# Regression Analysis on Salary of NBA Players

Tianyi Zhou[1], Fengjie Chen[2], Yikun Zhang[2]
[1]Information School, [2]Departments of Statistics,
University of Washington

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# Background

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- As the premier men's professional basketball league in the world, National Basketball Association (NBA) embraces high reputations in modern competitive sports and captures the eyes of millions of basketball fans worldwide.
- Big fans judge the performance of a superstar simply based on the point that he scored each game or in the whole season, while basketball mavens evaluate the capability and potential of a player by more statistics.
- Goal: Predict the salary of a NBA player in 2017 based on his season-long performance statistics.
- Evaluation metrics: We choose `Mean Sqaured Error(MSE)` as a metric to evaluate performace of a model in 5-fold cross validation.

# Data Description

- Datasets available on Kaggle, skip procedure of collection.
- Combine team statistics with individual statistics, remove adundant predictors and impute missing values by our understandings of those statistics

# Data Description

Table 1: Head of selected columns

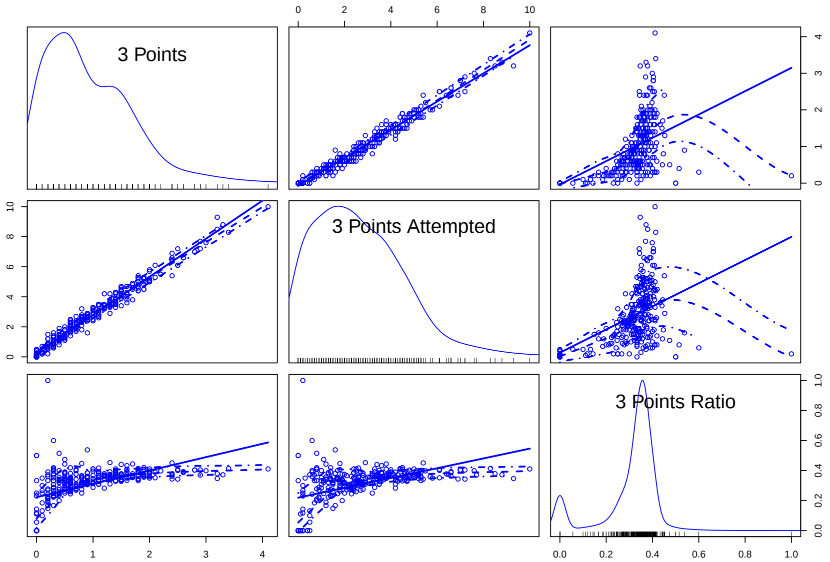
| Player | Age | Turnover | Foul | Points | Salary |
|---|---|---|---|---|---|
| Russell Westbrook | 28 | 1.9 | 2.3 | 31.6 | 26.5 |
| James Harden | 27 | 1.9 | 2.7 | 29.1 | 26.5 |
| Isaiah Thomas | 27 | 1.3 | 2.2 | 28.9 | 6.6 |
| Anthony Davis | 23 | 1.2 | 2.2 | 28.0 | 22.1 |
| DeMarcus Cousins | 26 | 1.5 | 3.9 | 27.0 | 17.0 |
| Damian Lillard | 26 | 1.3 | 2.0 | 27.0 | 24.3 |
| LeBron James | 32 | 1.6 | 1.8 | 26.4 | 31.0 |
| Kawhi Leonard | 25 | 1.1 | 1.6 | 25.5 | 17.6 |

# Data Preprocessing

# Data Preprocessing

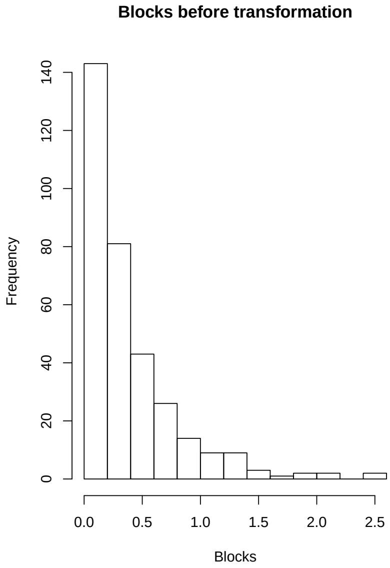
- Too many predictors (team,individual,social media etc.), relatively few samples, implicit relationships between predictors.
- Multicollinearity (Remove some predictors which can be determined by others, regression only on predictors with high correlation with responses,...)

