = 46 then seconds_remaining2 = "77.2";
else if seconds_remaining = 45 then seconds_remaining2 = "75.5";
else if seconds_remaining = 44 then seconds_remaining2 = "73.8";
else if seconds_remaining = 43 then seconds_remaining2 = "72.2";
else if seconds_remaining = 42 then seconds_remaining2 = "70.5";
else if seconds_remaining = 41 then seconds_remaining2 = "68.8";
else if seconds_remaining = 40 then seconds_remaining2 = "67.1";
else if seconds_remaining = 39 then seconds_remaining2 = "65.4";
else if seconds_remaining = 38 then seconds_remaining2 = "63.8";
else if seconds_remaining = 37 then seconds_remaining2 = "62.1";
else if seconds_remaining = 36 then seconds_remaining2 = "60.4";
else if seconds_remaining = 35 then seconds_remaining2 = "58.7";
else if seconds_remaining = 34 then seconds_remaining2 = "57.1";
```

```
else if seconds_remaining = 33 then seconds_remaining2 = "55.4";
else if seconds_remaining = 32 then seconds_remaining2 = "53.7";
else if seconds_remaining = 31 then seconds_remaining2 = "52";
else if seconds_remaining = 30 then seconds_remaining2 = "50.3";
else if seconds_remaining = 29 then seconds_remaining2 = "48.7";
   else if seconds_remaining = 28 then seconds_remaining2 = "47";
else if seconds_remaining = 27 then seconds_remaining2 = "45.3";
else if seconds_remaining = 26 then seconds_remaining2 = "43.6";
else if seconds_remaining = 25 then seconds_remaining2 = "41.9";
else if seconds_remaining = 24 then seconds_remaining2 = "40.3";
else if seconds_remaining = 23 then seconds_remaining2 = "38.6";
else if seconds_remaining = 22 then seconds_remaining2 = "36.9";
else if seconds_remaining = 21 then seconds_remaining2 = "35.2";
else if seconds_remaining = 20 then seconds_remaining2 = "33.6";
else if seconds_remaining = 19 then seconds_remaining2 = "31.9";
else if seconds_remaining = 18 then seconds_remaining2 = "30.2";
else if seconds_remaining = 17 then seconds_remaining2 = "28.5";
else if seconds_remaining = 16 then seconds_remaining2 = "26.8";
else if seconds_remaining = 15 then seconds_remaining2 = "25.2";
else if seconds_remaining = 14 then seconds_remaining2 = "23.5";
else if seconds_remaining = 13 then seconds_remaining2 = "21.8";
else if seconds_remaining = 12 then seconds_remaining2 = "20.1";
else if seconds_remaining = 11 then seconds_remaining2 = "18.5";
else if seconds_remaining = 10 then seconds_remaining2 = "16.8";
else if seconds_remaining = 9 then seconds_remaining2 = "15.1";
   else if seconds_remaining = 8 then seconds_remaining2 = "13.4";
else if seconds_remaining = 7 then seconds_remaining2 = "11.7";
else if seconds_remaining = 6 then seconds_remaining2 = "10.1";
else if seconds_remaining = 5 then seconds_remaining2 = "08.4";
else if seconds_remaining = 4 then seconds_remaining2 = "06.7";
else if seconds_remaining = 3 then seconds_remaining2 = "05";
else if seconds_remaining = 2 then seconds_remaining2 = "03.4";
else if seconds_remaining = 1 then seconds_remaining2 = "01.7";
else if seconds_remaining = 0 then seconds_remaining2 = "00";
se seconds_remaining2 = seconds_remaining;
n;
```

```

 print data */
oc print data=train2 (obs=10);
n;

 concatenante data */
ta train2;
t train2;
s_remaining = cat(periods_remaining2, minutes_remaining2, seconds_remaining2);
n;

 print data */
oc print data=train2 (obs=10);
n;

 make field numeric (some components contained leading zeroes */
ta train2;
t train2;
 n_pms_remaining = input(pms_remaining,8.);
n;

 drop original non-numeric concetenanted data field */
ta train2;
t train2 (drop = pms_remaining);
n;
ta train2;

 rename new numeric concatenated data field  */
t train2 (rename=(
_pms_remaining'n='pms_remaining'n));
n;

 print data */
oc print data=train2 (obs=10);
n;
```

```
 check data - histogram */
s graphics on;
oc univariate data = train2;
r pms_remaining;
stogram;
n;
s graphics off;

 check data - scatter plot */
oc sgplot data=train2;
 scatter x=pms_remaining y=shot_made_flag / group=shot_made_flag;
n;


 transform data - log transformation on shot distance and time
↪  remaining */
ta train3;
t train2;
shot_distance = log(shot_distance);
pms_remaining = log(pms_remaining);
n;


 check data - scatter plot */
s graphics on;
oc univariate data = train3 plot;
r l_shot_distance l_pms_remaining;
n;
s graphics off;
```

```
 correlation analysis */
s graphics on;
oc corr data=train2 plots=matrix(histogram);
r recId
me_event_id
me_id
t
c_x
c_y
n
nutes_remaining
riod
ayoffs
ason
conds_remaining
ot_distance
ot_made_flag
am_id
me_date
ot_id
tendance
ena_temp
gnoisedb;
n;
s graphics off;



 principal component analysis */
s graphics on;
oc princomp plots=all data=train2 cov out=pca;
r recId
me_event_id
```

```
me_id
t
c_x
c_y
n
nutes_remaining
riod
ayoffs
ason
conds_remaining
ot_distance
ot_made_flag
am_id
me_date
ot_id
tendance
ena_temp
gnoisedb;
n;
s graphics off;


 correlation analysis using train2 data vs shot made flag */
oc corr data=train2 plots=matrix(histogram);
    var shot_made_flag game_event_id lat loc_y minutes_remaining
    period seconds_remaining shot_distance attendance arena_temp
    avgnoisedb;
    run;


 correlation analysis using pricipal components vs shot made flag */
oc corr data=pca plots=matrix(histogram);
    var shot_made_flag prin1 - prin10;
    run;
```

```
 model 1 - GLM select using PCA */
oc glmselect data=pca plots=all seed=3;
del shot_made_flag =prin1-prin10 / selection = stepwise(choose=CV select=CV stop=CV);
n;


 model 2 - Logistic using PCA */
s graphics on;
oc logistic data=pca plots(only)=(roc(id=obs) effect);
model shot_made_flag (event='1') =prin1-prin10 / scale=none
                                          clparm=wald
                                          clodds=pl
                                          rsquare
                                                        lackfit
                                                        ctable;
output out = model_2_results p = Predict;
n;
s graphics off;


 model 3 - Logistic using train2 dataset (not PCA) only by distance */
s graphics on;
oc logistic data=train2 plots(only)=(roc(id=obs) effect);
model shot_made_flag (event='1') = shot_distance / scale=none
                                          clparm=wald
                                          clodds=pl
                                          rsquare
                                                        lackfit
                                                        ctable;
output out = model_3_results p = Predict;
n;
s graphics off;
```

```
 create data for model 4 - data sets for playoffs and not at playoffs
 ↪  */

ta train2_playoffs;
t train2;
ere playoffs = 1;
n;

ta train2_no_playoffs;
t train2;
ere playoffs = 0;
n;


 model 4A - Logistic using train2 dataset (not PCA) during playoffs
 ↪  */

s graphics on;
oc logistic data=train2_playoffs plots(only)=(roc(id=obs) effect);
model shot_made_flag (event='1') = shot_distance / scale=none
                                          clparm=wald
                                          clodds=pl
                                          rsquare
                                                        lackfit
                                                        ctable;
output out = model_4A_results p = Predict;
n;
s graphics off;


 model 4B - Logistic using train2 dataset (not PCA) during playoffs
 ↪  */

s graphics on;
oc logistic data=train2_no_playoffs plots(only)=(roc(id=obs) effect);
model shot_made_flag (event='1') = shot_distance / scale=none
```

```
                                          clparm=wald
                                          clodds=pl
                                          rsquare
                                                        lackfit
                                                        ctable;
output out = model_4B_results p = Predict;
n;
s graphics off;


 model 5 - Logistic using train2 dataset (not PCA) during playoffs */
s graphics on;
oc logistic data=train2 plots(only)=(roc(id=obs) effect);
model shot_made_flag (event='1') = shot_distance playoffs arena_temp game_event_id lat lon / scale=none
                                          clparm=wald
                                          clodds=pl
                                          rsquare
                                                        lackfit
                                                        ctable;
output out = model_5_results p = Predict;
n;
s graphics off;


 model 6 - Logistic using train2 dataset (not PCA) for all variables that had corr p < 0.0001 */
s graphics on;
oc logistic data=train2 plots(only)=(roc(id=obs) effect);
model shot_made_flag (event='1') = shot_distance playoffs period minutes_remaining seconds_remaining attendance arena_temp avgnoisedb / scale=none
                                          clparm=wald
                                          clodds=pl
                                          rsquare
```

```
                                                        lackfit
                                                        ctable;
output out = model_6_results p = Predict;
n;
s graphics off;


 Model 7 - LDA Model */

oc discrim data=train2 outstat=LDAstat method=normal pool=yes
              list crossvalidate;
    class shot_made_flag;
    priors prop;
    var shot_distance playoffs period minutes_remaining
     ↪  seconds_remaining attendance arena_temp avgnoisedb;
 run;









