

IST 687 – MLB Dataset

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Overview of Dataset

- Major League Baseball dataset spanning from 1871 to 2016 from the [Lahman](#) package
- The [Lahman](#) R library contains 27 data frames
 - Dataset includes offense, defense, pitching, salary, all stars, hall of famers, attendance, and team statistics
- Pros:
 - [Widely known public database](#)
 - Plenty of resources and discussion boards
 - Has a large, complex volume of data available.
- Cons:
 - Large volume of data:
 - requires extensive cleaning
 - May get “lost in the information”- since there are a lot of variables to look at.
 - Need to be slightly familiar with baseball

SeanLahman.com

Baseball, data, and storytelling



Menu



Baseball database update available

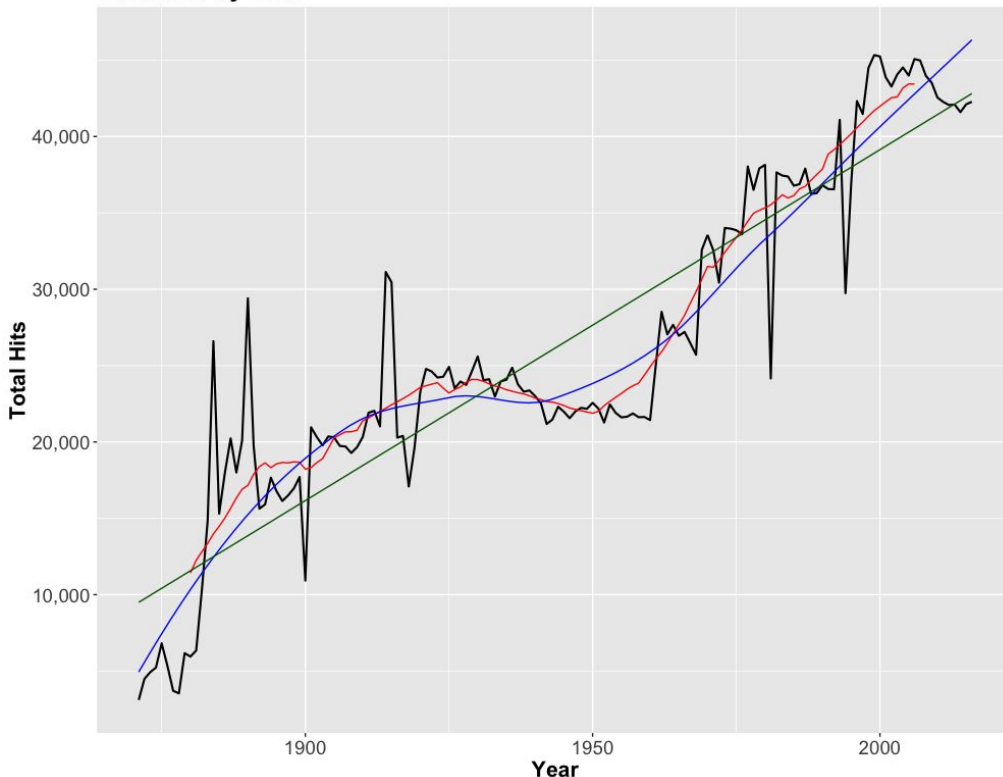
Posted on March 1, 2018 by Sean Lahman

Summary of Project

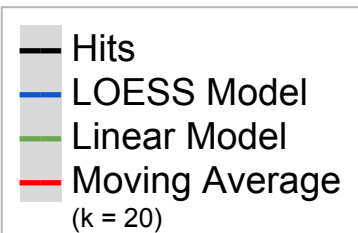
- [Batting Stats – Hits](#)
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- [Batting Stats – Hitsa](#)
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- [Batting Stats – RBIs](#)
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Batting Stats – Hits

Total Hits by Year

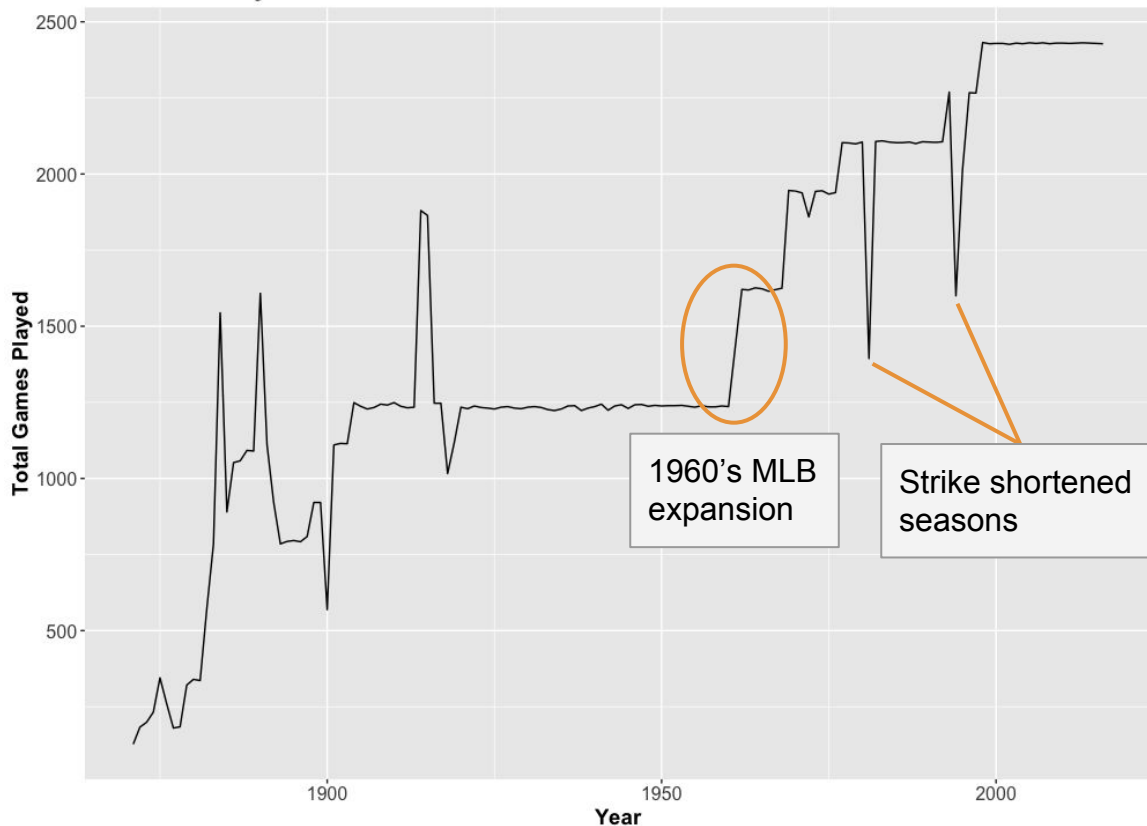


- Moving average using `rollmean()` in `zoo` library ($k = 20$)
- Linear model
 - $R^2 = 0.8241$
 - $p\text{-value} < 2.2e-16$
- LOESS model using `loess()` function in `ggplot2` ($\text{span} = 0.75$)



