p8106 - Final Project - NBA Players Salary Prediction

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Introduction

Describe your data set. Provide proper motivation for your work.

What questions are you trying to answer? How did you prepare and clean the data?

Data Preprocessing

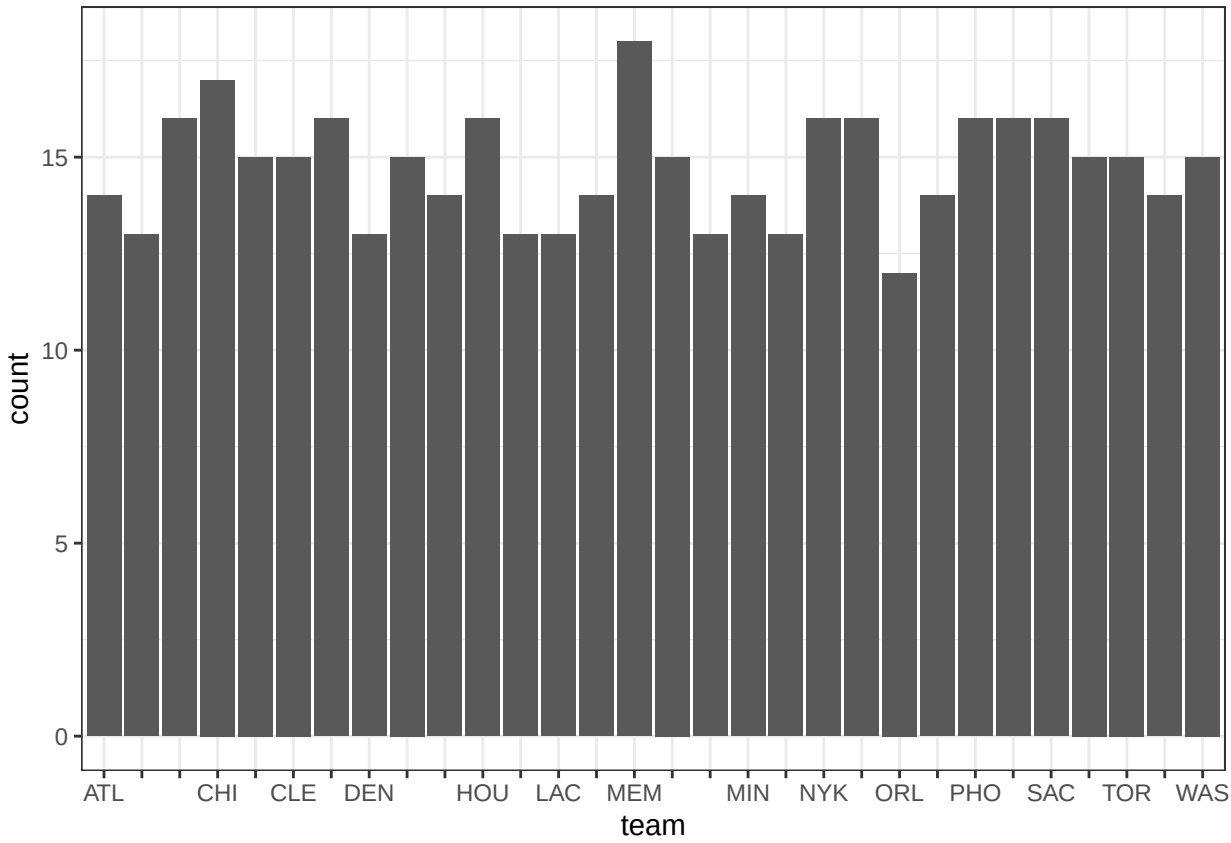
Part 0 - Data Preprocessing

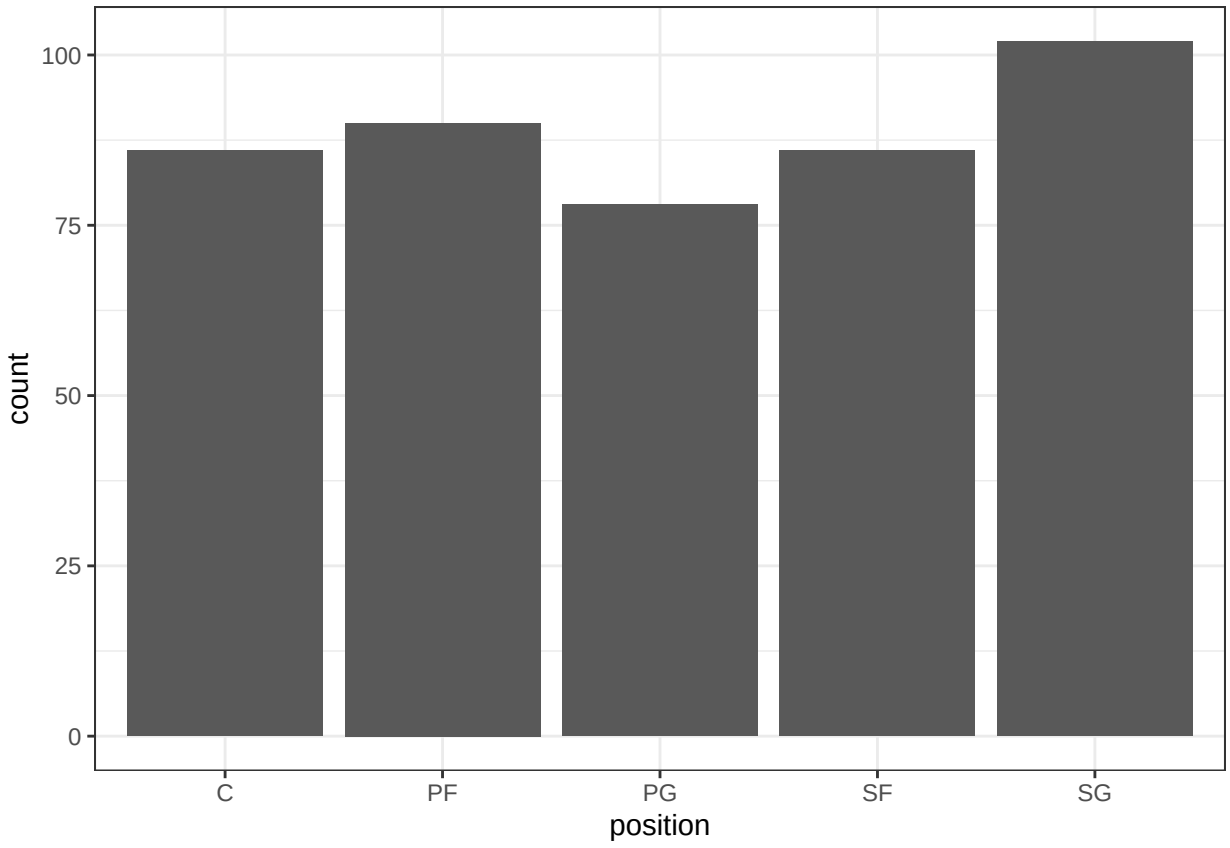
Part 1 - Exploratory Analysis

Since `minute` stands for minutes played per game, we will divided variables stands for counts by `minute` to get a rate. These variables includes `field_goal`, `fg_attempt x3p`, `x3p_attempt`, `x2p`, `x2p_attempt`, `free_throw`, `ft_attempt`, `offensive_rb defenssive_rb`, `total_rb`, `assistance`,`steal`, `block`, `turnover`, `personal_foul` and `point`.