 Import test data for prediction model */

 import test data */
oc import datafile="c:\users\allen\documents\smu data science\MSDS
 ↪  6372 - Applied Statistics\project 2\project2pred.csv"
        dbms=dlm out=test replace;
   delimiter=',';
   getnames=yes;
n;

 print data */
```

```
oc print data=test (obs=10);
n;

 investigate data for variable types*/
oc contents data=test;
n;

 look for missing numeric data - may need to impute */
oc means data = test n nmiss;
var _numeric_;
n;

 investigate means of training data */
oc means data = test n nmiss;
n;

 univariate data analysis */
oc univariate data = test;
r season;
n;

 note that certain "season" fields are missing */
ta _seasontest;
  set test;
  where missing (season);
n;

 print "season" data, where "season" is missing */
oc print data=_seasontest (obs=200);
n;

 add empty predicted response field */
ta test2;
t test;
ot_made_flag = .;
```

```
print data */
oc print data=test2 (obs=200);
n;


Create TRAIN and TEST fields to distinguish test vs train data.
↪  Combine data, predict missing values, create final data set */

ta train2b;
t train2;
le = "TRAIN";
n;

oc print data=train2b (obs=10);
n;

ta test2b;
t test2;
le = "TEST";
n;

oc print data=test2b (obs=10);
n;




make a numeric shot_made_flag variable in test data */

ta test2c;
t test2b;
 n_shot_made_flag = input(shot_made_flag,8.);
n;

drop original non-numeric shot_made_flag */
```

```
ta test2c;
t test2c (drop = shot_made_flag);
n;

 rename numeric shot_made_flag */
ta test2c;
t test2c (rename=(
_shot_made_flag'n='shot_made_flag'n));
n;

 drop the n_shot_made_flag variable */
ta test2c;
t test2c (drop = shot_made_flag);
n;

 rename rannum variable to recId */
ta test2c;
t test2c (rename=(
annum'n='recId'n));
n;



 combine data sets */

ta test3;
t train2b test2c;
n;

oc print data=test3 (obs=10);
n;

oc contents data=test3;
n;
```

```
 predict response field (shot_made_flag) using desired method */
s graphics on;
oc logistic data=test3 plots(only)=(roc(id=obs) effect);
model shot_made_flag (event='1') = shot_distance playoffs period
↪  minutes_remaining seconds_remaining attendance arena_temp
↪  avgnoisedb / scale=none
                                          clparm=wald
                                          clodds=pl
                                          rsquare
                                                        lackfit
                                                        ctable;
tput out = model_test_results p = Predict;
n;
s graphics off;


 check data for completeness */

oc means data = results n nmiss;
var _numeric_;
n;

oc print data=results (obs=10);
ere file = "TEST";
n;

oc contents data=results;
n;

oc means data=results
 Mean Std Min Q1 Median Q3 Max;
n;

 This is the final step that maps the predicted value into the
↪  shot_made_flag variable
d then drops all variables except shot_id and shot_made_flag. */
```

```
ta results_final;
tain shot_id shot_made_flag;
t model_test_results;
 shot_made_flag < 1 then shot_made_flag = predict;
ep shot_id shot_made_flag;
ere file = "TEST";
n;

oc print data=results_final (obs=100);
n;

oc contents data=results_final;
n;











s graphics on;
oc logistic data=test3 plots(only)=(roc(id=obs) effect);
model shot_made_flag (event='1') = shot_distance / scale=none
                                          clparm=wald
                                          clodds=pl
                                          rsquare
                                                        lackfit
                                                        ctable;
output out = model_test3_results p = Predict;
n;
```

```
s graphics off;



 model 5 - Logistic using train2 dataset (not PCA) during playoffs */
s graphics on;
oc logistic data=test3 plots(only)=(roc(id=obs) effect);
model shot_made_flag (event='1') = shot_distance playoffs arena_temp game_event_id lat lon / scale=none
                                          clparm=wald
                                          clodds=pl
                                          rsquare
                                                        lackfit
                                                        ctable;
output out = model_test5_results p = Predict;
n;
s graphics off;


 model 6 - Logistic using train2 dataset (not PCA) for all variables that had corr p < 0.0001 */
s graphics on;
oc logistic data=test3 plots(only)=(roc(id=obs) effect);
model shot_made_flag (event='1') = shot_distance playoffs period minutes_remaining seconds_remaining attendance arena_temp avgnoisedb / scale=none
                                          clparm=wald
                                          clodds=pl
                                          rsquare
                                                        lackfit
                                                        ctable;
output out = model_test6_results p = Predict;
n;
s graphics off;

```

```
ta results_final_6;
tain shot_id shot_made_flag;
t model_test6_results;
 shot_made_flag < 1 then shot_made_flag = predict;
ep shot_id shot_made_flag;
ere file = "TEST";
n;
```

6.4 Python Code

```
  # MSDS 6371 - Applied Statistics  #
  # Allen Crane and Brock Friedrich #
  # Kobe Bryant Shot Selection      #
  # November 2018                   #


port warnings
rnings.filterwarnings("ignore")

port os
port sys
port seaborn as sns
port matplotlib.pyplot as plt
port pandas as pd
port numpy as np
port statsmodels.api as sm
om statsmodels.stats.outliers_influence import
 ↪  variance_inflation_factor
om sklearn.feature_selection import RFE
om sklearn.discriminant_analysis import LinearDiscriminantAnalysis
om sklearn.model_selection import train_test_split
om sklearn.metrics import confusion_matrix, log_loss, roc_auc_score
om sklearn.linear_model import LogisticRegression

```

```
port statsmodels.formula.api as smf
om scipy import stats
port matplotlib.pyplot as plt
port numpy as np
port pandas as pd
om pandas.plotting import (lag_plot,
                                        autocorrelation_plot,
                                        table, scatter_matrix,
                                        boxplot)

om patsy import dmatrices
om math import degrees, acos
om scipy.spatial import distance


os.chdir(os.path.dirname(__file__))
s.path.insert(0, os.getcwd()+'/src')
om eda import *
om confusion_matrix_pretty import *
from plotting import *
om logistic_regression import *
om linear_discriminant_analysis import *

f cols(df: pd.DataFrame) -> list:
  """Extract list of columns from input DataFrame and removing the
  ↪   dependent variable."""

  return [x for x in df.columns.tolist() if x not in [DEPENDENT]]

f get_dummies(df: pd.DataFrame, drop_first = False):
  """Replace catagorical varables with indicators"""

  df = pd.get_dummies(df, dtype = float)
  df.columns = df.columns \
                  .str.lower() \
                  .str.replace(" ", "_")
```

```
  return df

f LogRegModel(data: pd.DataFrame, add_constant = False):
  if add_constant:
      data = sm.add_constant(data)
  model = LogR(data, DEPENDENT)
  model.sm = model.statsmodel()

  model.yhat = model.sm.predict(model.test_x)
  print("\n Predicted Log Loss: {}\n".format(
      round(
          log_loss(model.test_y, model.yhat)
          , 4)))
  return model

f summarize_model(model: LogR):
  print(model.describe_features())
  print(model.sm.summary())
  print(model.sm.summary2())
  print(model.sm.wald_test_terms())

Import Data
TA = pd.read_excel('data/project2Data.xlsx', index_col = 'recId')
R_PREDICTION = pd.read_excel('data/project2Pred.xlsx', index_col =
↪  'rannum')
PENDENT = "shot_made_flag"

DUNDANT_FEATURES = [
'team_id', # constant term
'team_name', # constant term
'season',
'game_id', # violates independence
'matchup',
'shot_id',
'recId',
'shot_zone_area',
```

```
'shot_zone_basic',
'shot_zone_range',
'minutes_remaining',
'seconds_elapsed_in_game',
'game_event_id',  # violates independence
'game_date', # violates independence
'action_type',
      'loc_x', # collinear with lat
      'loc_y', # collinear with lon






f to_latex(df):
  pd.set_option('display.float_format', lambda x: '%.0f' % x)
  with open('temp.txt', 'w') as f:
      f.write(r'\resizebox{\textwidth}{!}{'+
          df.to_latex()
          + r'}\captionof{table}{Feature Summary}\label{tbl:featuresummary}')
  pd.set_option('display.float_format', lambda x: '%.4f' % x)


f desc(df: pd.DataFrame):
""Produces a summary of the input DataFrame

rguments:
df {pd.DataFrame} -- [description]

eturns:
pd.DataFrame -- DataFrame of summary statistics
""

esc = df.describe(percentiles = None).T
```

```
esc['missing'] = len(df.index) - desc['count']
 desc = desc.astype('int')
esc['median'] = df.median()
esc['missing %'] = desc.missing / len(df.index) * 100
eturn desc.T

"############# Model 0 - Predicted Log Loss: 0.6552 #############"""


"Dataset: d0 | Prediction set: d0_pred
  - Full Model
"

 = prepare_data(DATA.drop(columns = ['action_type']))
.game_date = d0.game_date.apply(lambda x: x.toordinal())
 = get_dummies(d0).fillna(0) # Get dummy variables for categoricals
_pred = wrangle_features(FOR_PREDICTION)
_pred.game_date = d0_pred.game_date.apply(lambda x: x.toordinal())
_pred = get_dummies(d0_pred).fillna(0) # Get dummy variables for
↪  categoricals
_pred = d0_pred[cols(d0)]

"Fit d2"""

del0 = LogRegModel(d0)
mmarize_model(model0)
del0.roc_plot()

"############# Model 1 - Predicted Log Loss: 0.6652 #############"""


