Modeling Kobe

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## Abstract

Sports data modeling has been a staple of video game development for many years. The major leagues leagues NBA, NFL, NHL have all partnered with software development companies to produce realistic video games depicting the leagues’s top stars acting and scoring as they do in real life.

With the $20 billion video game industry fueled by the now growing e-sports segment, ever more realistic models are needed for developers to build the characters in their games. We explore a common dataset of Kobe Bryant’s career shots, and try to build a model that would predict the likelihood of his making or missing a shot.

We show that our final model is moderately successful, 65%, as in predicting a shot. We further speculate that additional data points commonly captured in sport statistics such as whether or not the shot was contested could add specificity to the model.

## Introduction

Kobe Bryan is a retired professional basketball player who spent 20 years with the Los Angles Lakers. Kobe entered the NBA directly out of High School. He won 5 NBA Championships, was selected to the All-Star team 18 times, and won 2 Olympic gold medals.

Using 20 years of data on Kobe’s shots made and shots missed, we explore potential models that attempt to predict whether or not his shot went in. The data set project2Data.xlsx contains the location on the floor and supporting observations of every shot he attempted in the NBA. We attempt to build a model from this data that can predict whether the shot went in or missed. We tested our final model against the held out project2Pred.xlsx dataset which was not used in training or testing the iterative models.

This type of model could be used in building a simulation or video game mimicking Kobe’s game. Sports data modeling has been a staple of video game development for many years. The major leagues leagues NBA, NFL, NHL have all partnered with software companies to produce realistic video games depicting their league’s top stars acting and scoring as they do in real life. With the $20 billion video game industry fueled by the now growing e-sports segment, realistic models are needed for developers to build these characters in their games and to stay competitive.

## Data Description

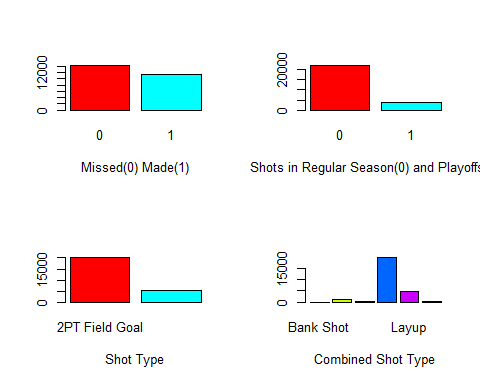
The field names are self explanatory. The predictors our analysis focused on are as follows:

|  |  |
| --- | --- |
| Data Label | Description |
| combined\_shot\_type | Type of shot combined with action |
| loc\_y | Vertical position on floor |
| minutes\_remaining | Minutes remaining in quarter |
| playoffs | Playoff game or not |
| seconds\_remaining | Seconds remaining in quarter |
| shot\_distance | Distance from goal |
| shot\_made\_flag | 1- shot went I, 0 - shot missed |
| shot\_type | 2pt or 3pt shot |
| attendance | The attendance in the stadium |
| arena\_temp | The average temperature during the game |
| avgnoisedb | The average noise level in dB during the game |

## Data Analysis

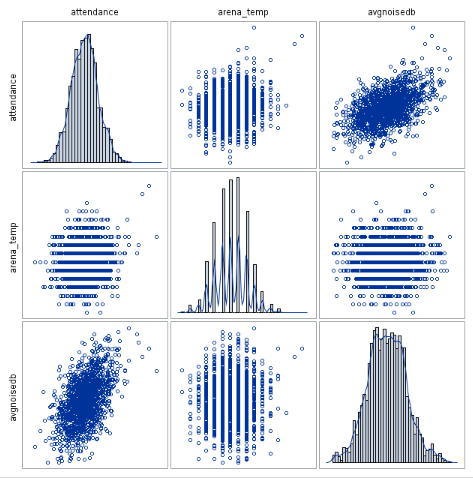
We evaluated a large but not exhaustive number of predictive variable combinations and potential models in our analysis. The following variables played a part in our final model

* Shot\_distance : We analyzed the hyphothesis that Kobe’s odds of making his shots decreased as the shot distance increased and whether or not this was a linear phenomenon.
* Shot\_type : We saw a statistically signifigant contribution from shot\_type which led us to include this variable into our final model.
* Combined\_shot\_type : Likewise combined\_shot\_type showed a statistically signifigant contribution.
* Playoffs : Used to evaluate Kobe’s performance in the regular season vs. the playoffs



We combined the following continuous variables into their principle components to include in out final model.