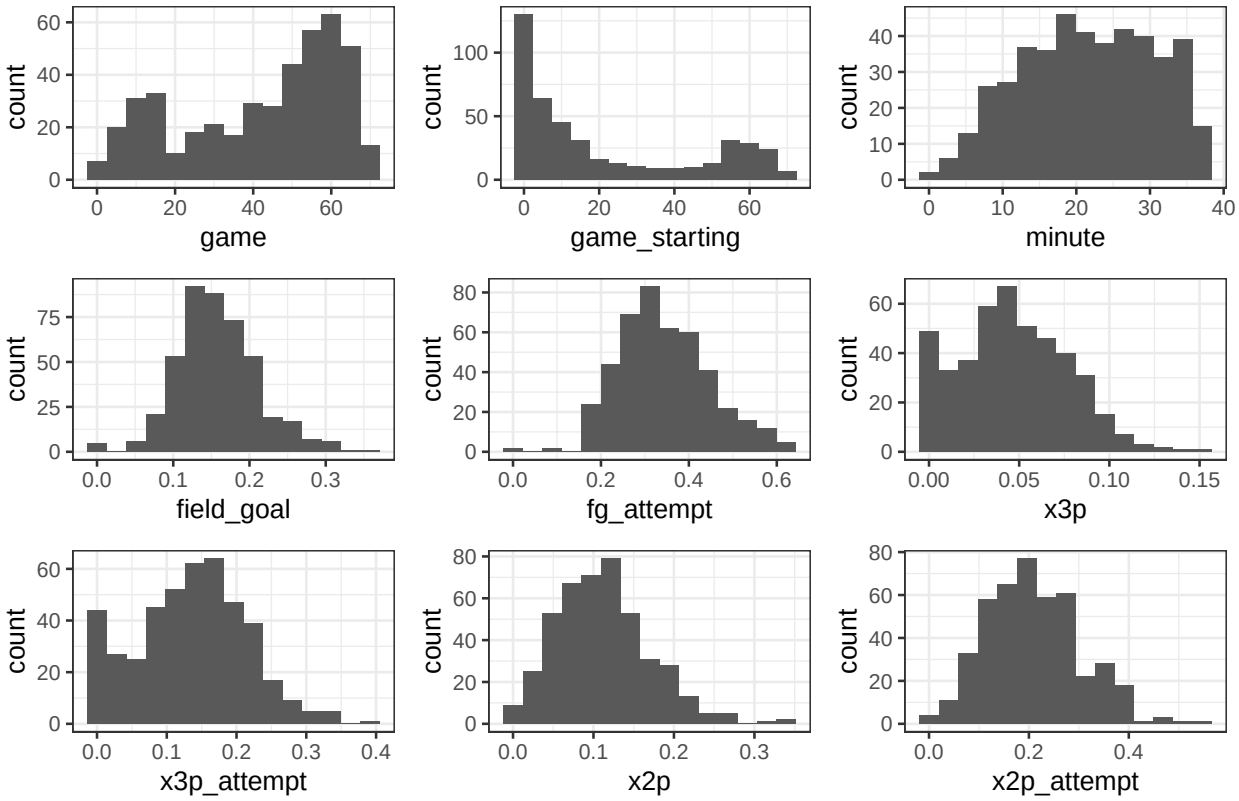
Univariate Analysis

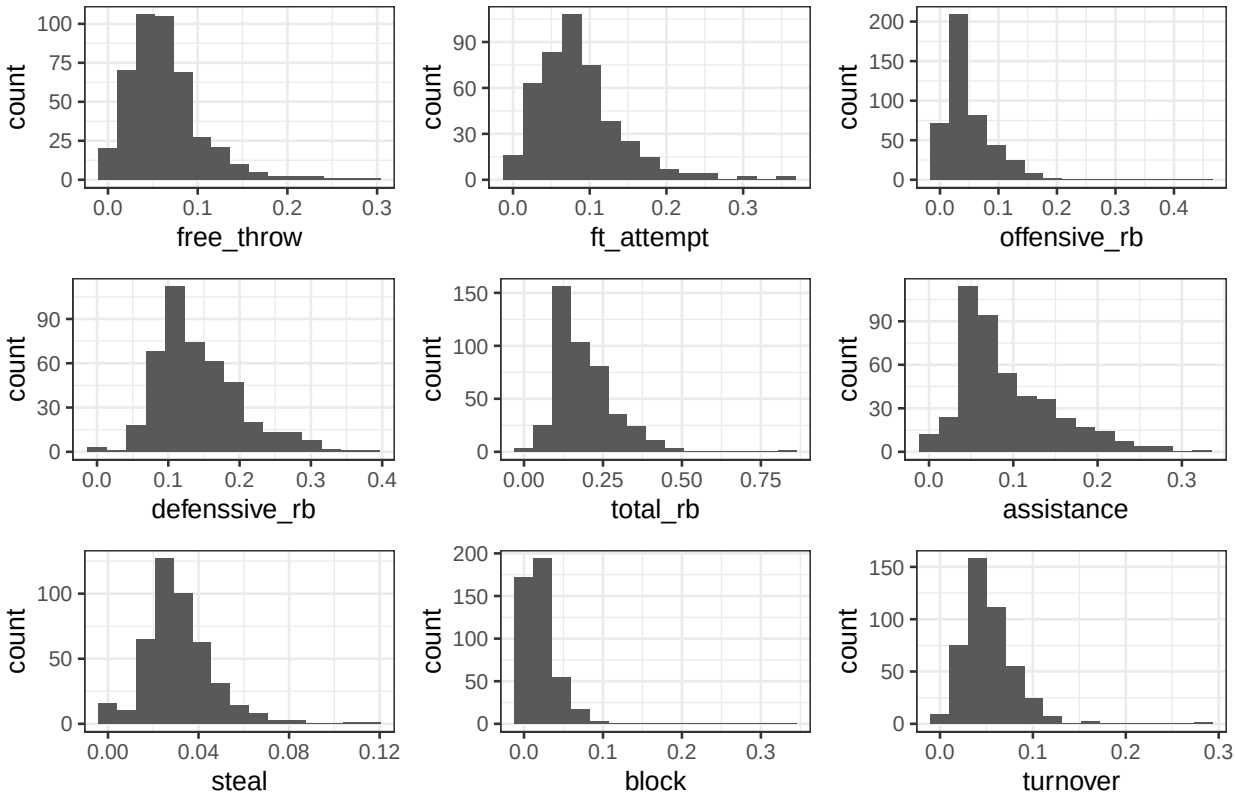
Distributions of the two categorical variables, `team` and `position`.