"Dataset: d1 | Prediction set: d1_pred
  - No categorical features
"
 = prepare_data(DATA, drop_categorical = True) # Wrangle Data
.game_date = d1.game_date.apply(lambda x: x.toordinal())
```

```
 = d1.fillna(0)
d1_pred = wrangle_features(FOR_PREDICTION)
d1_pred.game_date = d1_pred.game_date.apply(lambda x: x.toordinal())
d1_pred = d1_pred[cols(d1)].fillna(0)

"Fit d1"""
del1 = LogRegModel(d1)
mmarize_model(model1)
del1.roc_plot()

"############ Model 2 - Predicted Log Loss: 0.6479 ############"""

"Dataset: d2 | Prediction set: d2_pred
  - Categorical features as indicators
  - Drop redundant features
"

 = prepare_data(DATA, drop_columns= REDUNDANT_FEATURES)
d2.game_date = d2.game_date.apply(lambda x: x.toordinal())
d2.last_seconds_of_period = d2.last_seconds_of_period.astype(int)
 = get_dummies(d2).fillna(0) # Get dummy variables for categoricals
_pred = wrangle_features(FOR_PREDICTION)
_pred = get_dummies(d2_pred).fillna(0) # Get dummy variables for
↪  categoricals
_pred = d2_pred[cols(d2)]

"Fit d2"""
del2 = LogRegModel(d2)
mmarize_model(model2)
del2.sm2 = model2.statsmodel_()
del2.sm2.fitted = model2.sm2.fit()
model2.sm.summary2()
del2.sm2.fitted.predict(model2.test_x)
pd.Series(model2.predict_labels(d2_pred)).set_index(d2_pred.sho)
model2.roc_plot()

```

```
f_train_x = model2.sm2.pdf(model2.train_x)
f_train_x = model2.sm2.cdf(model2.train_x)

sult = model2.sm.summary2()
godds = result.tables[1]
ds[['Coef.','[0.025', '0.975]']] = np.exp(logodds[['Coef.','[0.025',
↪  '0.975]']])
t_change = (odds[['Coef.','[0.025', '0.975]']] - 1) * 100


rr_matrix(wrangle_features(DATA.drop(columns = ['action_type'])))
ot_proba(model2)
ot_regular_vs_post_season(model2)
ot_confusion_matrix(model2)


"

 logOdds
--------------------------------------------------------------------------------------
                               Coef.    Std.Err.      z     P>|z|
↪  [0.025        0.975]
t                            -0.6565       0.3081 -2.1307 0.0331
↪  -1.2604       -0.0526
n                            -0.0526       0.1710 -0.3076 0.7584
↪  -0.3879        0.2826
ayoffs                        0.0417       0.0462  0.9019 0.3671
↪  -0.0489        0.1324
conds_remaining               0.0014       0.0009  1.5626 0.1182
↪  -0.0004        0.0031
ot_distance                  -0.0189       0.0044 -4.2505 0.0000
↪  -0.0275       -0.0102
tendance                      0.0002       0.0000 10.3586 0.0000
↪  0.0001        0.0002
ena_temp                      0.0328       0.0076  4.3008 0.0000
↪  0.0178        0.0477
```

```
gnoisedb                    0.0025        0.0078  0.3175 0.7509
  ↪  -0.0128         0.0177
conds_left_in_period        0.0001        0.0001  0.7850 0.4325
  ↪  -0.0001         0.0002
st_seconds_of_period       -0.8629        0.1282 -6.7335 0.0000
  ↪  -1.1141        -0.6117
conds_left_in_game          0.0001        0.0000  2.2041 0.0275
  ↪   0.0000         0.0001
me_or_away                 -0.0259        0.0305 -0.8465 0.3973
  ↪  -0.0857         0.0340
m_shots_cumulative          0.0005        0.0042  0.1257 0.9000
  ↪  -0.0077         0.0087
gle_from_basket             0.0002        0.0004  0.3873 0.6985
  ↪  -0.0006         0.0009
ason_count                  0.0093        0.0034  2.7567 0.0058
  ↪   0.0027         0.0159

 Odds

                            Coef.      Std.Err.        z  P>|z|   [0.025
  ↪   0.975]

lat                          0.5175        0.3082 -2.1377 0.0325
  ↪   0.2829   0.9467
n                          0.9476        0.1711 -0.3144 0.7532   0.6777
  ↪   1.3251
ayoffs                     1.0214        0.0586  0.3602 0.7187   0.9105
  ↪   1.1458
conds_remaining            1.0014        0.0009  1.5652 0.1175   0.9996
  ↪   1.0031
shot_distance                0.9813        0.0044 -4.2570 0.0000
  ↪   0.9728   0.9899
me_date                    1.0002        0.0003  0.5708 0.5681   0.9995
  ↪   1.0008
attendance                   1.0002        0.0000 10.3607 0.0000
  ↪   1.0001   1.0002
```

```
arena_temp                    1.0331        0.0076  4.2622 0.0000
  ↪  1.0177   1.0486
gnoisedb                    1.0025        0.0078  0.3238 0.7461   0.9873
  ↪  1.0180
conds_left_in_period        1.0001        0.0001  0.7873 0.4311   0.9999
  ↪  1.0002
last_seconds_of_period        0.4220        0.1282 -6.7317 0.0000
  ↪  0.3283   0.5425
seconds_left_in_game          1.0001        0.0000  2.2072 0.0273
  ↪  1.0000   1.0001
me_or_away                  0.9739        0.0306 -0.8659 0.3865   0.9173
  ↪  1.0340
m_shots_cumulative          1.0005        0.0042  0.1242 0.9011   0.9923
  ↪  1.0088
gle_from_basket             1.0002        0.0004  0.3880 0.6980   0.9994
  ↪  1.0009
ason_count                  0.9419        0.1212 -0.4942 0.6212   0.7427
  ↪  1.1944

 Percent Changes
                                  Coef.     Std.Err.        z   P>|z|
  ↪  [0.025    0.975]
lat                             -48.1343        0.3081 -2.1307 0.0331
  ↪  -71.6464   -5.1247
n                             -5.1247        0.1710 -0.3076 0.7584
  ↪  -32.1487   32.6623
ayoffs                          4.2596        0.0462  0.9019 0.3671
  ↪  -4.7756   14.1521
conds_remaining                 0.1395        0.0009  1.5626 0.1182
  ↪  -0.0354    0.3147
shot_distance                     -1.8678        0.0044 -4.2505 0.0000
  ↪  -2.7173   -1.0109
attendance                         0.0173        0.0000 10.3586 0.0000
  ↪  0.0141    0.0206
arena_temp                         3.3317        0.0076  4.3008 0.0000
  ↪  1.7998    4.8866
```

```
gnoisedb                        0.2476        0.0078  0.3175 0.7509
  ↪  -1.2714   1.7900
conds_left_in_period            0.0061        0.0001  0.7850 0.4325
  ↪  -0.0092   0.0215
last_seconds_of_period          -57.8070        0.1282 -6.7335 0.0000
  ↪  -67.1786 -45.7595
seconds_left_in_game              0.0070        0.0000  2.2041 0.0275
  ↪   0.0008   0.0132
me_or_away                     -2.5519        0.0305 -0.8465 0.3973
  ↪  -8.2134   3.4588
m_shots_cumulative              0.0527        0.0042  0.1257 0.9000
  ↪  -0.7654   0.8775
gle_from_basket                 0.0150        0.0004  0.3873 0.6985
  ↪  -0.0610   0.0911
ason_count                      0.9308        0.0034  2.7567 0.0058
  ↪   0.2681   1.5979

 Significant features
                      Coef.  Std.Err.       z  P>|z|  [0.025  0.975]
t                    0.5175    0.3082 -2.1377 0.0325  0.2829  0.9467
ot_distance          0.9813    0.0044 -4.2570 0.0000  0.9728  0.9899
tendance             1.0002    0.0000 10.3607 0.0000  1.0001  1.0002
ena_temp             1.0331    0.0076  4.2622 0.0000  1.0177  1.0486
st_seconds_of_period 0.4220    0.1282 -6.7317 0.0000  0.3283  0.5425
conds_left_in_game   1.0001    0.0000  2.2072 0.0273  1.0000  1.0001

"



" #! Interpretation
e p value is calculated based on the assumption that the null
  ↪  hypothesis is true.

```

```
think about it this way: "assuming the null hypothesis is true, the probability of the observed test statistic occurring is 0.02. That's not very probable. But the observed test statistic definitely occurred, because it was observed. Therefore, it seems more likely that the null hypothesis is not true, i.e. It should be rejected."

suming the null hypothesis is true, the probability of measuring at least the observed test occurring is 0.02."