Total Games per year

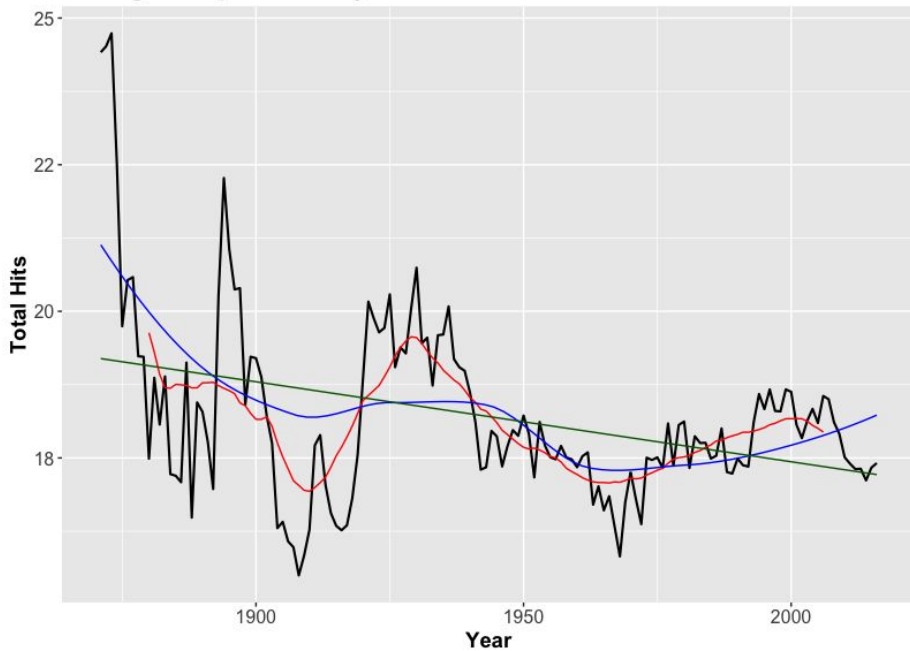
Total Games by Year



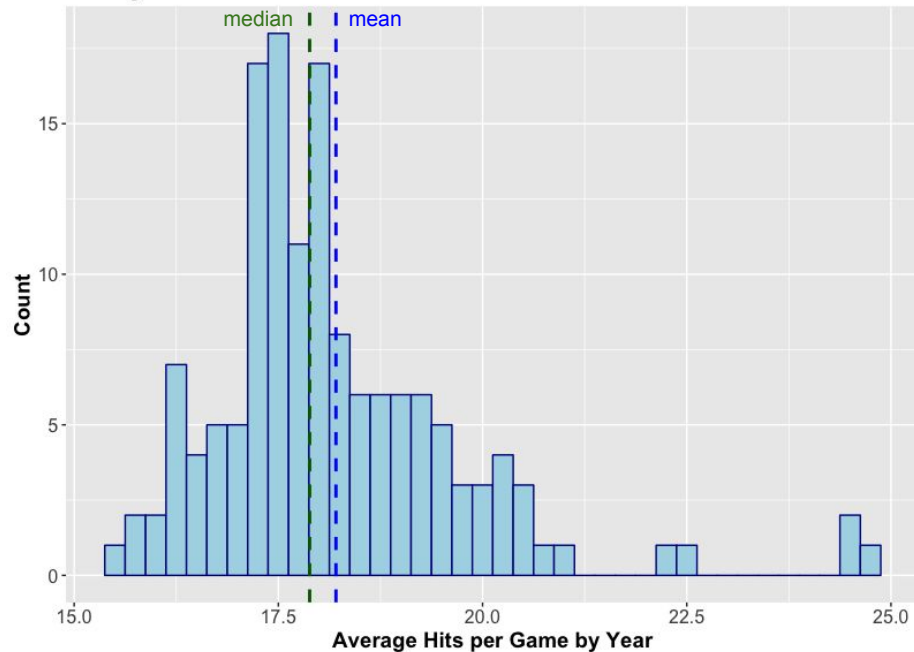
- MLB currently has 30 teams
 - Only 16 teams in 1903
- Each team has 162 scheduled games per year
 - Some games delayed by weather may be cancelled
 - A 163rd game may be played as a tie-breaker
- 1981 strike cancelled over 700 midseason games
- 1994–1995 strike ended the 1994 season 7 weeks early
- MLB had three leagues in the 1914–1915 seasons, and two since