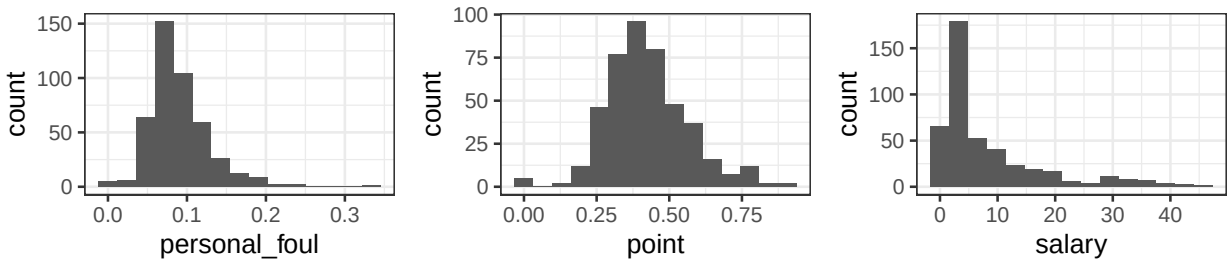

count
15
10
5
0
ATL
CHI
CLE
DEN
HOU
LAC
MEM
MIN
NYK
ORL
PHO
SAC
TOR
WAS
team



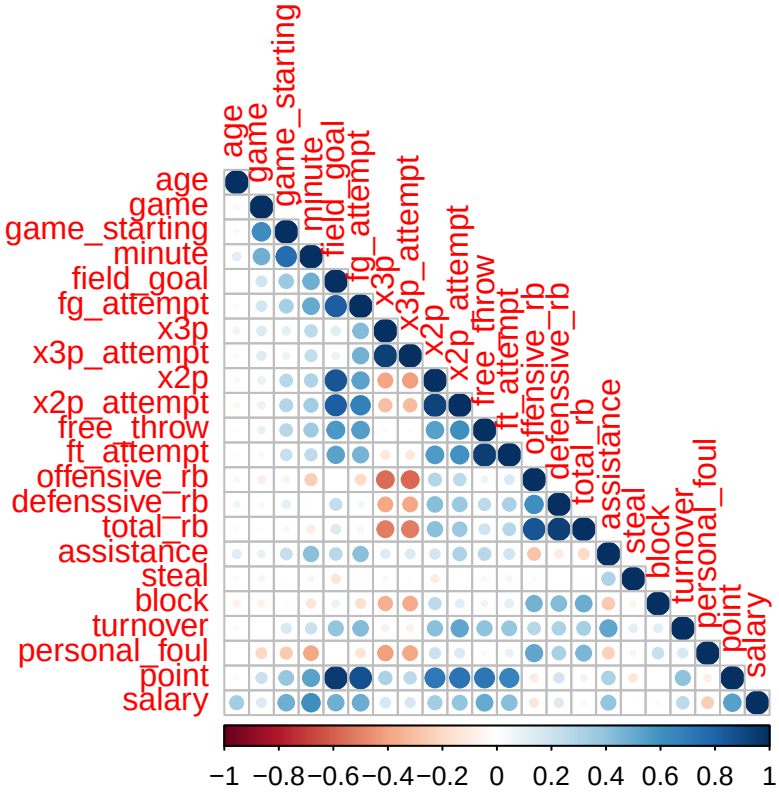
Distributions of other numeric variables.