* Time\_remaining : We created this datapoint from minutes\_remaining\*60+seconds\_remaining
* Average Attendance
* Average Temperature
* Average Noise Level (dB)

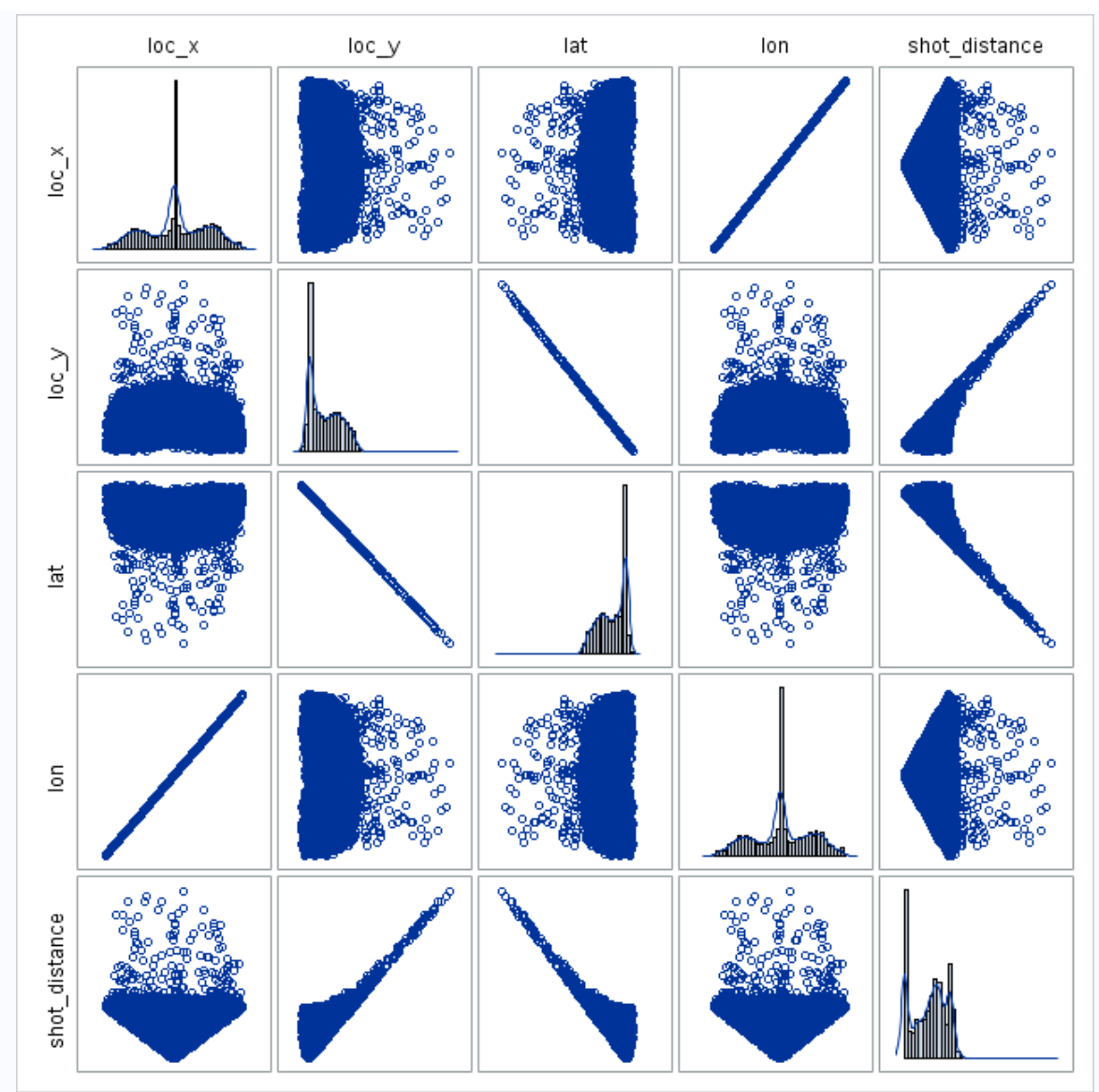


## Multicollinearity Analysis

High bivariate correlations were easy to spot bwhen we ran correlation calculations among our target predictors. We noticed signifigant correlations between loc\_y and shot\_distance, loc\_x and lon and loc\_y and lat. Coincidently we did not find models with both loc\_y and shot\_distance or with loc\_x and lon or loc\_y and lat to be good models due to their colinearity.

## loc\_x loc\_y lat lon  
## loc\_x 1.00000000 -0.01757819 0.01757819 1.00000000  
## loc\_y -0.01757819 1.00000000 -1.00000000 -0.01757819  
## lat 0.01757819 -1.00000000 1.00000000 0.01757819  
## lon 1.00000000 -0.01757819 0.01757819 1.00000000

## loc\_y shot\_distance  
## loc\_y 1.000000 0.818124  
## shot\_distance 0.818124 1.000000



There are also some similarities betweeb categorical variables although categorical variables cannot be colinear. They do not represent linear measures in Euclidean space. We use chi-square tests to determine independence of categorical variables.