Batting Stats – Hits

Average Hits per Game by Year



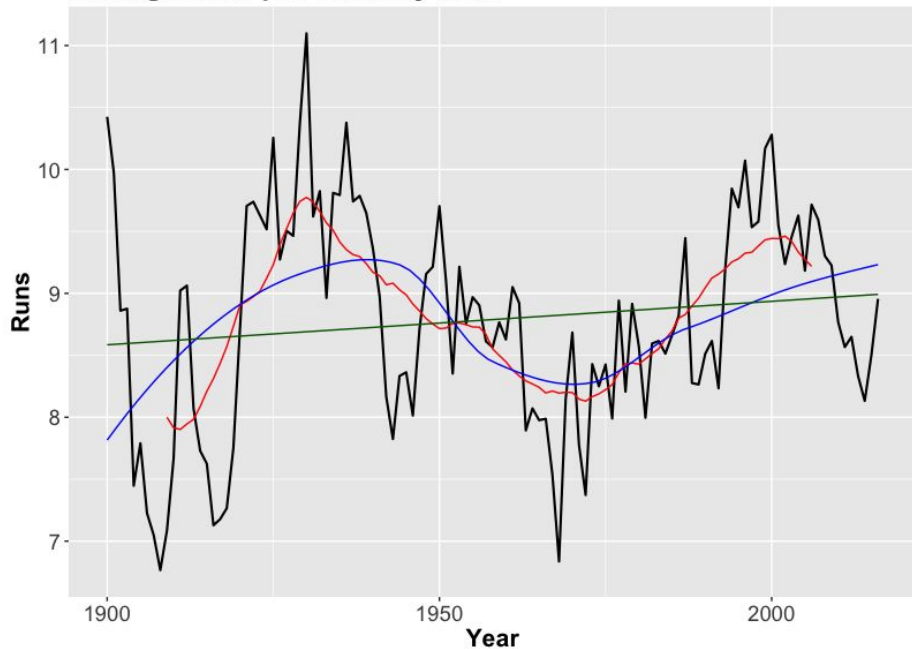
Histogram of Hits



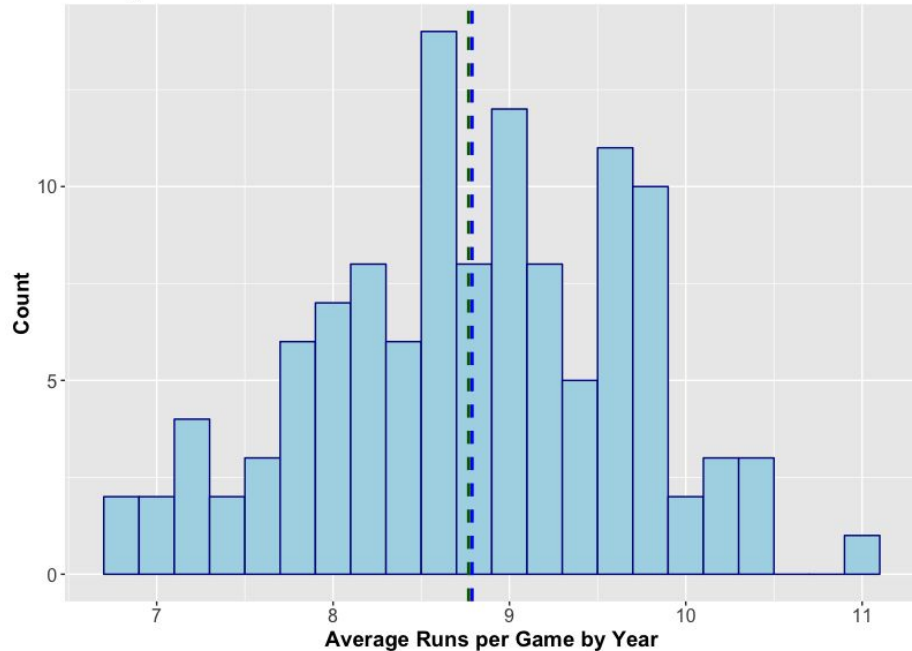
— Hits — LOESS Model — Linear Model — Moving Average ($k = 20$)

Batting Stats – Runs

Average Runs per Game by Year



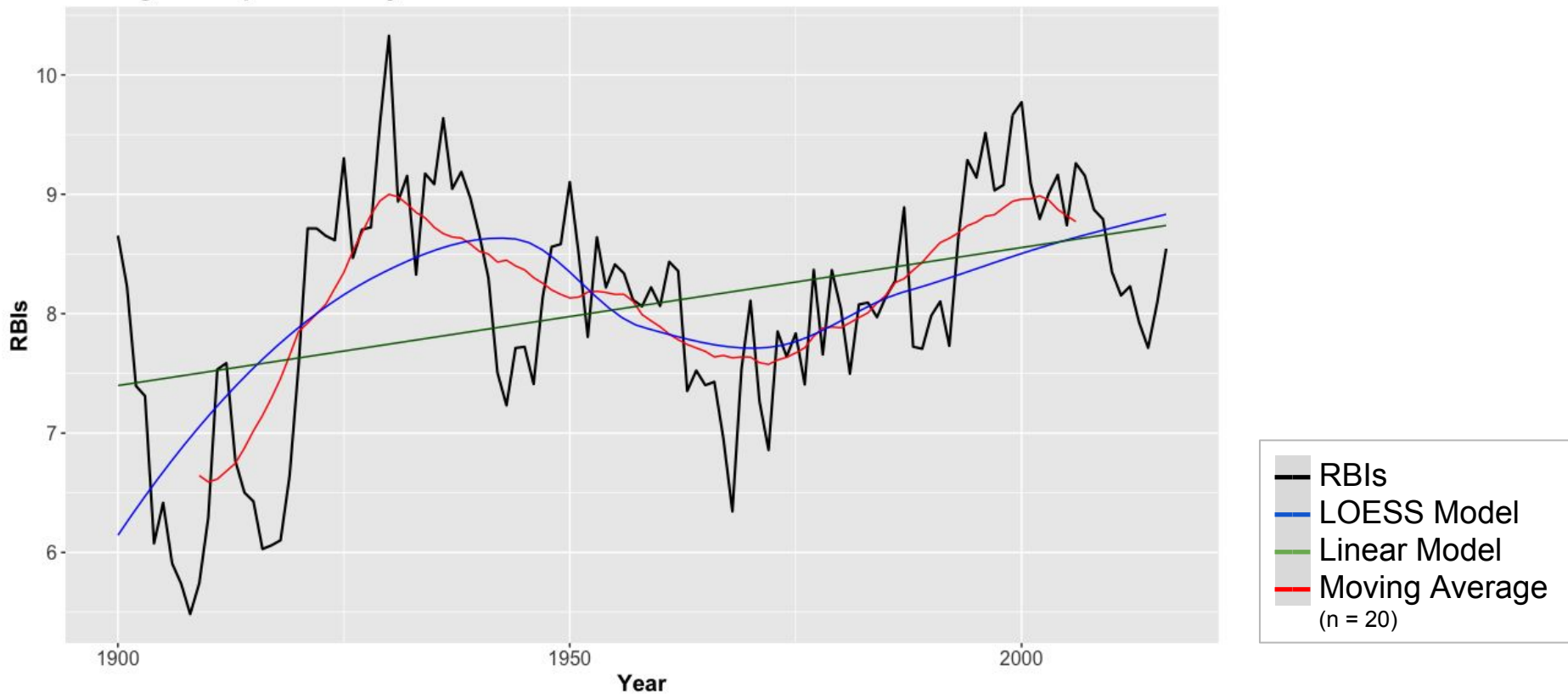
Histogram of Runs



— Runs — LOESS Model — Linear Model — Moving Average (k = 20)