Histograms of Predictive Variables (Group A)
count
game
game_starting
minute
field_goal
fg_attempt
x3p
x3p_attempt
x2p
x2p_attempt


Histograms of Predictive Variables (Group B)
count
free_throw
ft_attempt
offensive_rb
defenssive_rb
total_rb
assistance
steal
block
turnover

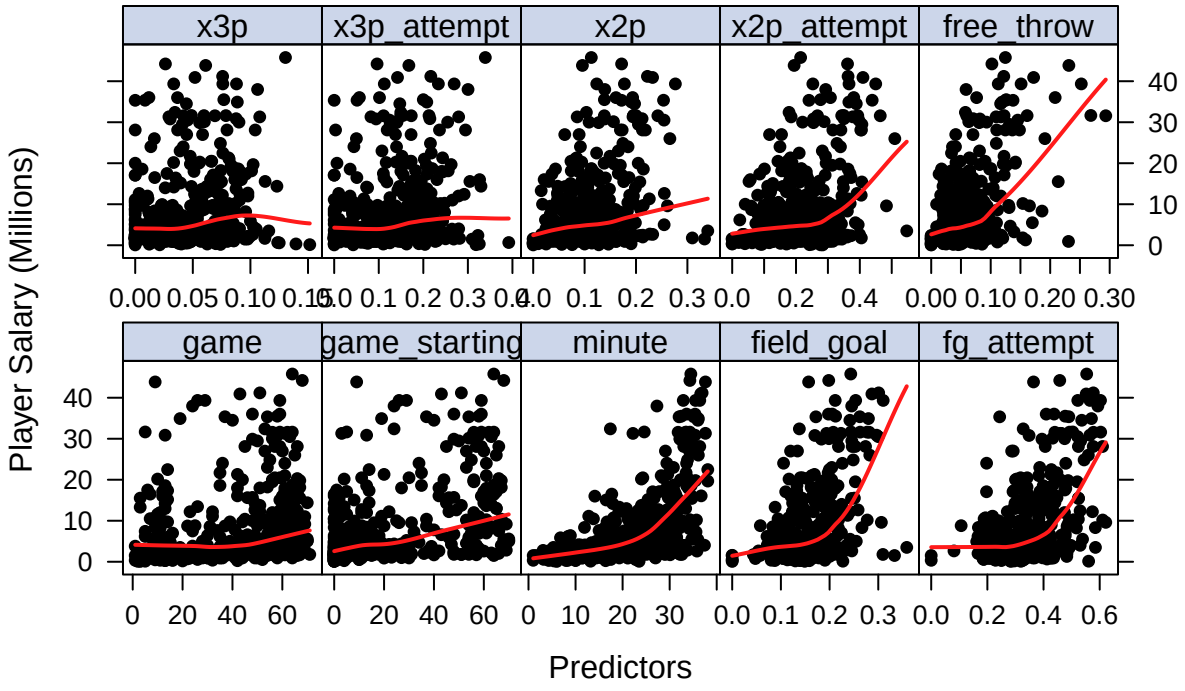

Histograms of Predictive Variables (Group C)
count
150
100
50
0
0.0
0.1
0.2
0.3
personal_foul
count
100
75
50
25
0
0.00
0.25
0.50
0.75
point
count
150
100
50
0
0
10
20
30
40
salary