"

f_test_x = sm2.pdf(model2.test_x)

" Refine Model 2 """

ld = model2.sm.wald_test_terms()
ld.df = wald.summary_frame()
ld.significant = wald.df[wald.df['P>chi2'] < 0.1].index.tolist()

" Refined Fit - Predicted Log Loss: 0.6634 """

del2r = LogRegModel(d2[wald.significant + [DEPENDENT]])

"
t                       -0.1393
ot_distance             -0.0447
tendance                 0.0002
ena_temp                 0.0337
conds_left_in_game       0.0001
st_seconds_of_period    -0.8275
"
```

```
Interpret: http://www-hsc.usc.edu/~eckel/biostat2/notes/notes14.pdf

"############# Model 3 - Predicted Log Loss: 0.669 #############"""

"Dataset: d3 | Prediction set: d3_pred
  - Allen's Model
"
cols = [
  'shot_distance',
  'playoffs',
  'arena_temp',
  'game_event_id',
  'lat',
  'lon',
  'shot_made_flag'
  ]
 = DATA[d3cols]
_pred = FOR_PREDICTION[d3cols].drop(columns = [DEPENDENT]).fillna(0)

"Fit d3"""
del3 = LogRegModel(d3)
mmarize_model(model3)



"############# Model 4 - LDA - Predicted Log Loss: 9.351
 ↪ #############"""

a = LinearDiscriminantAnalysis()
a = lda.fit(model2.train_x, model2.train_y)
a_x = lda.transform(model2.train_x)
= lda.transform(model2.test_x)
labels = lda.predict(model2.test_x)

g_loss(model2.test_y, z)

```

```

"############# Model 5 #############"""

"Dataset: d5 | Prediction set: d5_pred
  - shot_distance only predictor
"

 = DATA[[DEPENDENT, 'shot_distance']]
d3_pred = FOR_PREDICTION[d3cols].drop(columns =
↪  [DEPENDENT]).fillna(0)

"Fit d5"""
 = sm.add_constant(d5)
del5 = LogR(d5, DEPENDENT)
del5.sm = model5.statsmodel()

del5.yhat = model5.sm.predict(model.test_x)

del5 = LogRegModel(d5)
 = model5.sm.summary2()

 = np.exp(s5.tables[1]['Coef.'])


"############# Model 6 - Log Loss: 0.669 #############"""

"Dataset: d6 | Prediction set: d6_pred
  - Allen's model 5
"

 = DATA[[DEPENDENT, 'shot_distance', 'playoffs', 'arena_temp',
 ↪  'game_event_id', 'lat', 'lon']]

"Fit d6"""
d5 = sm.add_constant(d5)
model5 = LogR(d5, DEPENDENT)
```

```
del6 = LogRegModel(d6)
 = model6.sm.summary2()


 = np.exp(s6.tables[1]['Coef.'])

ot_confusion_matrix(model6)

del6.sensitivity()
del6.specificity()


 Data Overview

TODO: Add Univariate Plots
  # QQ
  # Hist




= d6 .select_dtypes(np.number)


cNoFocus = "red"


 Correlation Matrix


TA.shape

 better model was at the cost of explainability and violation of
↪  parsimony
```

```
"
The __odds of Kobe making a shot decrease with respect to the distance he is from the hoop__.  If there is evidence of this, quantify this relationship.  (CIs, plots, etc.)

 Yes. His odds go down by  -1.87% +-.85 %  (-2.72% -1.01%) for every additional foot away from the basket.
"

"
The __probability of Kobe making a shot decreases linearly with respect to the distance he is from the hoop__.    If there is evidence of this, quantify this relationship.  (CIs, plots, etc.)

 It doesn't. Show pdf plot.

near up to 23ft, but is not at zero at 23ft, so probability curve must be curved.


"



"
The relationship between the __distance Kobe is from the basket and the odds of him making the shot is different if they are in the playoffs__.  Quantify your findings with statistical evidence one way or the other. (Tests, CIs, plots, etc.)



"
```

```

" Odds Ratios
ds ratios that are greater than 1 indicate that the event is more
↪  likely to occur as the predictor increases. Odds ratios that are
↪  less than 1 indicate that the event is less likely to occur as
↪  the predictor increases.

tps://www.predictiveanalyticsworld.com/patimes/on-variable-importance-in-logistic-regress

 The model indicates a 4.25% increase in shooting ability during the
↪  playoffs, however, the result was not statistically significant.

's overlap and contain zero. zome evidence but not enough to conclude
↪  there is a difference.


om sklearn.linear_model import LogisticRegression
om sklearn.model_selection import train_test_split
om sklearn.feature_selection import chi2
om sklearn.metrics import (
      classification_report,
      roc_curve,
      auc

      )
port pandas as pd
om confusion_matrix_pretty import *
port statsmodels.api as sm
om sklearn.metrics import confusion_matrix

ass LogR(LogisticRegression):
  """Sparse extension of sklearn.linear_model.LogisticRegression.

  """

  def __init__(self,
```

```
            data: pd.DataFrame,
            dependent_name: None,
            store_covariance: bool = True,
            test_size: float = 0.25,
            fit_intercept = False):
        super().__init__(solver = 'lbfgs',
                    fit_intercept = fit_intercept
                    )
        self.yhat = None

        self.train_x, self.test_x, self.train_y, self.test_y = train_test_split(data.drop(columns = [dependent_name]), data[dependent_name], test_size = test_size, random_state = 0)

    def __repr__(self):
        return super().__repr__()

    def __str__(self):
        return super().__str__()

    def describe_features(self):

        print(f"""
        X: features: {len(self.train_x)}

            dtypes:
            -------""")

        for k, v in self.train_x.dtypes.sort_index().items():
            print(f'''\t\t{k:<30}{v.name:} ''')

        print(f"""
        Y: {self.train_y.name}: {self.train_y.dtype}
        """)

    def confusion_matrix(self, test = False, plot = True):
```

```
        """Generate, and optionally plot, a confusion matrix for the test or train datasets

        Keyword Arguments:
            plot {bool} -- optionally plot the confusion matrix (default: {True})

        Returns:
            pd.DataFrame -- confusion matrix
        """
        if test:
            x = self.test_x
            y = self.test_y
        else:
            x = self.train_x
            y = self.train_y

        # if y is not None and x is not None:
        self.cm = pd.DataFrame(confusion_matrix(y, self.sm2.fitted.predict(x)), index = [0, 1], columns = [0, 1])
        if plot:
            pretty_plot_confusion_matrix(self.cm, cmap='PuRd')
        return self.cm
        # else:
        #     print('X or Y is empty. Check parameters.')
        #     return None

    def score(self) -> float:
        """Wrapper for parent class method using xy's stored in child class object.  Scores model fit using test data.

        Returns:
            float -- model score

        """

```

```
        x = self.test_x
        y = self.test_y

        score = super().score(x, y)
        print(f'''
        Features:
            {' | '.join([x for x in x.columns])}

        Accuracy: {score:.2%}

        ''')
        return score

    def plot_separability() -> None:
        """Plots a heatmap of fitted coefficients, highlighting
    ↪   features that are more likely seperable by a linear hyperplane.
        """

        x = self.train_x
        if len(x.columns.tolist()) == len(self.coef_[0]):
            fig, ax = plt.subplots(1, 1, figsize=(12, 10))
            sns.heatmap(pd.DataFrame(self.coef_[0],
                                     columns=[1],
                                     index=x.columns.tolist()),
                        ax=ax, cmap='RdBu', annot=True)

            plt.title('LDA Feature Separability')
            plt.tight_layout()
        else:
            print('Length of input "x" does not match number of
    ↪   coefficients. Refit the model using the dependents in x.')
            return None

    def fit(self):
        """Wrapper for parent class method using xy's stored in child
    ↪   class object.
```

```

        Fit the model.

        Returns:
            pd.Series -- array of x values projected to maximize
            ↪ seperation

        """
        super().fit(self.train_x, self.train_y)

    def predict(self, x):

        self.yhat = super().predict(x)
        return self.yhat

    def transform(self):
        """Wrapper for parent class method using xy's stored in child
    ↪ class object.

        Transform x to maximize seperation.

        Returns:
            pd.Series -- array of x values projected to maximize
            ↪ seperation

        """
        return super().transform(self.x)

    def log_loss(self, x = None):

        if self.yhat is not None:
            self.yhat = self.sm.predict(x or self.test_x)

        return round(log_loss(self.test_y, self.yhat), 2)

    def _decision_function(self):
```

```
        #TODO: Implement, time permitting
        raise NotImplementedError()

    def classification_report(self):
        """Class wrapper for sklearn.metrics.classification_report
        """

        classification_report(
            self.test_y,
            self.yhat,
            target_names=self.classes_.astype(str).tolist())

    def statsmodel(self):
        """Model using statsmodels library.

        Returns:
            statsmodels result object

        """

        return sm.Logit(self.train_y, self.train_x).fit()

    def statsmodel_(self):
        """Model using statsmodels library.