## Outlier Analysis

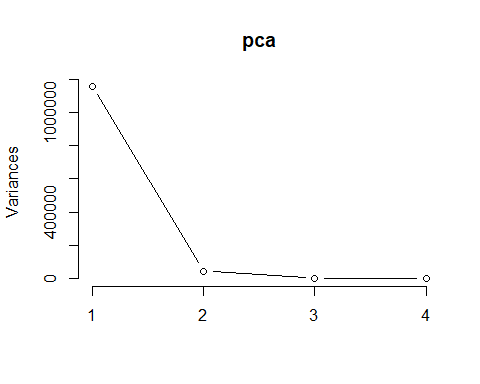
Based on Cooks’s D data and plain data analysis, we are seeing no outlier present in the selected variables. Here is the first 5 observations with highest cook’s D value. Since these values are less than 3, we assume that there are no outliers.

## Analysis Questions

We set out to test the following hyphothesis:

1. The odds of Kobe making a shot decrease with respect to the distance he is from the hoop.
2. The probability of Kobe making a shot decreases linearly with respect to the distance he is from the hoop.
3. 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.

To test these hyphothesis we evaluated several models. For the first we evelated a logisic regression model consisting of shot\_distance, shot\_type, combined\_shot\_type and a linear combination of the continuous variables time\_remaining, attendance, arena\_temp, avgnoisedb using principal componenet analysis. Our PCA analysis revealed that the first orthoganol combination contributed nealy 95% of the variance of these variables where as the remaining transformations did not contribute signifigantly.