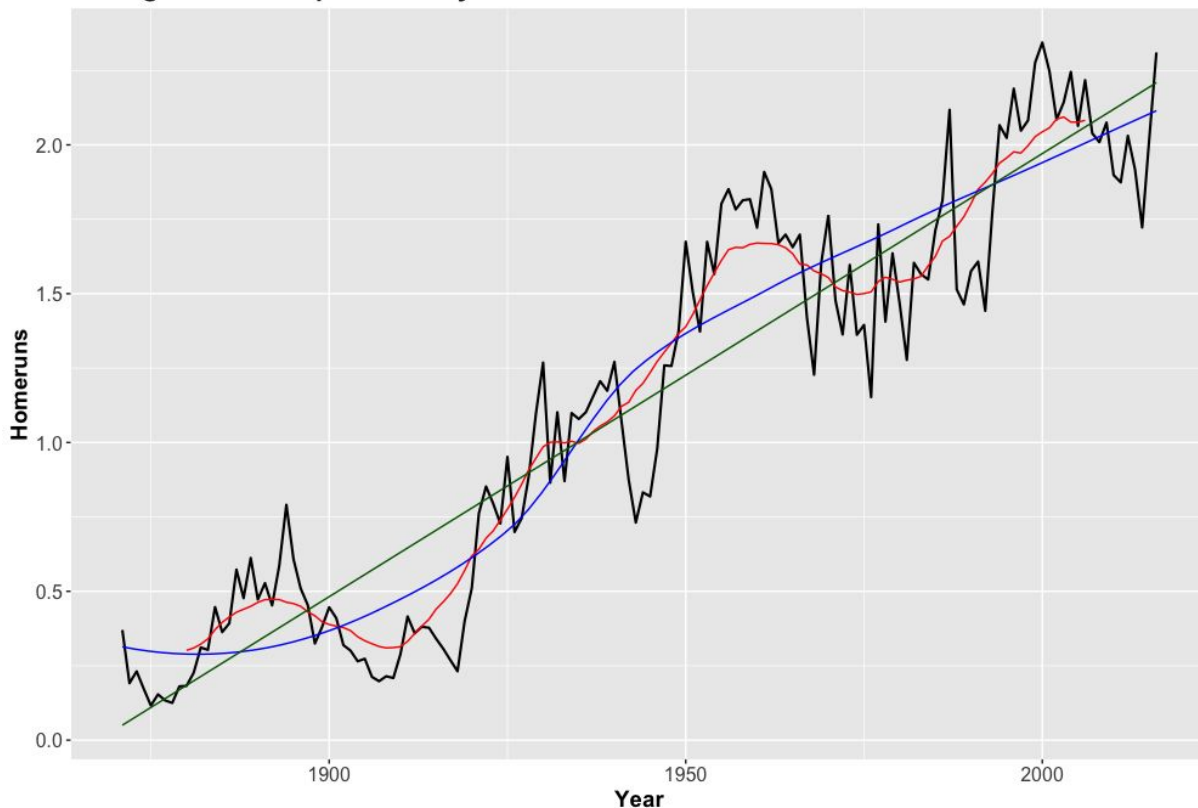
Batting Stats – RBIs

Average RBIs per Game by Year



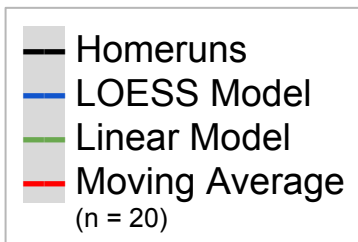
Batting Stats – Home Runs

Average Homeruns per Game by Year



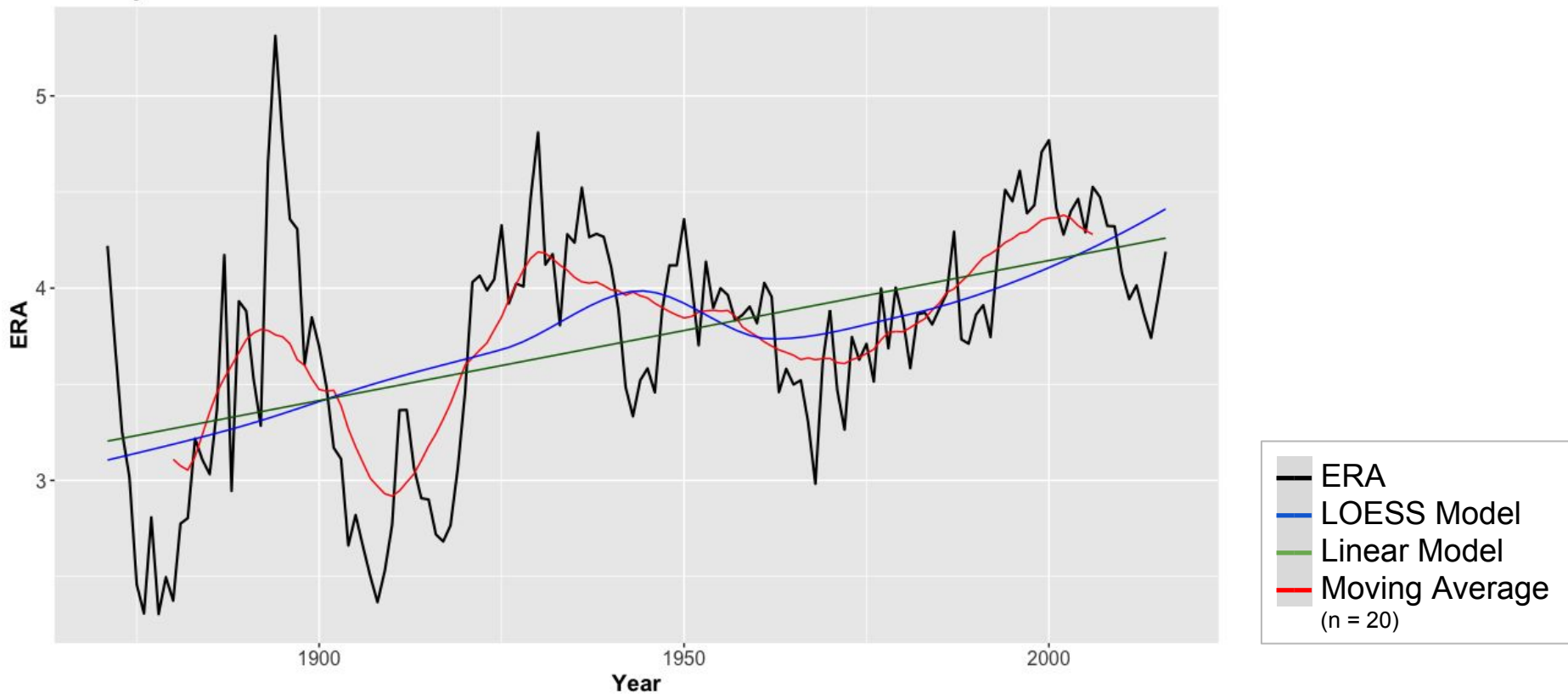
Strength of Linear Model

- $R^2 = 0.8663$
- p-value: $< 2.2e-16$