        Returns:
            statsmodels result object

        """

        return sm.Logit(self.train_y, self.train_x)


    def roc_plot(self, sm = True):
        """
        Referenced from:
```

```
    ↪ https://scikit-learn.org/stable/auto_examples/model_selection/plot_roc_crossval
    """

    y_score = self.predict_labels(self.test_x)

    fpr, tpr, _ = roc_curve(self.test_y, y_score)

    roc_auc = auc(fpr, tpr)
    plt.plot(fpr, tpr, lw=1, alpha=1,
                label='ROC fold %d (AUC = %0.2f)' % (1, roc_auc))

    g = plt.plot([0, 1], [0, 1], linestyle='--', lw=2, color='r',
            label='Chance', alpha=.8)

    plt.xlim([-0.05, 1.05])
    plt.ylim([-0.05, 1.05])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver operating characteristic example')
    plt.legend(loc="lower right")
    g.set_title(f'Distribution of {y}', color = cNoFocus)
    g.set_xlabel(f'{y}', size = 'xx-large', color = cNoFocus)
    g.set_ylabel(f'Density', size = 'xx-large', color = cNoFocus)
    g.set_xticklabels(g.get_xticklabels(), size = 'xx-large')
    g.set_yticklabels(g.get_yticklabels(), size = 'xx-large')
    g.tick_params(colors=cNoFocus)
    g.spines['bottom'].set_color(cNoFocus)
    g.spines['top'].set_color(cNoFocus)
    g.spines['left'].set_color(cNoFocus)
    g.spines['right'].set_color(cNoFocus)
    g.xaxis.label.set_color(cNoFocus)
    g.yaxis.label.set_color(cNoFocus)
    return
```

```
  def predict_labels(self, x, thresh = 0.5):
      """Predict class labels"""

      self.yhat = self.sm.fitted.predict(x)
      pc = np.zeros(len(self.yhat))
      pc[self.yhat > thresh] = 1
      return pc

  def sensitivity(self):
      """Sensitivity - TP/(TP+FN)"""

      cm = self.sm.pred_table()
      sens = cm[0,0]/(cm[0,0]+cm[0,1])
      print('Sensitivity : ', sens )
      return sens


  def specificity(self):
      """Specificity = TN/(TN+FP)"""

      cm = self.sm.pred_table()
      spec = cm[1,1]/(cm[1,0]+cm[1,1])
      print('Specificity : ', spec)
      return spec




f RecursiveFeatureSelection(X, y):
  logreg = LogisticRegression()
  rfe = RFE(logreg, 20)
  rfe = rfe.fit(X.fillna(0), y.values.ravel())
  return rfe


Evaluate Model
```

```
https://www.r-bloggers.com/evaluating-logistic-regression-models/



 http://blog.yhat.com/posts/logistic-regression-and-python.html

 Dont use r-sq
https://stats.stackexchange.com/questions/3559/which-pseudo-r2-measure-is-the-one-to-repo

TODO: Kobe last minute shots are outliers





X_train, X_test, y_train, y_test = train_test_split(
    d3.drop(columns=[DEPENDENT]),
     d3[DEPENDENT], test_size=0.3, random_state=0)
logreg = LogisticRegression(fit_intercept = True, C = 1e9)
logreg.fit(X_train, y_train)
y_pred = logreg.predict(X_test)
print('Accuracy of logistic regression classifier on test set:
↪  {:.2f}'.format(logreg.score(X_test, y_test)))
log_loss(y_test, y_pred)
logreg.coef_

# sm
logit = sm.Logit(y_train, X_train)
logit.fit().params

port os
port sys
port seaborn as sns
port matplotlib.pyplot as plt
port pandas as pd
port numpy as np
```

```
port statsmodels.api as sm
om statsmodels.stats.outliers_influence import
↪  variance_inflation_factor
om sklearn.discriminant_analysis import LinearDiscriminantAnalysis
om sklearn.model_selection import train_test_split
om sklearn.metrics import confusion_matrix, log_loss
om sklearn.linear_model import LogisticRegression

port statsmodels.formula.api as smf
om scipy import stats
port matplotlib.pyplot as plt
port numpy as np
port pandas as pd
om pandas.plotting import (lag_plot,
                                        autocorrelation_plot,
                                        table, scatter_matrix,
                                        boxplot)

om patsy import dmatrices
om math import degrees, acos
om scipy.spatial import distance


os.chdir(os.path.dirname(__file__))
s.path.insert(0, os.getcwd()+'/src')
om eda import *
om confusion_matrix_pretty import *
from plotting import *

ass LDAB(LinearDiscriminantAnalysis):
  """Sparse extension of
↪  sklearn.discriminant_analysis.LinearDiscriminantAnalysis for
↪  handling binary class cases.

  """

```

```
def __init__(self,
        data: pd.DataFrame,
        dependent_name: None,
        store_covariance: bool = True,
        solver = 'eigen',
        test_size: float = 0.25):
    super().__init__(
                    # n_components = 2,
                    solver = solver,
                    store_covariance = store_covariance
                    )
    self.yhat = None

    self.train_x, self.test_x, self.train_y, self.test_y =
↪  train_test_split(
                    data.drop(columns = [dependent_name]),
                    data[dependent_name],
                    test_size = test_size,
                    random_state = 0)

def __repr__(self):
    return super().__repr__()

def __str__(self):
    return super().__str__()

def explained_variance(self) -> float:
    """Get variance explained per discriminant.

    Returns:
        float -- explained variance ratio
    """

    print(f'''Explained variance ratio:
    Discriminant 1: {self.explained_variance_ratio_[0]: .2f}''')
    # return self.explained_variance_ratio_[0]
```

```
    def describe_features(self):

        print(f"""
        X: features: {len(self.train_x)}

            dtypes:
            -------""")

        for k, v in self.train_x.dtypes.sort_index().items():
            print(f'''\t\t{k:<30}{v.name:} ''')

        print(f"""
        Y: {self.train_y.name}: {self.train_y.dtype}
        """)

    def confusion_matrix(self, test = False, plot = True):
        """Generate, and optionally plot, a confusion matrix for the test or train datasets

        Keyword Arguments:
            plot {bool} -- optionally plot the confusion matrix (default: {True})

        Returns:
            pd.DataFrame -- confusion matrix
        """
        if test:
            x = self.test_x
            y = self.test_y
        else:
            x = self.train_x
            y = self.train_y

        # if y is not None and x is not None:
```

```
        self.cm = pd.DataFrame(confusion_matrix(y, self.predict(x)),
    ↪  index = [0, 1], columns = [0, 1])
        if plot:
            pretty_plot_confusion_matrix(self.cm, cmap='PuRd')
        return self.cm
        # else:
        #     print('X or Y is empty. Check parameters.')
        #     return None

    def score(self, x, y) -> float:
        """Wrapper for parent class method using xy's stored in child
    ↪  class object.  Scores model fit using test data.

        Returns:
            float -- model score

        """

        # x = self.test_x
        # y = self.test_y

        score = super().score(x, y)
        print(f'''
        Features:
            {' | '.join([x for x in x.columns])}

        Accuracy: {score:.2%}

        ''')
        return score

    def plot_separability() -> None:
        """Plots a heatmap of fitted coefficients, highlighting
    ↪  features that are more likely seperable by a linear hyperplane.
        """

```

```
        x = self.train_x
        if len(x.columns.tolist()) == len(self.coef_[0]):
            fig, ax = plt.subplots(1, 1, figsize=(12, 10))
            sns.heatmap(pd.DataFrame(self.coef_[0],
                                     columns=[1],
                                     index=x.columns.tolist()),
                        ax=ax, cmap='RdBu', annot=True)

            plt.title('LDA Feature Separability')
            plt.tight_layout()
        else:
            print('Length of input "x" does not match number of coefficients. Refit the model using the dependents in x.')
            return None

    def fit(self):
        """Wrapper for parent class method using xy's stored in child class object.

        Fit the model.

        Returns:
            pd.Series -- array of x values projected to maximize seperation

        """
        super().fit(self.train_x, self.train_y)

    def predict(self, x):

        self.yhat = super().predict(x)
        return self.yhat

    def transform(self, x):
        """Wrapper for parent class method using xy's stored in child class object.
```

```

        Transform x to maximize seperation.

        Returns:
            pd.Series -- array of x values projected to maximize
             ↪  seperation

        """
        return super().transform(x)

    def log_loss(self, x = None):

        if self.yhat is not None:
            self.yhat = self.predict(x or self.test_x)

        return round(log_loss(self.test_y, self.yhat), 2)

    def _decision_function(self):
        #TODO: Implement, time permitting
        raise NotImplementedError()

    def classification_report(self):
        """Class wrapper for sklearn.metrics.classification_report
        """

        classification_report(
            self.test_y,
            self.yhat,
            target_names=self.classes_.astype(str).tolist())

    def roc_plot(self):
        """
        Referenced from:

        ↪  https://scikit-learn.org/stable/auto_examples/model_selection/plot_roc_crossval
        """
```

```

        y_score = self.decision_function(self.test_x)

        fpr, tpr, _ = roc_curve(self.test_y, y_score)

        roc_auc = auc(fpr, tpr)
        plt.plot(fpr, tpr, lw=1, alpha=1,
                     label='ROC fold %d (AUC = %0.2f)' % (1, roc_auc))

        plt.plot([0, 1], [0, 1], linestyle='--', lw=2, color='r',
                 label='Chance', alpha=.8)

        plt.xlim([-0.05, 1.05])
        plt.ylim([-0.05, 1.05])
        plt.xlabel('False Positive Rate')
        plt.ylabel('True Positive Rate')
        plt.title('Receiver operating characteristic example')
        plt.legend(loc="lower right")
        plt.show()




"
sumptions:
  - Each class must be:
        - normally distributed
        - identical cov matrices
        - independent

"

 __name__ == "__main__":


  #! Try full model
```

```
model = LDAB(data.fillna(0), DEPENDENT)
model.fit()
model.explained_variance()
model.score()
model.get_confusion_matrix()
model.plot_separability()
model_fi = model.feature_importance()
model.log_loss()

#! Try reduced model
data_reduced = data[model_fi.index]

ldab_reduced = LDAB(data_reduced, DEPENDENT)
ldab_reduced.fit()
ldab_reduced.explained_variance()
ldab_reduced.score_ ()
ldab_reduced.get_confusion_matrix()
ldab_reduced.plot_separability()
ldab_reduced.log_loss()

disc1 = ldab_reduced.fit_transform(train_x_reduced, train_y)


# Plot single discriminant
sns.distplot(disc1)

# TODO: Add plots

#! Yes! Shows no seperation

sns.pairplot(temp_x,
        hue="shot_made_flag",
        palette="husl",
        markers = ['<', '>'],
        plot_kws = {
            'alpha': 0.5,
```

```
        },
        diag_kws = {

        },
        )