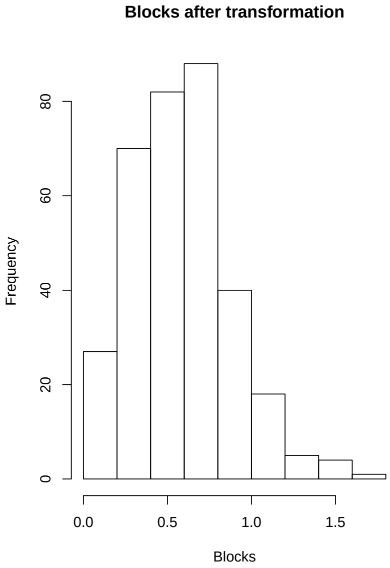
# Data Preprocessing



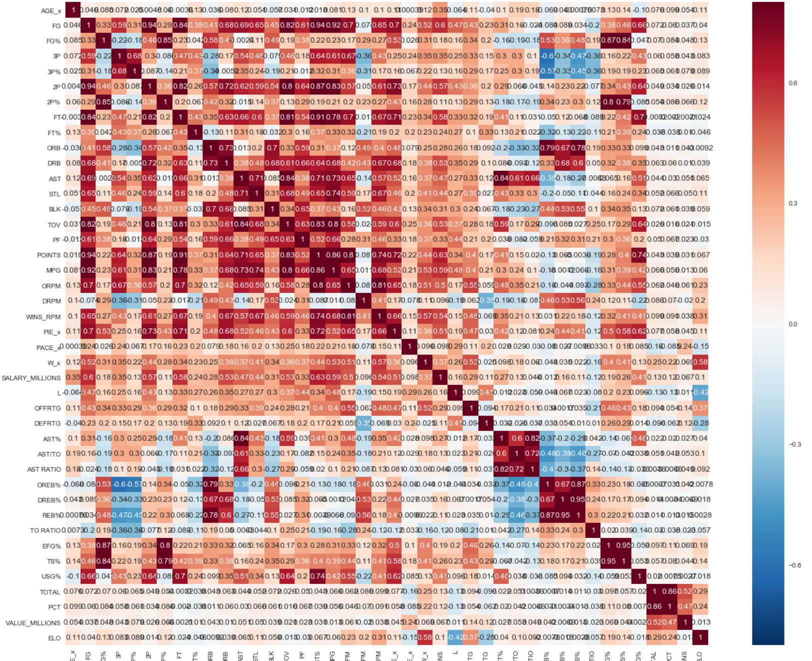
# Data Preprocessing

After preprocessing, data is of shape $335 \times 48$



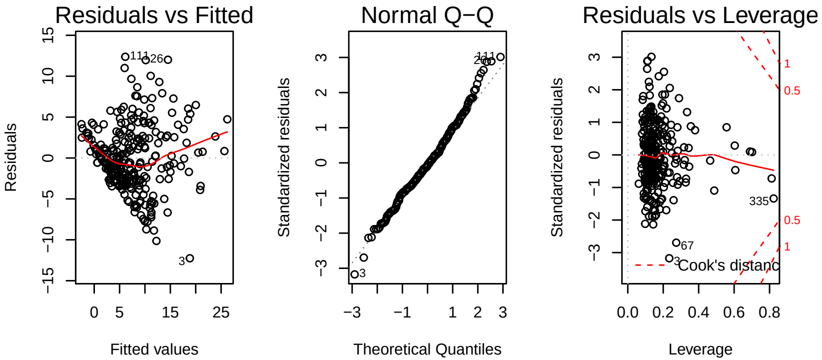
# Exploratory Data Analysis



# Linear Regression

# Linear Regression

- SALARY$\sim$ 42 continuous + 1 categorical with 6 levels (position)
- Leave one fold out, and train on other four folds