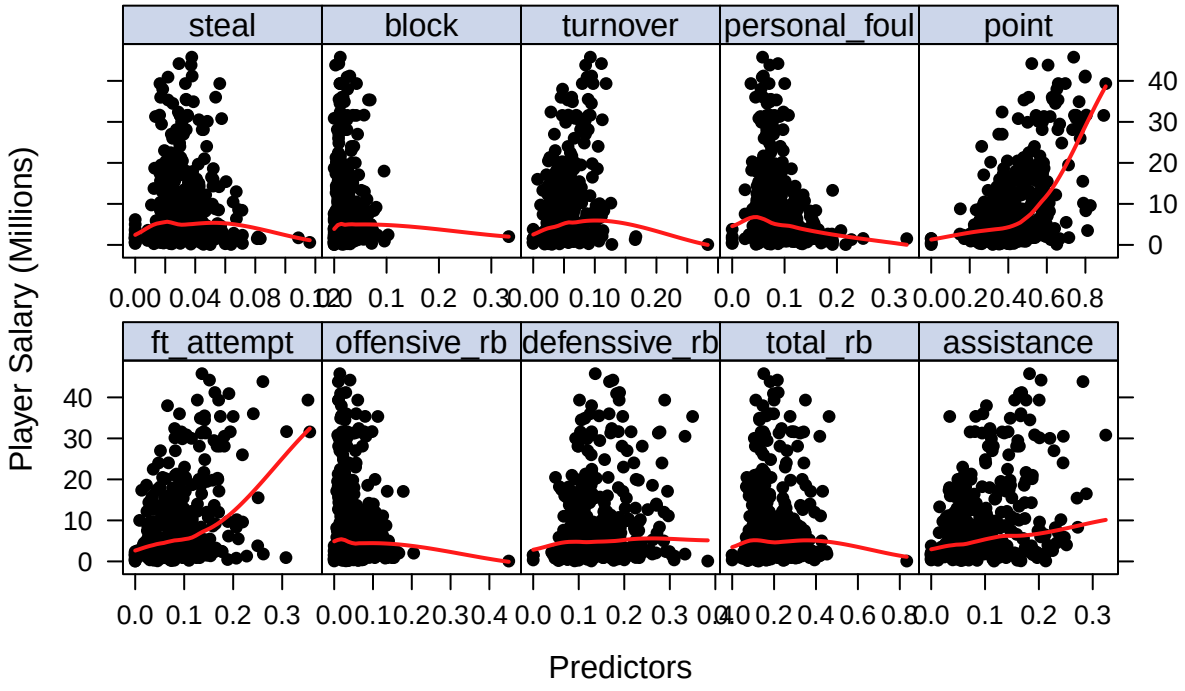
Correlation Analysis



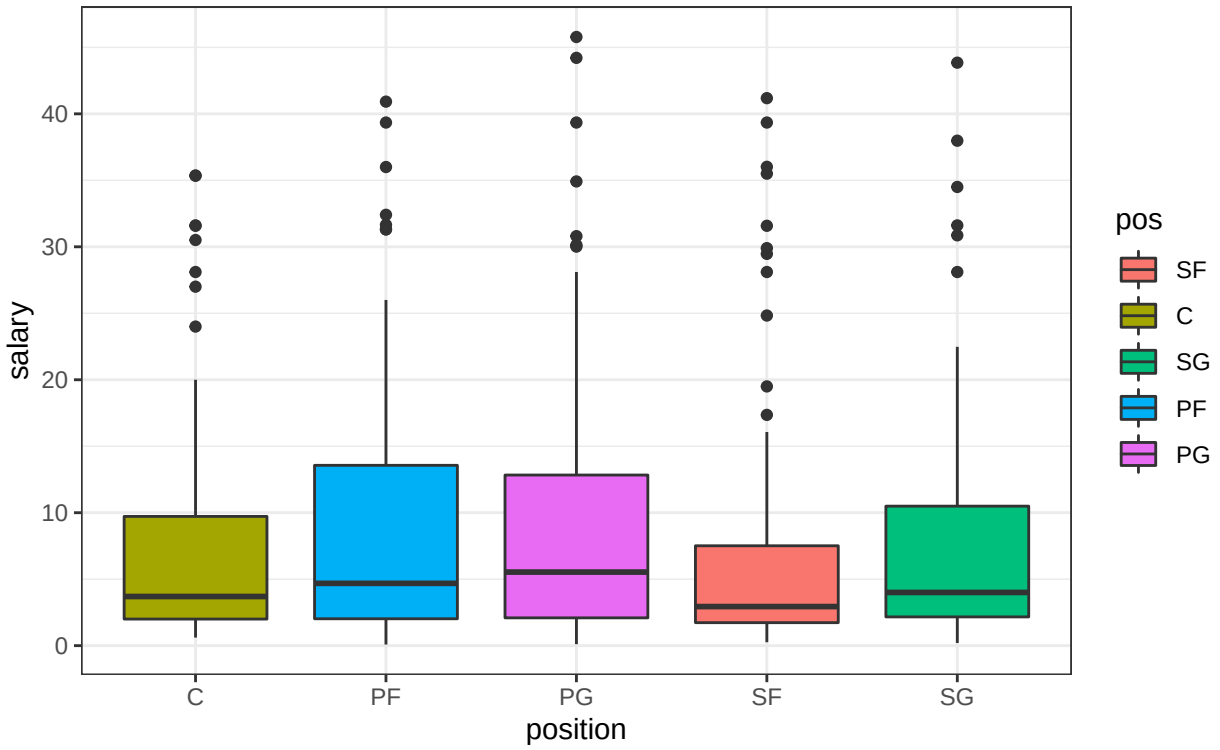
Analyzing trends in data

From numeric variables, we found that `stl`,`x3p`, `age`,`gs` seem to have some non-linear trends.





From categorical variable `position`, extremely high values in salary show in all positions and some teams.



Models

Data Partition

After getting an overview of data from exploratory analysis, we splitted the dataset into training (75%) and testing (20%). We would use 10 fold repeated cross validation to compare each model using training data and then select a best model to predict on testing data. Based on the exploratory analysis, we would build 8 models in four category: 1. Linear Regression: (1) simple Linear Regression Model, (2) Elastic-net Model, (3) Principal Component Regression Model (PCR) 2. Generalized Linear Regression: (4) Generalized Addictive Model (GAM), (5) Multivariate Adaptive Regression Splines Model (MARS) 3. Tree based Models Models: (6) Random Forest, (7) Generalized Boosted Regression Modeling (GBM) 4. Blackbox Model (8) neural network