"""
Conclusion:

Reduced model, with only 2 features, yields results effectively equivalent to those of the full model that uses 13 features.
"""

import os
import seaborn as sns
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
import statsmodels.api as sm
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn import linear_model
import statsmodels.formula.api as smf
from scipy import stats
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
from pandas.plotting import (lag_plot,
                             autocorrelation_plot,
                             table, scatter_matrix,
                             boxplot)

from patsy import dmatrices
from math import degrees, acos
```

```
from scipy.spatial import distance



pd.options.display.max_rows = None
pd.set_option('display.float_format', lambda x: '%.3f' % x)
pd.set_option('large_repr', 'truncate')
pd.set_option('precision',2)

# Matplotlib global config
plt.rcParams.update({'legend.fontsize': 'x-large',
           'figure.figsize': (10, 6),
          'axes.labelsize': 'large',
          'axes.titlesize':'xx-large',
          'xtick.labelsize':'small',
          'ytick.labelsize':'small',
          'savefig.dpi' : 300,
          'savefig.format' : 'png',
          'savefig.transparent' : True,
          'axes.labelpad' : 10,
          'axes.titlepad' : 10,
          'axes.titleweight': 'bold'
          })

# plt.style.use('seaborn-deep')


# Define Contants

DEPENDENT = "shot_made_flag"
PERIODS_IN_GAME = 4
MIN_IN_PERIOD = 12
MIN_IN_GAME = MIN_IN_PERIOD * PERIODS_IN_GAME
SECONDS_IN_PERIOD = MIN_IN_PERIOD * 60
SECONDS_IN_GAME = MIN_IN_GAME * 60
```

```

"""
LOGISTIC MODEL:

- Dependent: shot_made: bool

"""

"""
LDA MODEL:

- Dependent: shot_made: bool

"""



"""
EDA:

- Potential Mulicolinearity:
    - Court Position: lat/log
                      x/y
                      shot_zone_area (cat)
                      shot_zone_basic (cat)
                      shot_zone_range (cat)

    - (maybe) game_date:


- Add Features:

    - game_count: cumulative number of games
```

```
        - "distance" between games is more or less equivalent (except between seasons), so representation as an ordinal continuous value is appropriate. The effects of season changes will still be captures by season_count.

    - home_or_away: home ("vs.") or away ("@")

    - seconds_left_in_game: apply function

    - seconds_left_in_period: min_remaining * 60 + seconds_remaining

    - season_count: cumulative number of seasons
        - "distance" between seasons is more or less equivalent, so representation as an ordinal continuous value is appropriate.

    - num_shots_cumulative: running total of number of shots up to the current point in the game

    - (NotYetImplemented) shot_difficulty

Stretch Features:

    - altitude: obtain from lat/long

    - central_angle_to_basket: instead of x/y

    - vector_length_to_basket: instead of x/y

Drop Features:

    - team_id: constant

    - team_name: constant

```

```python
      - season: replace with season_count

      - game_id: replace with game_count

      - matchup: redundant with opponent

"""




def desc(df: pd.DataFrame):
    """Produces a summary of the input DataFrame

    Arguments:
        df {pd.DataFrame} -- [description]

    Returns:
        pd.DataFrame -- DataFrame of summary statistics
    """

    desc = df.describe().T
    desc['missing'] = len(df.index) - desc['count']
    # desc = desc.astype('int')
    desc['median'] = df.median()
    desc['missing %'] = desc.missing / len(df.index) * 100
    return desc.T

def vif(df: pd.DataFrame, dependent: str) -> pd.DataFrame:
    """Get Variance Inflation Factor for each feature in df via a simple, multiple regression.

    Arguments:
        df {pd.DataFrame} -- dataset
        dependent {str} -- column name of dependent feature in df

```

```
    Returns:
        pd.DataFrame -- DataFrame containing feature names and VIF measures.
    """

    # https://etav.github.io/python/vif_factor_python.html
    df = df.dropna()
    df = df._get_numeric_data() #drop non-numeric cols

    #gather features
    features = "+".join(df.columns.drop(dependent).tolist())

    # get y and X dataframes based on this regression:
    y, X = dmatrices('{} ~'.format(dependent) + features, df, return_type='dataframe')

    # For each X, calculate VIF and save in dataframe
    vif = pd.DataFrame()
    vif["VIF Factor"] = [variance_inflation_factor(X.values, i) for i in range(X.shape[1])]
    vif["features"] = X.columns

    return vif.round(1)

def angle(a: float, b: float, c: float) -> float:
    """ Calculate central angle for three known side lengths using Law of Cosines
    Arguments:
        a {Side} -- A side length
        b {Side} -- B side length
        c {Side} -- C side length

    Returns:
        Angle {float} -- central angle of A in degrees
    """

```

```
    return degrees(acos((c**2 - b**2 - a**2)/(-2.0 * a * b)))

def central_angle(x: float, y:float) -> float:
    """Calculate central angle of shot using NBA court grid coordinates.

    Arguments:
        x {float} -- X coordinate of shot
        y {float} -- Y coordinate of shot

    Returns:
        float -- angle in degrees of shot
    """

    # Hack
    if (y == 0) & (x < 0):
        return -90

    if (y == 0) & (x > 0):
        return 90

    if (y == 0) & (x == 0):
        return 0

    # Vertices
    vc_a = (x, y) # shot loation
    vc_b = (0,0) # origin
    vc_c = (0, y) # reference point (0, y)

    side_a = distance.euclidean(vc_b, vc_c)
    side_b = distance.euclidean(vc_a, vc_c)
    side_c = distance.euclidean(vc_a, vc_b)

    # A = angle(side_a, side_b, side_c)
    # C = angle(side_c, side_a, side_b)
    B = angle(side_b, side_c, side_a)
```

```

    return B if x > 0 else -B

def wrangle_features(data: pd.DataFrame) -> pd.DataFrame:
    feats = pd.Series(
                data = False,
                index = ['recId',
                        'action_type',
                        'combined_shot_type',
                        'game_event_id',
                        'game_id',
                        'lat',
                        'loc_x',
                        'loc_y',
                        'lon',
                        'minutes_remaining',
                        'period',
                        'playoffs',
                        'season',
                        'seconds_remaining',
                        'shot_distance',
                        'shot_made_flag',
                        'shot_type',
                        'shot_zone_area',
                        'shot_zone_basic',
                        'shot_zone_range',
                        'team_id',
                        'team_name',
                        'game_date',
                        'matchup',
                        'opponent',
                        'shot_id',
                        'attendance',
                        'arena_temp',
                        'avgnoisedb'],
                dtype = bool
```

```
                )

    # Flag features that were passed to the function
    feats.loc[feats.index.isin(data.columns)] = True
    try:
        if feats.minutes_remaining & feats.seconds_remaining:
            data['seconds_left_in_period'] = data.minutes_remaining * 60 + data.seconds_remaining
    except Exception as e:
        print('Failed to add feature: seconds_left_in_period. ({})'.format(e))

    try:
            data['last_seconds_of_period'] = data.seconds_left_in_period < 2
            data.last_seconds_of_period = data.last_seconds_of_period.astype(int)
    except Exception as e:
        print('Failed to add feature: last_seconds_of_period. ({})'.format(e))


    try:
        if feats.period:
            data['seconds_elapsed_in_game'] = SECONDS_IN_PERIOD * data.period - data.seconds_left_in_period
    except:
        print('Failed to add feature: seconds_elapsed_in_game')

    try:
        if True:
            data['seconds_left_in_game'] = SECONDS_IN_GAME - data.seconds_elapsed_in_game
    except:
        print('Failed to add feature: seconds_left_in_game')

```

```
    try:
        if feats.matchup:
            data['home_or_away'] = data.matchup.str.contains("@").astype(int)
    except:
        print('Failed to add feature: home_or_away')

    try:
        if feats.game_id:
            data['num_shots_cumulative'] = data.groupby(['game_id']).cumcount()
    except:
        print('Failed to add feature: num_shots_cumulative')

    try:
        if feats.loc_x & feats.loc_y:
            data['angle_from_basket'] = data.apply(lambda row: central_angle(row.loc_x, row.loc_y), axis = 1)
    except:
        print('Failed to add feature: angle_from_basket')

    try:
        if feats.season:
            # Convert season to ordered Categorical (Factor) type
            data.season = pd.Categorical(data.season, data.season.sort_values().unique().tolist(), ordered = True)
            data['season_count'] = data.season.cat.codes
    except:
        print('Failed to add feature: season_count')

    try:
        if len(data.select_dtypes('object').columns):
            # Convert other string fields to unordered Categorical
            data[data.select_dtypes('object').columns.tolist()] = data.select_dtypes('object').astype('category')
    except:
```

```
            print('Failed to convert objects to categories')

    return data

def drop_features(data, columns):

    # Remove columns in the 'remove' list if they are present in
↪   the dataset
    data = data.drop(columns = [x for x in columns if x in
↪   data.columns])
    return data

def eigen_solver():
    """Assess using Eigen values and vectors


    ↪   https://stackoverflow.com/questions/25676145/capturing-high-multi-collinea

    An almost zero eigen value shows a direction with zero
    ↪   variation, hence collinearity.