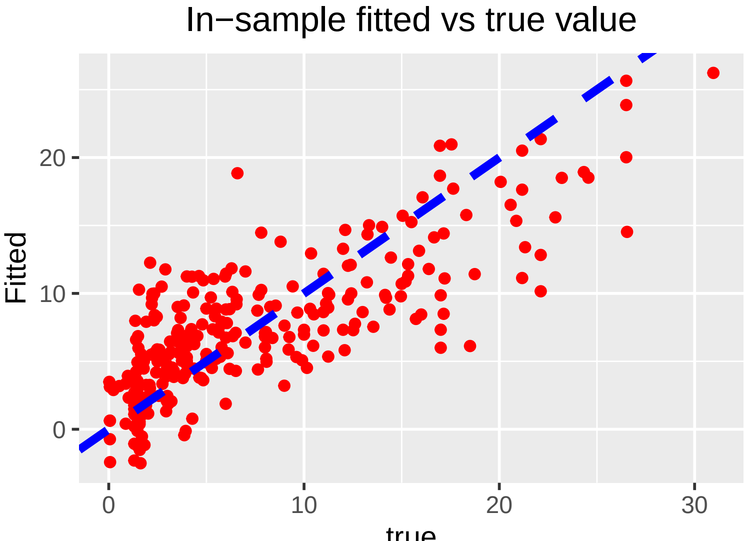


# Linear Regression

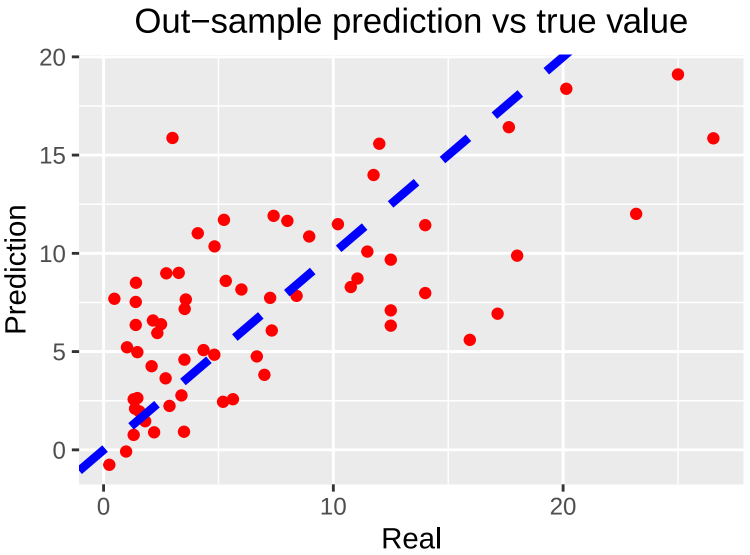
- The normal distribution seems plausible, and few outliers are presented.
- However, strong evidence is presented against constant-variance assumption, inference may not be solid.

## Linear Regression

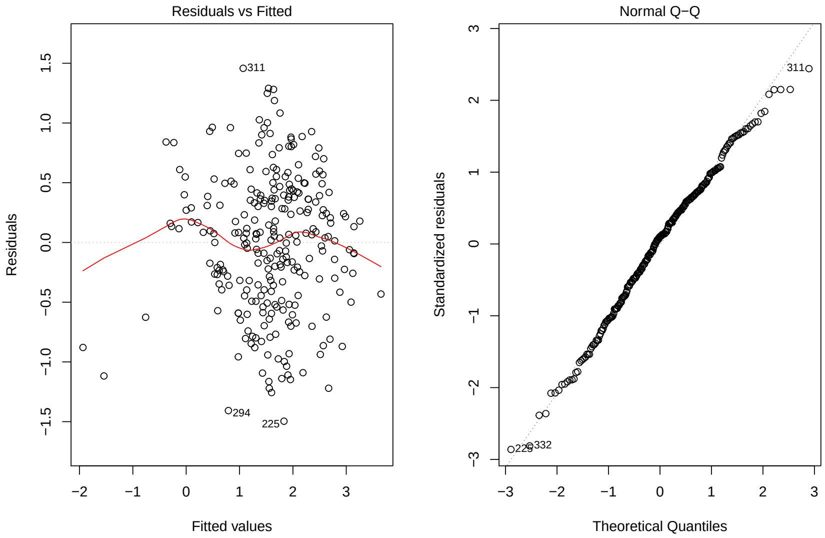
- conservative on the right-hand side, negative fitted value on the left-hand side. Corrected prediction or other models may be needed.