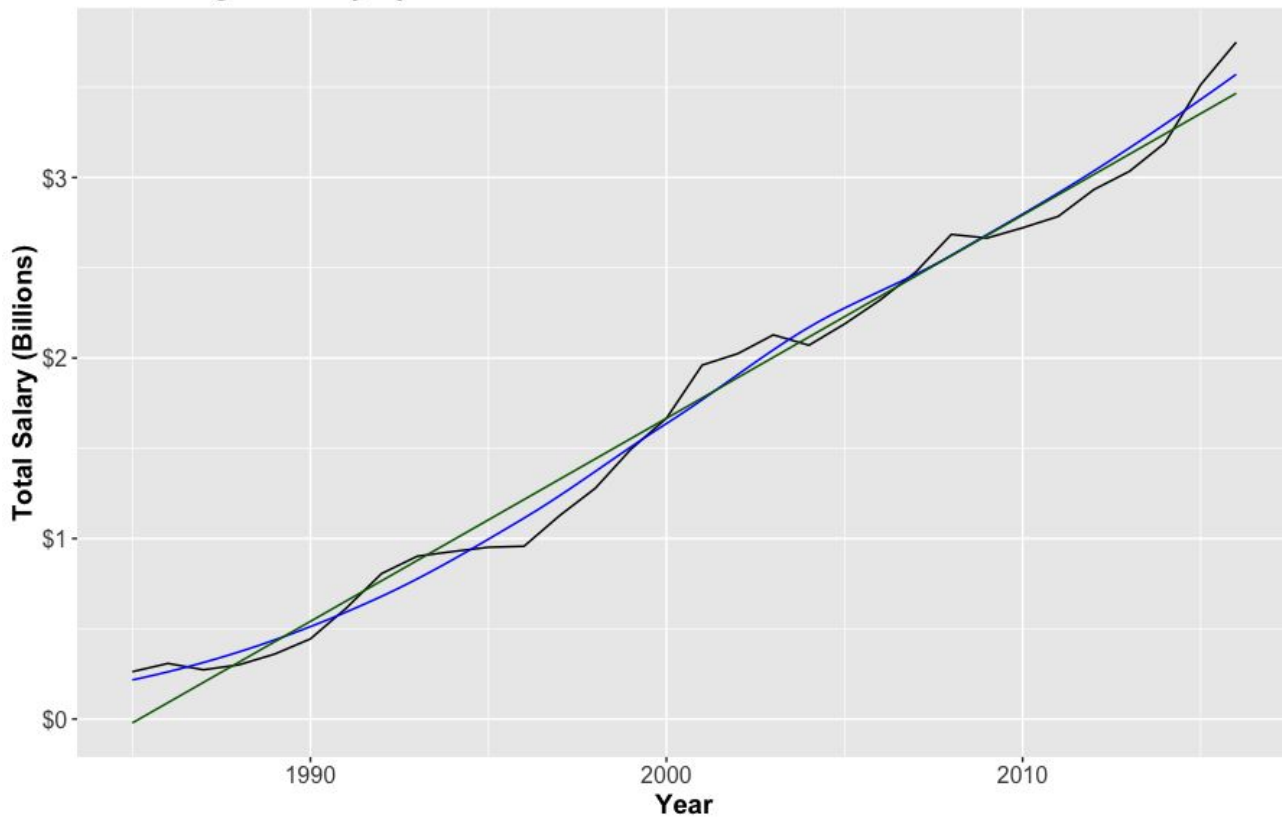
Pitching Stats – ERA

ERA by Year



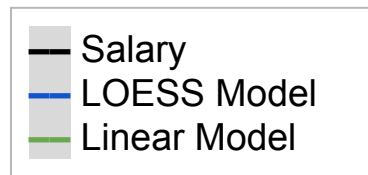
Total League Annual Salary

Total League Salary by Year



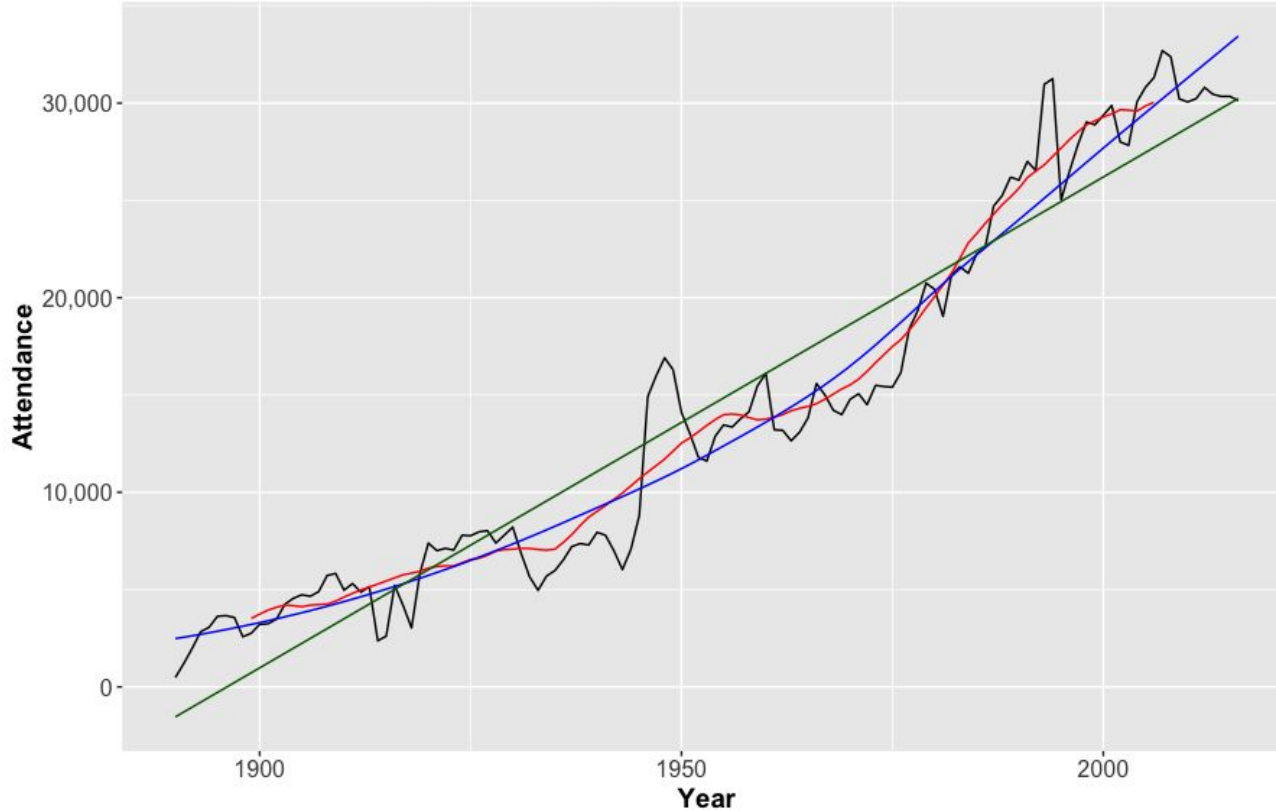
Strength of Linear Model

- $R^2 = 0.9845$
- p-value: $< 2.2e-16$



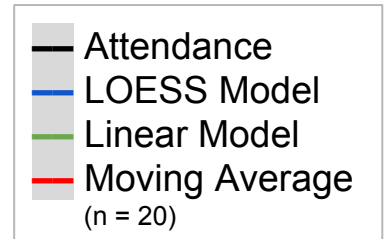