Part 1 Linear regression

(a) Standard Least-Squared

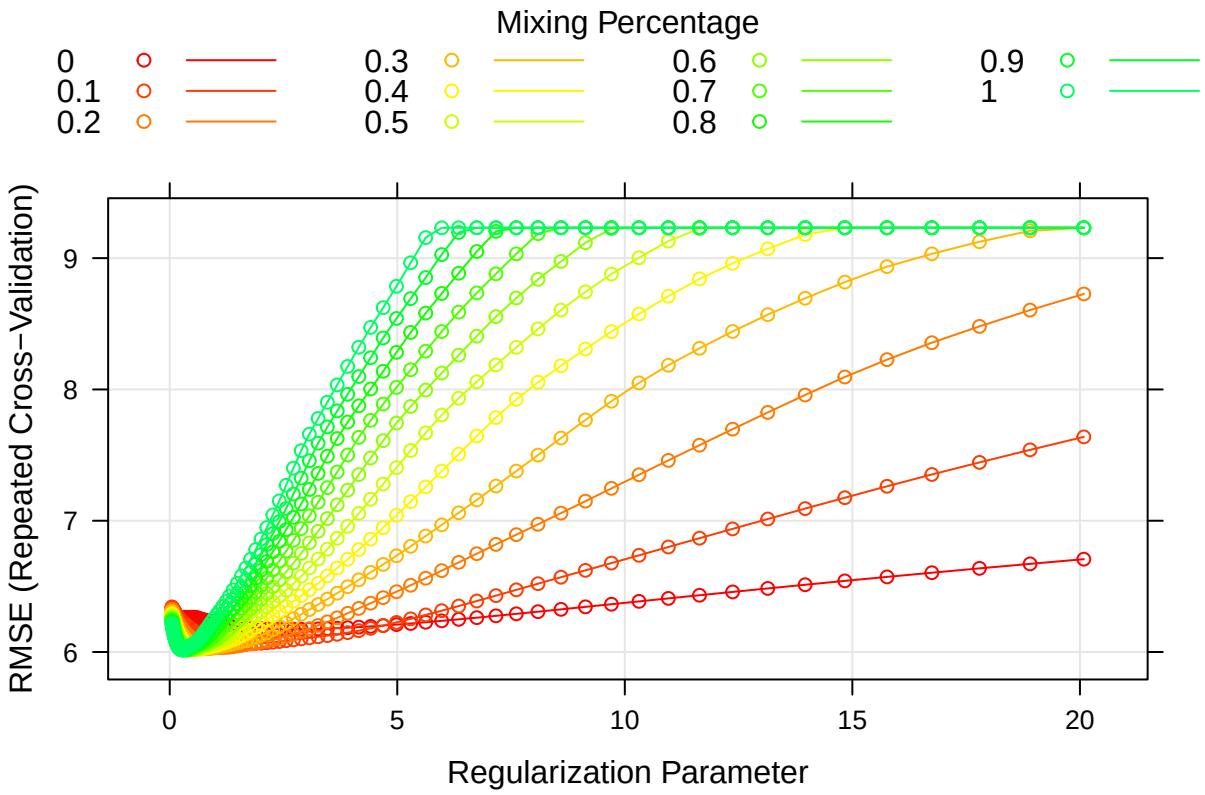
There is no tuning parameter for standard least-squared model.

```
## [1] 52.62129
```

(b) Elastic Net

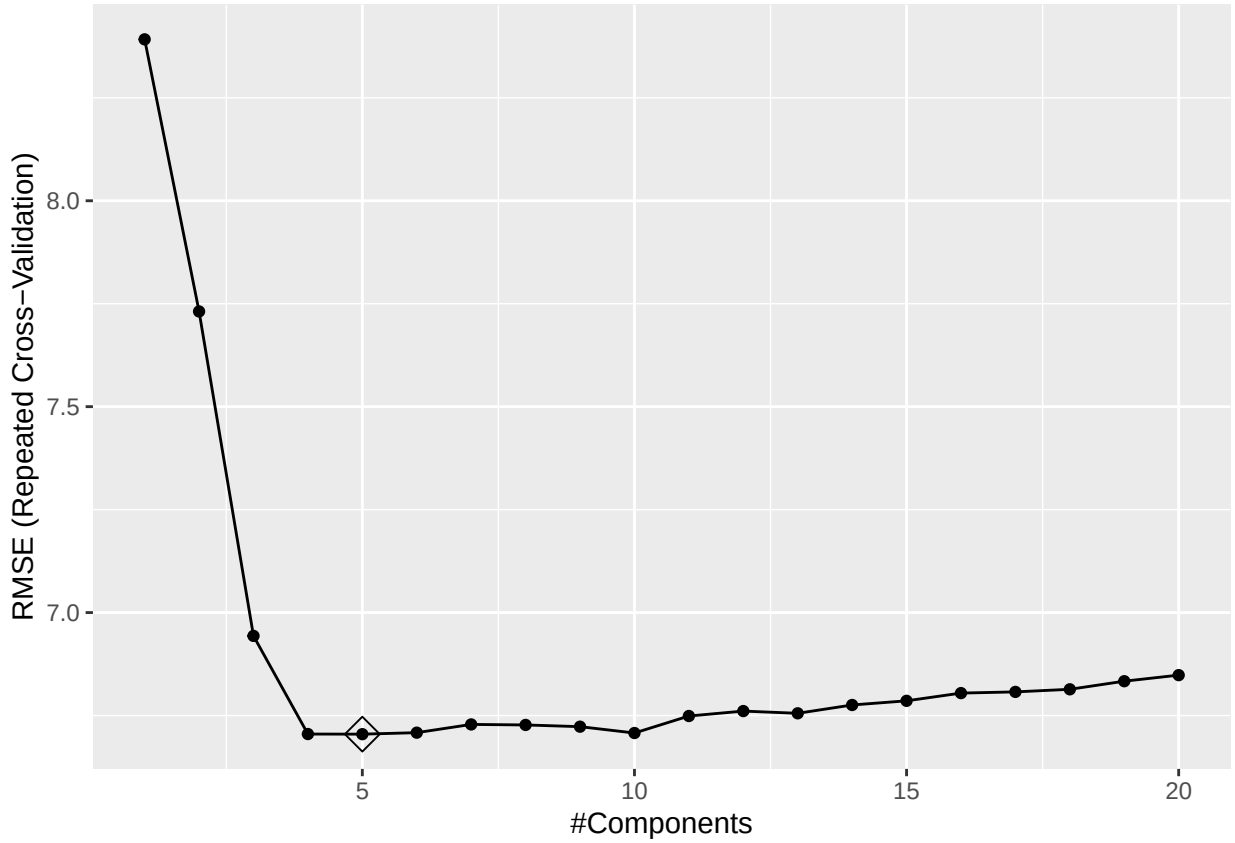
The elastic-net model has two parameter, which are alpha (compromise between LASSO and ridge) and lambda (the penalty term limits the number or magnitude of predictor coefficients). The elastic-net model reached its best tune at $\alpha = 1$ (i.e. LASSO model) and lambda = 0.27.

```
## [1] 0.2717072
```