# Linear Regression



# Log Transformation of Response



# Log Transformation of Response

- Age, 2 point%, Foul, Win, Offensive rating, Team value are significant at 5% level.
- Compared with null model, error sum of square shrinkages by 47%.

# Linear Regression Results

- Linear model including all predictors: $\texttt{MSE} = 23.4$
- Correct the predicted value using $max(0, x)$, $\texttt{MSE} = 23.2$
- After log-scaling reponse, $\texttt{MSE} = 23.8$

# Regularized Linear Models

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**Lasso Regression**:

$$\min_{\beta} ||y - X\beta||_2^2 + \lambda||\beta||_1$$

**Ridge Regression**:

$$\min_{\beta} ||y - X\beta||_2^2 + \lambda||\beta||_2^2$$

- Lasso Regression: $\texttt{MSE} = 27.26$
- Ridge Regression: $\texttt{MSE} = 32.24$

# Variants of Lasso (I)

**Lasso ($L^1$ Penalty)**:

$$\min_{\beta} ||y - X\beta||_2^2 + \lambda \sum_i |\beta_i|$$

$$\equiv \min_{\beta} ||y - X\beta||_2^2 + f_\lambda(\beta)$$

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**SCAD Penalty**:

$$\min_{\beta} ||y - X\beta||_2^2 + n \sum_i p_\lambda(\beta_i; a),$$

where for some $a > 2$ and $\lambda > 0$

$$p_\lambda(\beta_i; a) = \begin{cases} \lambda|\beta_i|, & \text{if } |\beta_i| \leq \lambda, \\ -\frac{(\beta_i^2 - 2a\lambda|\beta_i| + \lambda^2)}{2(a-1)} & \text{if } \lambda < |\beta_i| \leq a\lambda, \\ (a+1)\lambda^2/2 & \text{if} |\beta_i| > a\lambda. \end{cases}$$

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**Dantzig Selector**:

$$\min_{\beta} ||\beta||_1 \qquad \text{subject to } ||X^T(y - X\beta)||_\infty \leq s,$$

where $s$ is a tuning parameter.

# Comparison of Models

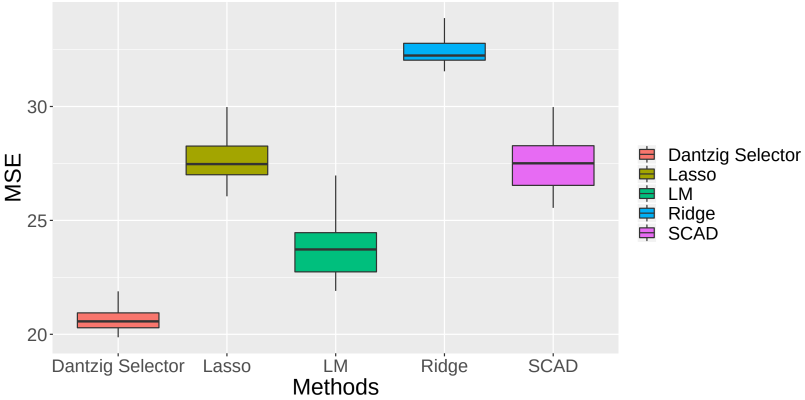


Figure 2: MSE of Different Models

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- Dantzig selector can further reduce MSE

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**Future Works**:

- Garner more predictors (e.g. social media stat), and collect more samples (from different years)
- Implement Grouped Lasso when more categorical variables are present

Thank you!