Attendance

Average Attendance per Game by Year



Strength of Linear Model

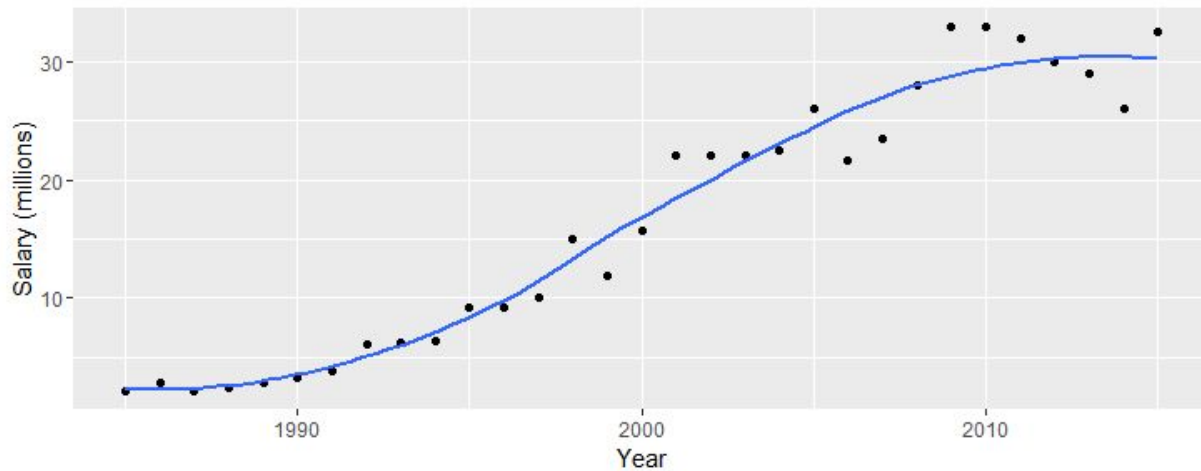
- $R^2 = 0.9181$
- p-value: $< 2.2e-16$



Highest MLB Salary by Year

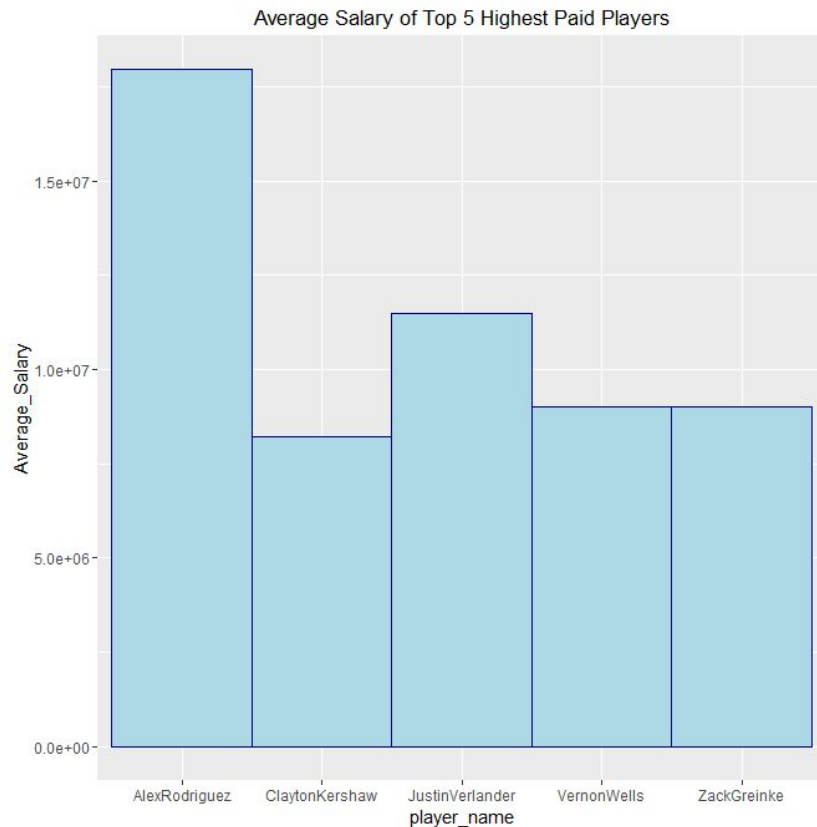
Based on highest player paid per year,
grouped by total team salaries