###(c) Principle Component Regression

The tuning parameter of PCR is the number of predictors included in the final model. There are 5 components included in the model with minimum RMSE.



Part 2 Generalized Linear Regression

(a) GAM

There is no tuning parameter for GAM. The GAM model can capture the non-linear trend in the model, but it may have a high variance. `age`, `game_starting`, `assistance`, `personal_foul`, and `point` are statistically significant predictors at 0.0001 significant level.

```
##
## Family: gaussian
## Link function: identity
##
## Formula:
## salary ~ s(age) + s(game) + s(game_starting) + s(free_throw) +
##     s(ft_attempt) + s(defenssive_rb) + s(assistance) + s(block) +
##     s(personal_foul) + s(point)
##
## Parametric coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)    8.151      0.301   27.08   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Approximate significance of smooth terms:
##                    edf Ref.df      F  p-value
```

```
## s(age)           4.722  5.775 14.002  < 2e-16 ***
## s(game)          1.000  1.000  4.324 0.038422 *
## s(game_starting) 1.532  1.883 23.181  < 2e-16 ***
## s(free_throw)    7.542  8.452  2.095 0.022370 *
## s(ft_attempt)    2.098  2.759  0.603 0.485917
## s(defenssive_rb) 1.330  1.585  2.465 0.065744 .
## s(assistance)    1.114  1.217 17.575 2.90e-05 ***
## s(block)         1.000  1.000  0.009 0.923298
## s(personal_foul) 7.693  8.529  3.699 0.000214 ***
## s(point)         3.351  4.242  6.044 7.88e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## R-sq.(adj) =  0.652   Deviance explained = 68.5%
## GCV = 33.514  Scale est. = 30.265    n = 334
```