    """
    # TODO: Implement, time permitting
    raise NotImplementedError()

def check_collinearity(data: pd.DataFrame):
    return vif(data, DEPENDENT) \
                .set_index('features') \
                .rename(columns = {'VIF Factor' : 'VIF'}) \
                .sort_values(by = 'VIF', ascending = False) \
                .drop('Intercept')

def check_collinearity_recursive(data: pd.DataFrame, vifs = None):
```

```
    """Recursively check the multicollinearity (MC) associated with each feature. Each iteration, the feature with the largest MC is dropped if the MC is infinite or if MC > x, where x is the standard deviation of the finite VIFs of the original features. A matrix containing VIFs for each iteration is returned once an iteration is reached where MC <= x.

    Arguments:
        data {pd.DataFrame} -- Matrix or DataFrame with shape(n_obs, n_features)

    Keyword Arguments:
        vifs {None} -- Recursive control parameter (default: {None})

    Returns:
        [pd.DataFrame] -- Matrix of VIFs per iteration. Nan (not a number) values represent features dropped from the assessment in either a previous or the current iteration.
    """

    prev_vifs = vifs

    vifs = vif(data, DEPENDENT) \
            .set_index('features') \
            .rename(columns = {'VIF Factor' : 'VIF'}) \
            .sort_values(by = 'VIF', ascending = False) \
            .drop('Intercept') # Drop intercept term


    vif0_name, vif0_val = vifs.iloc[0].name, vifs.iloc[0].values[0]

    drop_feature = False
    limit = None
```

```
    thresh = prev_vifs.VIF[np.isfinite(prev_vifs.VIF)].max() if prev_vifs is not None else 0
    # If inflated feature VIF is infinite, drop the feature
    if vif0_val == float('inf'):
        drop_feature = True
    else:
        # Otherwise, drop feature if VIF within 2.5 stds.
        limit = (vifs[vifs != float('inf')].std()*2.5).values[0]
        if vif0_val > limit > thresh:
            drop_feature = True

    if prev_vifs is not None:
        # print('\n\nprev_vifs')
        # print(prev_vifs)
        vifs = prev_vifs.join(vifs, rsuffix = '_'+str(len(vifs)))



    print(f'VIF: Dropping: {vif0_name} | limit: {limit or 0:.2f} | thresh: {thresh or 0:.2f}')

    if drop_feature:
        return check_collinearity_recursive(
                data.drop(columns = [vif0_name]),
                vifs = vifs
                )

    print('\n\nvifs')
    print(vifs)

    return vifs

def fix_mulitcollinearity(data: pd.DataFrame):
    """Remove multicollinear variables by assessing variance inflation factors.

```

```
    Arguments:
        data {pd.DataFrame} -- (n_obs, n_features)

    Returns:
        pd.DataFrame -- data
    """
    print('\n\n')
    vifs = check_collinearity_recursive(data)
    # vifs = check_collinearity(data)
    vifs = vifs.iloc[:, -1] # Get last column (the last iteration)

    # remove features with high MC from data set
    data = data.drop(columns = vifs[vifs.isna()].index)
    return data

def prepare_data(data: pd.DataFrame, drop_categorical = False, drop_columns: list = None) -> pd.DataFrame:
    """Template procedue to ingest new dataset.

    Arguments:
        data {pd.DataFrame} -- new dataset

    Returns:
        pd.DataFrame -- dataset for further prep or analysis
    """

    data = wrangle_features(data)
    if drop_columns is not None:
        data = drop_features(data, drop_columns)
    data = fix_mulitcollinearity(data)

    # Drop remaining categoricals
    if drop_categorical:
        data = data.select_dtypes(exclude = ['object', 'category'])

```

```
    return data

def identify_outliers(data):
    pass



# action_counts = DATA['action_type'].value_counts().sort_values(ascending = False)

# from scipy import stats
# d2[(np.abs(stats.zscore(d2)) < 3).any(axis=1)]
# d2[np.abs(d2-d2.mean()) <= (3*d2.std())]
# stats.trimb

# data = data.drop(columns = [
#     'minutes_remaining',
#     'seconds_remaining',
#     'seconds_elapsed_in_game',
#     'lat',
#     'lon',
#     'game_event_id',
#     'period',
#     'seconds_left_in_period',]
#     )

# Sort features by VIF

# NOTE: PLOTS

# fig, ax = plt.subplots(figsize=(12,8))
# ax = sns.scatterplot('loc_x', 'loc_y', hue = 'shot_made_flag', data = data)
# ax.set_title('Shot Location')
# ax.set_xlabel('X')
```

```
# ax.set_ylabel('Y')
# ax.set_ylim(0, 400)
# fig.savefig('figs/p2-3_price-v-months.png')

# fig, ax = plt.subplots(figsize=(12,8))
# ax = data.boxplot()
# ax.set_xticklabels(data.columns, rotation=90)
# fig.tight_layout()

# fig, ax = plt.subplots(figsize=(12,8))
# ax = data.select_dtypes(include=[np.number]).hist()
# # ax.set_xticklabels(data.columns, rotation=90)
# fig.tight_layout()

# import time
# from sklearn.linear_model import LassoCV
# print("Computing regularization path using the coordinate descent
↪ lasso...")
# t1 = time.time()
# model = LassoCV(cv=5).fit(X, y)
# t_lasso_cv = time.time() - t1

# # Display results
# m_log_alphas = -np.log10(model.alphas_)

# plt.figure()
# ymin, ymax = 2300, 3800
# plt.plot(m_log_alphas, model.mse_path_, ':')
# plt.plot(m_log_alphas, model.mse_path_.mean(axis=-1), 'k',
#          label='Average across the folds', linewidth=2)
# plt.axvline(-np.log10(model.alpha_), linestyle='--', color='k',
#             label='alpha: CV estimate')

# plt.legend()

# plt.xlabel('-log(alpha)')
```

```
# plt.ylabel('Mean square error')
# plt.title('Mean square error on each fold: coordinate descent '
#           '(train time: %.2fs)' % t_lasso_cv)
# plt.axis('tight')
# plt.ylim(ymin, ymax)


# def correct_multicollinearity(data: pd.DataFrame) -> pd.DataFrame:
#         print('Anterior VIF')
#         print(vif(data, DEPENDENT))

#         # Drop multicolinear features
#         data = data.drop(columns = [
#                 'minutes_remaining',
#                 'seconds_remaining',
#                 'seconds_elapsed_in_game',
#                 'lat',
#                 'lon',
#                 'game_event_id',
#                 'period',
#                 'seconds_left_in_period',

#         ])

#         print('Posterior VIF')
#         v = vif(data, DEPENDENT)
#         print(v)
#         return data

"""
plot a pretty confusion matrix with seaborn
Created on Mon Jun 25 14:17:37 2018
@author: Wagner Cipriano - wagnerbhbr - gmail - CEFETMG / MMC
@repository:
 ↪ https://github.com/wcipriano/pretty-print-confusion-matrix/blob/master/confusi
```

```
References:
  https://www.mathworks.com/help/nnet/ref/plotconfusion.html
  ↪ https://stackoverflow.com/questions/28200786/how-to-plot-scikit-learn-classificat
  ↪ https://stackoverflow.com/questions/5821125/how-to-plot-confusion-matrix-with-str
  https://www.programcreek.com/python/example/96197/seaborn.heatmap
  ↪ https://stackoverflow.com/questions/19233771/sklearn-plot-confusion-matrix-with-l
  ↪ http://scikit-learn.org/stable/auto_examples/model_selection/plot_confusion_matri
"""

#imports
from pandas import DataFrame
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.font_manager as fm
from matplotlib.collections import QuadMesh
import seaborn as sns


def _get_new_fig(fn, figsize=[9,9]):
    """ Init graphics """
    fig1 = plt.figure(fn, figsize)
    ax1 = fig1.gca()   #Get Current Axis
    ax1.cla() # clear existing plot
    return fig1, ax1
#

def _configcell_text_and_colors(array_df, lin, col, oText,
↪ facecolors, posi, fz, fmt, show_null_values=0):
    """
      config cell text and colors
      and return text elements to add and to dell
      @TODO: use fmt
```

```
    """
    text_add = []; text_del = [];
    cell_val = array_df[lin][col]
    tot_all = array_df[-1][-1]
    per = (float(cell_val) / tot_all) * 100
    curr_column = array_df[:,col]
    ccl = len(curr_column)

    #last line  and/or last column
    if(col == (ccl - 1)) or (lin == (ccl - 1)):
        #tots and percents
        if(cell_val != 0):
            if(col == ccl - 1) and (lin == ccl - 1):
                tot_rig = 0
                for i in range(array_df.shape[0] - 1):
                    tot_rig += array_df[i][i]
                per_ok = (float(tot_rig) / cell_val) * 100
            elif(col == ccl - 1):
                tot_rig = array_df[lin][lin]
                per_ok = (float(tot_rig) / cell_val) * 100
            elif(lin == ccl - 1):
                tot_rig = array_df[col][col]
                per_ok = (float(tot_rig) / cell_val) * 100
            per_err = 100 - per_ok
        else:
            per_ok = per_err = 0

        per_ok_s = ['%.2f%%'%(per_ok), '100%'] [per_ok == 100]

        #text to DEL
        text_del.append(oText)

        #text to ADD
        font_prop = fm.FontProperties(weight='bold', size=fz)
        text_kwargs = dict(color='w', ha="center", va="center", gid='sum', fontproperties=font_prop)
```