Highest:
Alex Rodriguez- \$33,000,000.00



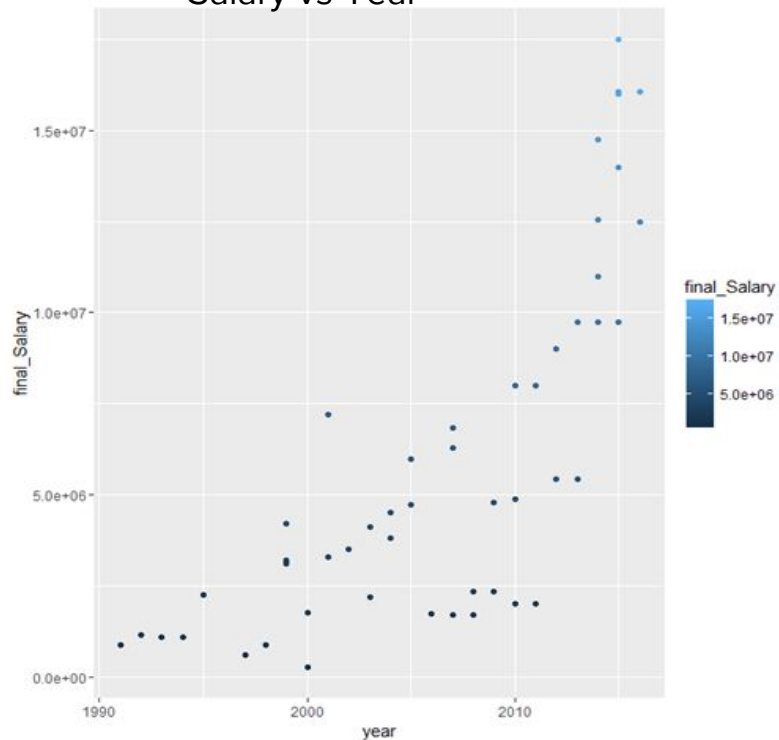
Top 5 Average Salaries

- Alex Rodriguez
- Clayton Kershaw
- Justin Verlander
- Vernon Wells
- Zack Greinke

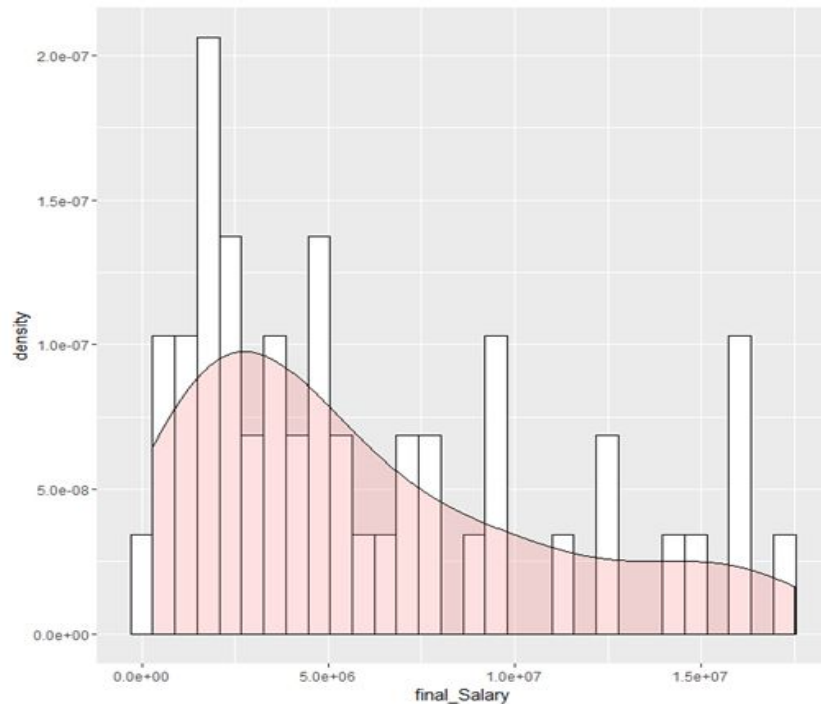


Salary of Hall of Fame Players

Salary vs Year



Salary Range of HOF Players

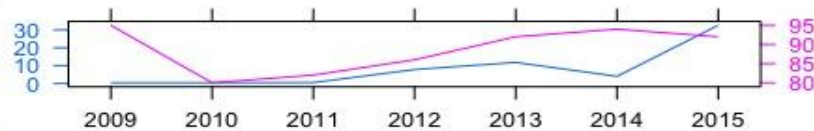


Top 5 Salaries and Team Wins

Salary and Team Wins

Kershaw

Salary (Millions)

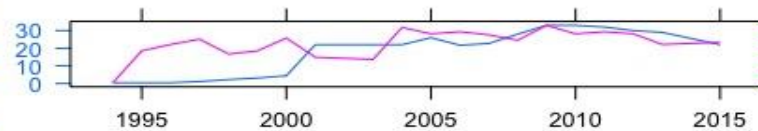


Year

Wins

Rodriguez

Salary (Millions)

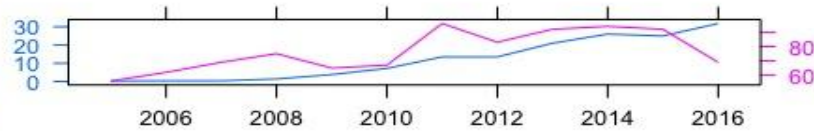


Year

Wins

Greinke

Salary (Millions)

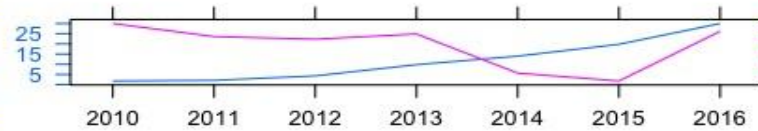


Year

Wins

Price

Salary (Millions)

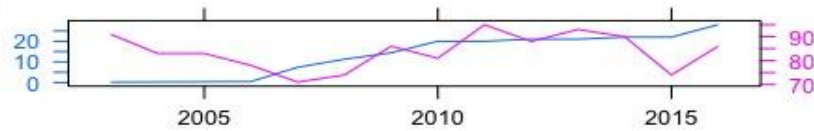


Year

Wins

Cabrera

Salary (Millions)



Year

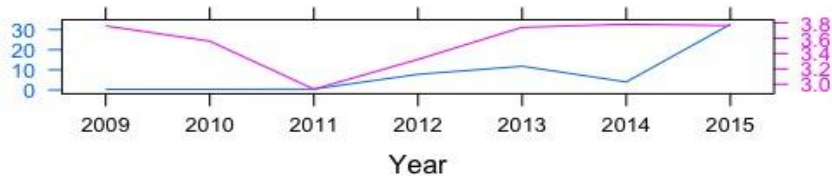
Wins

Top 5 Salaries and Team Attendance

Salary and Team Attendance (Year Total)