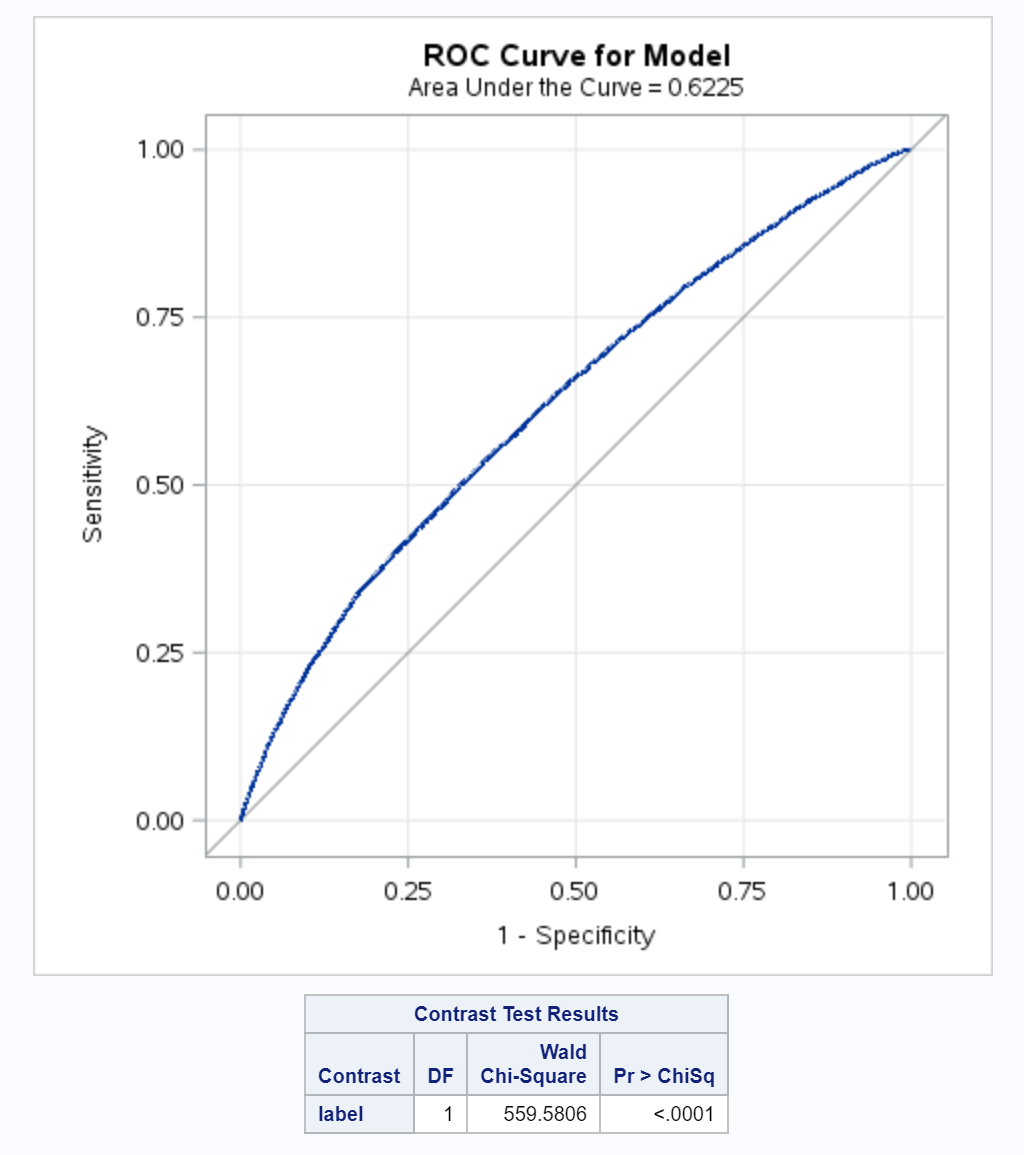
## Standard deviations (1, .., p=4):  
## [1] 1076.227723 208.308920 2.023717 1.961407  
##   
## Rotation (n x k) = (4 x 4):  
## PC1 PC2 PC3 PC4  
## time\_remaining 0.0008978239 9.999996e-01 -6.443052e-05 -9.139863e-06  
## attendance -0.9999989991 8.978220e-04 1.330830e-04 -1.085390e-03  
## arena\_temp -0.0001498820 -6.414719e-05 -9.998808e-01 1.543873e-02  
## avgnoisedb -0.0010831965 1.110603e-05 1.543888e-02 9.998802e-01

In final SAS model then we only included k1, the first orthagonal combination of PCA analysis.

class shot\_type home combined\_shot\_type(ref='Jump Shot') /param=ref;  
 model shot\_made\_flag(event='1') = shot\_distance shot\_type k1 combined\_shot\_type

Regression analysis revealed that shot\_distance, combined\_shot\_type, shot\_type, and k1 all appear to be statistically signifigant with p-values << 0.

Furthermore the wald ChiSquare test statistics (5 df, p-value << 0) for combined\_shot\_type and (chi^2 =8.23 , p-value << .0041) for shot\_type indicates that the overall effect of the categorical variables are independant and also statistically significant.



The ROC curve revealed an AUC of .63, which is less than ideal. .7 Is the usual target for this statistic.

The logistic model shows that or a 1 unit increase in shot\_distance, the odds of Kobe making his shot decreases by ~2%.