```
            lis_txt = ['%d'%(cell_val), per_ok_s, '%.2f%%'%(per_err)]
            lis_kwa = [text_kwargs]
            dic = text_kwargs.copy(); dic['color'] = 'g'; lis_kwa.append(dic);
            dic = text_kwargs.copy(); dic['color'] = 'r'; lis_kwa.append(dic);
            lis_pos = [(oText._x, oText._y-0.3), (oText._x, oText._y), (oText._x, oText._y+0.3)]
            for i in range(len(lis_txt)):
                newText = dict(x=lis_pos[i][0], y=lis_pos[i][1], text=lis_txt[i], kw=lis_kwa[i])
                #print 'lin: %s, col: %s, newText: %s' %(lin, col, newText)
                text_add.append(newText)
            #print '\n'

            #set background color for sum cells (last line and last column)
            carr = [0.27, 0.30, 0.27, 1.0]
            if(col == ccl - 1) and (lin == ccl - 1):
                carr = [0.17, 0.20, 0.17, 1.0]
            facecolors[posi] = carr

        else:
            if(per > 0):
                txt = '%s\n%.2f%%' %(cell_val, per)
            else:
                if(show_null_values == 0):
                    txt = ''
                elif(show_null_values == 1):
                    txt = '0'
                else:
                    txt = '0\n0.0%'
            oText.set_text(txt)

            #main diagonal
```

```
        if(col == lin):
            #set color of the textin the diagonal to white
            oText.set_color('w')
            # set background color in the diagonal to blue
            facecolors[posi] = [0.35, 0.8, 0.55, 1.0]
        else:
            oText.set_color('r')

    return text_add, text_del
#

def _insert_totals(df_cm):
    """ insert total column and line (the last ones) """
    sum_col = []
    for c in df_cm.columns:
        sum_col.append( df_cm[c].sum() )
    sum_lin = []
    for item_line in df_cm.iterrows():
        sum_lin.append( item_line[1].sum() )
    df_cm['sum_lin'] = sum_lin
    sum_col.append(np.sum(sum_lin))
    df_cm.loc['sum_col'] = sum_col
    #print ('\ndf_cm:\n', df_cm, '\n\b\n')
#

def pretty_plot_confusion_matrix(df_cm, annot=True, cmap="Oranges", fmt='.2f', fz=11,
      lw=0.5, cbar=False, figsize=[8,8], show_null_values=0, pred_val_axis='y'):
    """
      print conf matrix with default layout (like matlab)
      params:
        df_cm          dataframe (pandas) without totals
        annot          print text in each cell
        cmap           Oranges,Oranges_r,YlGnBu,Blues,RdBu, ... see:
```

```
        fz             fontsize
        lw             linewidth
        pred_val_axis  where to show the prediction values (x or y axis)
                        'col' or 'x': show predicted values in columns (x axis) instead lines
                        'lin' or 'y': show predicted values in lines   (y axis)
    """
    if(pred_val_axis in ('col', 'x')):
        xlbl = 'Predicted'
        ylbl = 'Actual'
    else:
        xlbl = 'Actual'
        ylbl = 'Predicted'
        df_cm = df_cm.T

    # create "Total" column
    _insert_totals(df_cm)

    #this is for print allways in the same window
    fig, ax1 = _get_new_fig('Conf matrix default', figsize)

    #thanks for seaborn
    ax = sns.heatmap(df_cm, annot=annot, annot_kws={"size": fz}, linewidths=lw, ax=ax1,
                    cbar=cbar, cmap=cmap, linecolor='w', fmt=fmt)

    #set ticklabels rotation
    ax.set_xticklabels(ax.get_xticklabels(), rotation = 45, fontsize = 10)
    ax.set_yticklabels(ax.get_yticklabels(), rotation = 25, fontsize = 10)

    # Turn off all the ticks
    for t in ax.xaxis.get_major_ticks():
```

```
        t.tick1On = False
        t.tick2On = False
    for t in ax.yaxis.get_major_ticks():
        t.tick1On = False
        t.tick2On = False

    #face colors list
    quadmesh = ax.findobj(QuadMesh)[0]
    facecolors = quadmesh.get_facecolors()

    #iter in text elements
    array_df = np.array( df_cm.to_records(index=False).tolist() )
    text_add = []; text_del = [];
    posi = -1 #from left to right, bottom to top.
    for t in ax.collections[0].axes.texts: #ax.texts:
        pos = np.array( t.get_position()) - [0.5,0.5]
        lin = int(pos[1]); col = int(pos[0]);
        posi += 1
        #print ('>>> pos: %s, posi: %s, val: %s, txt: %s' %(pos, posi, array_df[lin][col], t.get_text()))

        #set text
        txt_res = _configcell_text_and_colors(array_df, lin, col, t, facecolors, posi, fz, fmt, show_null_values)

        text_add.extend(txt_res[0])
        text_del.extend(txt_res[1])

    #remove the old ones
    for item in text_del:
        item.remove()
    #append the new ones
    for item in text_add:
        ax.text(item['x'], item['y'], item['text'], **item['kw'])

    #titles and legends
```

```
    ax.set_title('Confusion matrix')
    ax.set_xlabel(xlbl)
    ax.set_ylabel(ylbl)
    plt.tight_layout()  #set layout slim
    plt.show()
    return ax


def plot_confusion_matrix_from_data(y_test, predictions, columns=None, annot=True, cmap="Oranges",
      fmt='.2f', fz=11, lw=0.5, cbar=False, figsize=[8,8], show_null_values=0, pred_val_axis='lin'):
    """
        plot confusion matrix function with y_test (actual values) and predictions (predic),
        whitout a confusion matrix yet
    """
    from sklearn.metrics import confusion_matrix
    from pandas import DataFrame

    #data
    if(not columns):
        #labels axis integer:
        ##columns = range(1, len(np.unique(y_test))+1)
        #labels axis string:
        from string import ascii_uppercase
        columns = ['class %s' %(i) for i in list(ascii_uppercase)[0:len(np.unique(y_test))]]

    confm = confusion_matrix(y_test, predictions)
    cmap = 'Oranges';
    fz = 11;
    figsize=[9,9];
    show_null_values = 2
    df_cm = DataFrame(confm, index=columns, columns=columns)
```

```
    pretty_plot_confusion_matrix(df_cm, fz=fz, cmap=cmap, figsize=figsize, show_null_values=show_null_values, pred_val_axis=pred_val_axis)
#



#
#TEST functions
#
def _test_cm():
    #test function with confusion matrix done
    array = np.array( [[13,  0,  1,  0,  2,  0],
                       [ 0, 50,  2,  0, 10,  0],
                       [ 0, 13, 16,  0,  0,  3],
                       [ 0,  0,  0, 13,  1,  0],
                       [ 0, 40,  0,  1, 15,  0],
                       [ 0,  0,  0,  0,  0, 20]])
    #get pandas dataframe
    df_cm = DataFrame(array, index=range(1,7), columns=range(1,7))
    #colormap: see this and choose your more dear
    cmap = 'Oranges'
    pretty_plot_confusion_matrix(df_cm, cmap=cmap)
#

def _test_data_class():
    """ test function with y_test (actual values) and predictions (predic) """
    #data
    y_test = np.array([1,2,3,4,5, 1,2,3,4,5, 1,2,3,4,5, 1,2,3,4,5, 1,2,3,4,5, 1,2,3,4,5, 1,2,3,4,5, 1,2,3,4,5, 1,2,3,4,5, 1,2,3,4,5, 1,2,3,4,5, 1,2,3,4,5, 1,2,3,4,5, 1,2,3,4,5, 1,2,3,4,5, 1,2,3,4,5, 1,2,3,4,5, 1,2,3,4,5, 1,2,3,4,5, 1,2,3,4,5, 1,2,3,4,5])
```

```
    predic = np.array([1,2,4,3,5, 1,2,4,3,5, 1,2,3,4,4, 1,4,3,4,5, 1,2,4,4,5, 1,2,4,4,5, 1,2,4,4,5, 1,2,4,4,5, 1,2,3,3,5, 1,2,3,3,5, 1,2,3,4,4, 1,2,3,4,1, 1,2,3,4,1, 1,2,3,4,1, 1,2,4,4,5, 1,2,4,4,5, 1,2,4,4,5, 1,2,4,4,5, 1,2,3,4,5, 1,2,3,4,5, 1,2,3,4,5, 1,2,3,4,5])
    """
      Examples to validate output (confusion matrix plot)
        actual: 5 and prediction 1   >>  3
        actual: 2 and prediction 4   >>  1
        actual: 3 and prediction 4   >>  10
    """
    columns = []
    annot = True;
    cmap = 'Oranges';
    fmt = '.2f'
    lw = 0.5
    cbar = False
    show_null_values = 2
    pred_val_axis = 'y'
    #size::
    fz = 12;
    figsize = [9,9];
    if(len(y_test) > 10):
        fz=9; figsize=[14,14];
    plot_confusion_matrix_from_data(y_test, predic, columns,
      annot, cmap, fmt, fz, lw, cbar, figsize, show_null_values, pred_val_axis)
#


#
#MAIN function
#
if(__name__ == '__main__'):
    print('__main__')
```

```
    print('_test_cm: test function with confusion matrix done\nand
↪   pause')
    _test_cm()
    plt.pause(5)
    print('_test_data_class: test function with y_test (actual
↪   values) and predictions (predic)')
    _test_data_class()
```

Bibliography

[1] Sports Analytics Market*Sports Analytics Market.* Market Research Firm, www.marketsandmarkets.com/Market-Reports/sports-analytics-market-35276513.html.

[2] Confusion Matrix Pretty Print: Wagner Cipriano, https://github.com/wcipriano/pretty-print-confusion-matrix/blob/master/confusion$_{m}atrix_{p}retty_{p}rint.py$