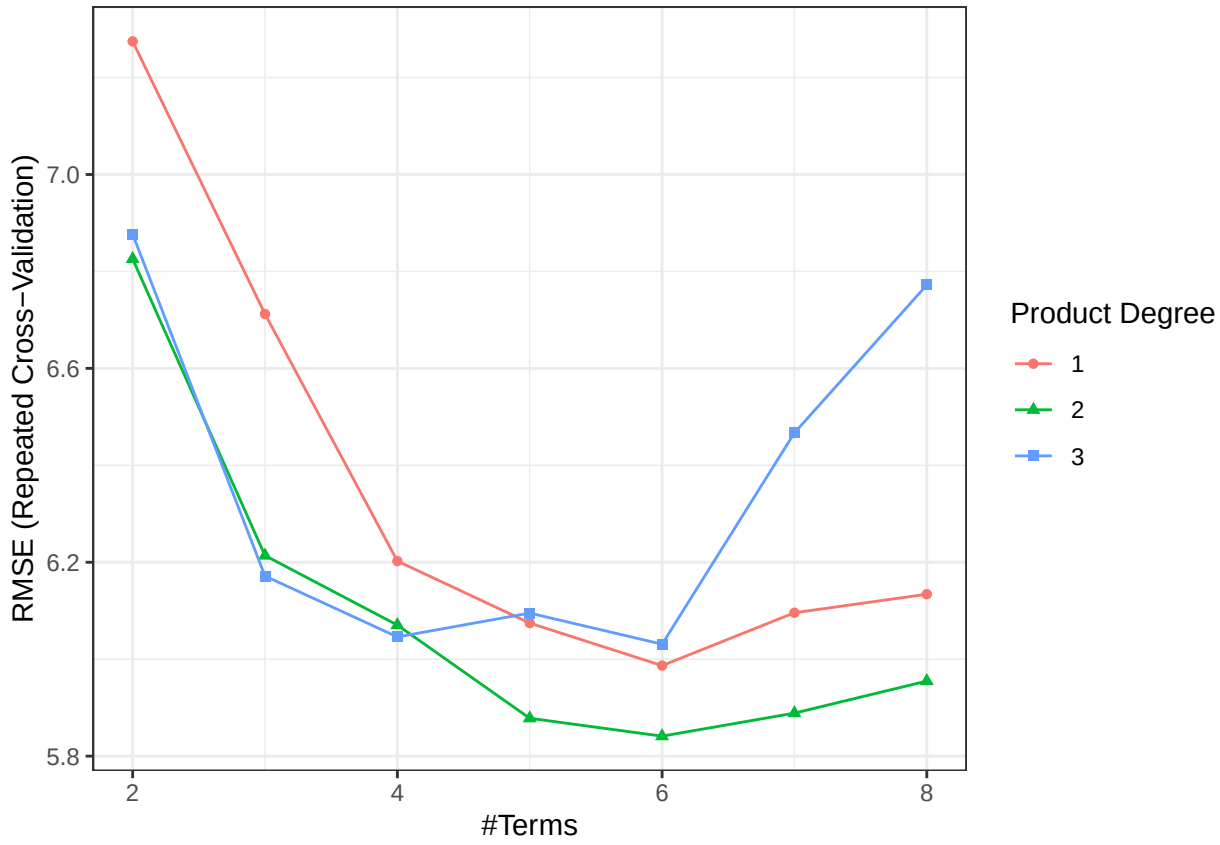
```
## [1] 51.72913
```

(b) MARS

The tuning parameter for MARS is `nprune` and `degree`. When attempting to fit the MARS model, we noticed that the RMSE increased drastically when degree is over 3 and nprune is over 8. Therefore, we would choose the range of degrees as 1:3 and range of nprune as 2:8. When number of terms is 6 and product degree is 2, MARS model reached its best tune and RMSE is lowest. The MARS model selected 6 of 69 terms, and 6 of 54 predictors. And the top 3 important predictors are: `age`, `minute`, `game`. MARS model is highly adaptive comparing with previous models and has a higher prediction accuracy.

```
##    nprune degree
## 12      6      2
```

```
## Call: earth(x=matrix[334,54], y=c(3.98,3.63,2,9...), keepxy=TRUE, degree=2,
##             nprune=6)
##
##                                      coefficients
## (Intercept)                               4.00399
## h(minute-28.7)                            0.80909
## teamWAS * h(free_throw-0.0879121)       146.14964
## teamCLE * h(free_throw-0.0879121)       803.51599
## h(age-22) * h(minute-22.8)                0.17834
## h(game-30) * h(free_throw-0.0879121)      4.82540
##
## Selected 6 of 69 terms, and 6 of 54 predictors (nprune=6)
## Termination condition: RSq changed by less than 0.001 at 69 terms
## Importance: age, minute, game, free_throw, teamWAS, teamCLE, ...
## Number of terms at each degree of interaction: 1 1 4
## GCV 27.39806    RSS 8426.154    GRSq 0.6863058    RSq 0.7094144
```




```
## [1] 40.30051
```

Model Comparison

The CV RMSE are shown as followed. We can see MARS model has lowest RMSE.

Table 1: RMSE of Different Models

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
LeastSquare	4.92	5.92	6.41	6.44	6.89	9.04	0
ElasticNet	4.36	5.44	5.88	6.02	6.59	8.22	0
PCR	4.07	6.10	6.78	6.70	7.41	8.80	0
MARS	4.04	5.38	5.82	5.84	6.45	8.25	0

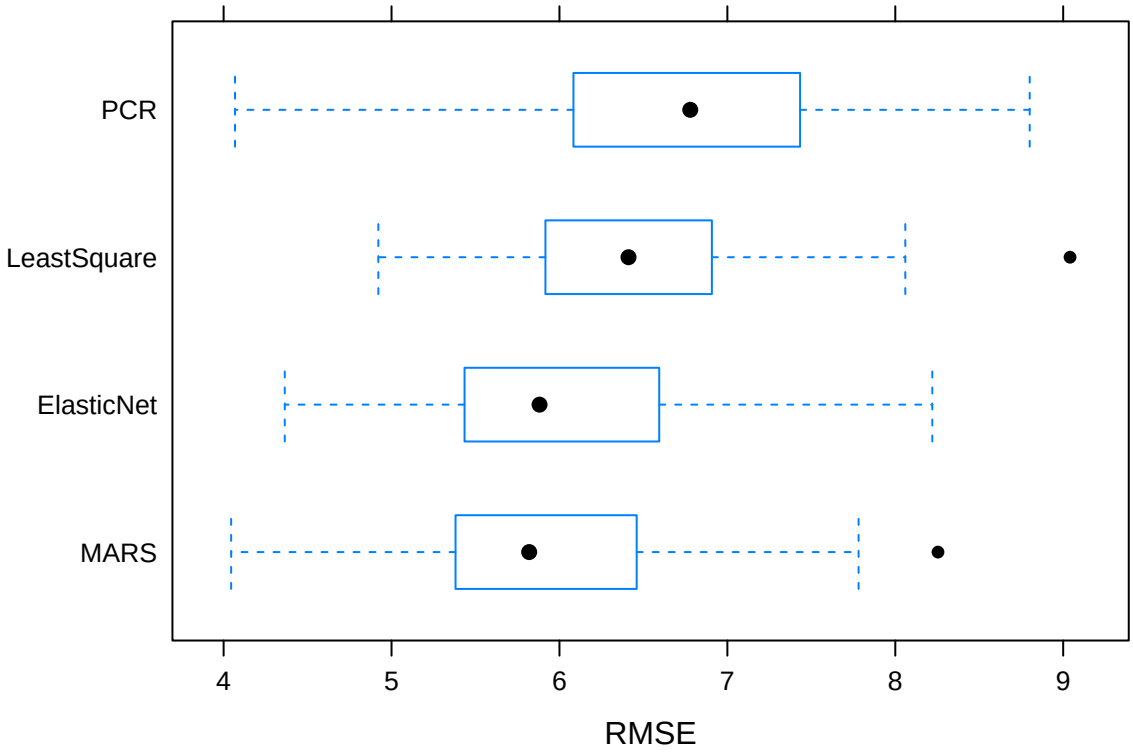


Table 2: RMSE of Different Models on Test Set

	Linear	ElasticNet	PCR	GAM	MARS
RMSE	7.25	7.21	7.34	7.19	6.35