Kershaw

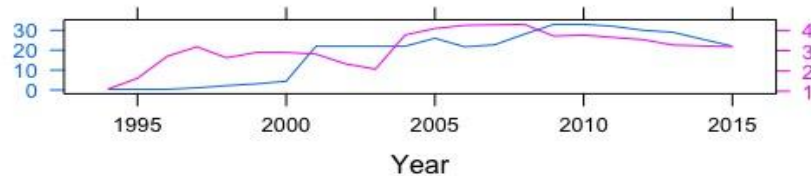
Salary (Millions)



Attendance (Millions)

Rodriguez

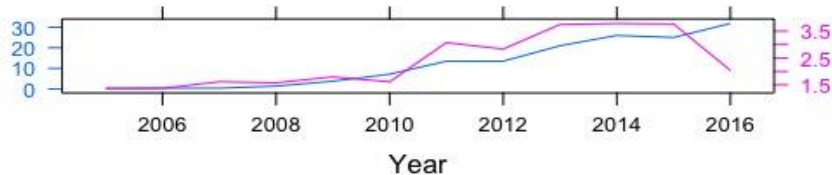
Salary (Millions)



Attendance (Millions)

Greinke

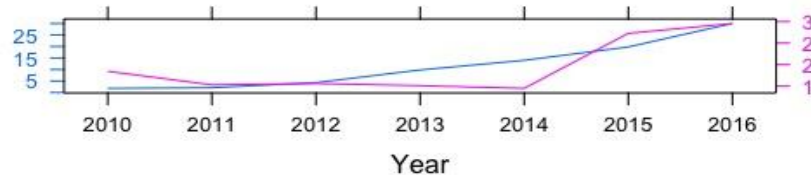
Salary (Millions)



Attendance (Millions)

Price

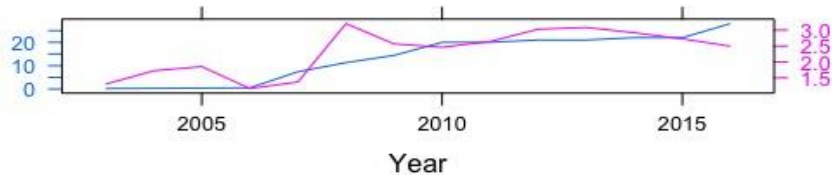
Salary (Millions)



Attendance (Millions)

Cabrera

Salary (Millions)



Attendance (Millions)

Model for Predicting Hitters' All Star Appearances

- Use only non-categorical variables
- Shuffled rows to randomize order of data, and split data into training and test set (80% train, 20% test)
- Generate the model with `glm()` and a logit model
 - Estimates the likelihood a player will have an All Star appearance based on their stats
- The model determined that most stats were significant in predicting All Star appearances, with the exception of doubles, triples, hit-by-pitch, sacrifice fly, and grounded into double play

```
Call:
glm(formula = asAppearance ~ ., family = binomial(link = "logit"), data = as.train)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-2.5490	-0.2799	-0.2135	-0.1714	3.1304

Coefficients:

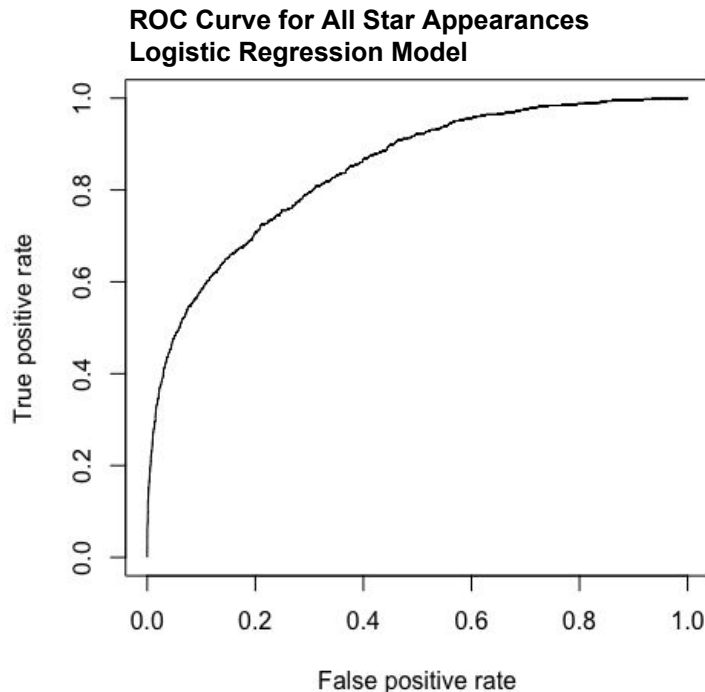
	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	19.7349588	2.7757849	7.110	1.16e-12 ***
birthYear	-0.0159859	0.0013787	-11.595	< 2e-16 ***
weight	0.0091644	0.0013651	6.713	1.90e-11 ***
height	0.0762822	0.0120807	6.314	2.71e-10 ***
G	0.0151576	0.0013901	10.904	< 2e-16 ***
AB	-0.0169273	0.0008828	-19.176	< 2e-16 ***
R	0.0182937	0.0034740	5.266	1.40e-07 ***
H	0.0453672	0.0030362	14.942	< 2e-16 ***
X2B	-0.0046418	0.0050015	-0.928	0.35336
X3B	-0.0110108	0.0119935	-0.918	0.35858
HR	0.0551743	0.0069754	7.910	2.58e-15 ***
RBI	0.0094905	0.0031036	3.058	0.00223 **
SB	0.0243994	0.0036063	6.766	1.33e-11 ***
CS	-0.0474472	0.0105630	-4.492	7.06e-06 ***
BB	-0.0053448	0.0018166	-2.942	0.00326 **
SO	-0.0074015	0.0013097	-5.651	1.59e-08 ***
IBB	0.0792122	0.0073409	10.790	< 2e-16 ***
HBP	-0.0054817	0.0080496	-0.681	0.49588
SH	0.1632589	0.0070484	23.162	< 2e-16 ***
SF	0.0162876	0.0129292	1.260	0.20776
GIDP	0.0112144	0.0065215	1.720	0.08550 .

Null deviance: 24820 on 53020 degrees of freedom
Residual deviance: 17976 on 53000 degrees of freedom
AIC: 18018

Number of Fisher Scoring iterations: 6

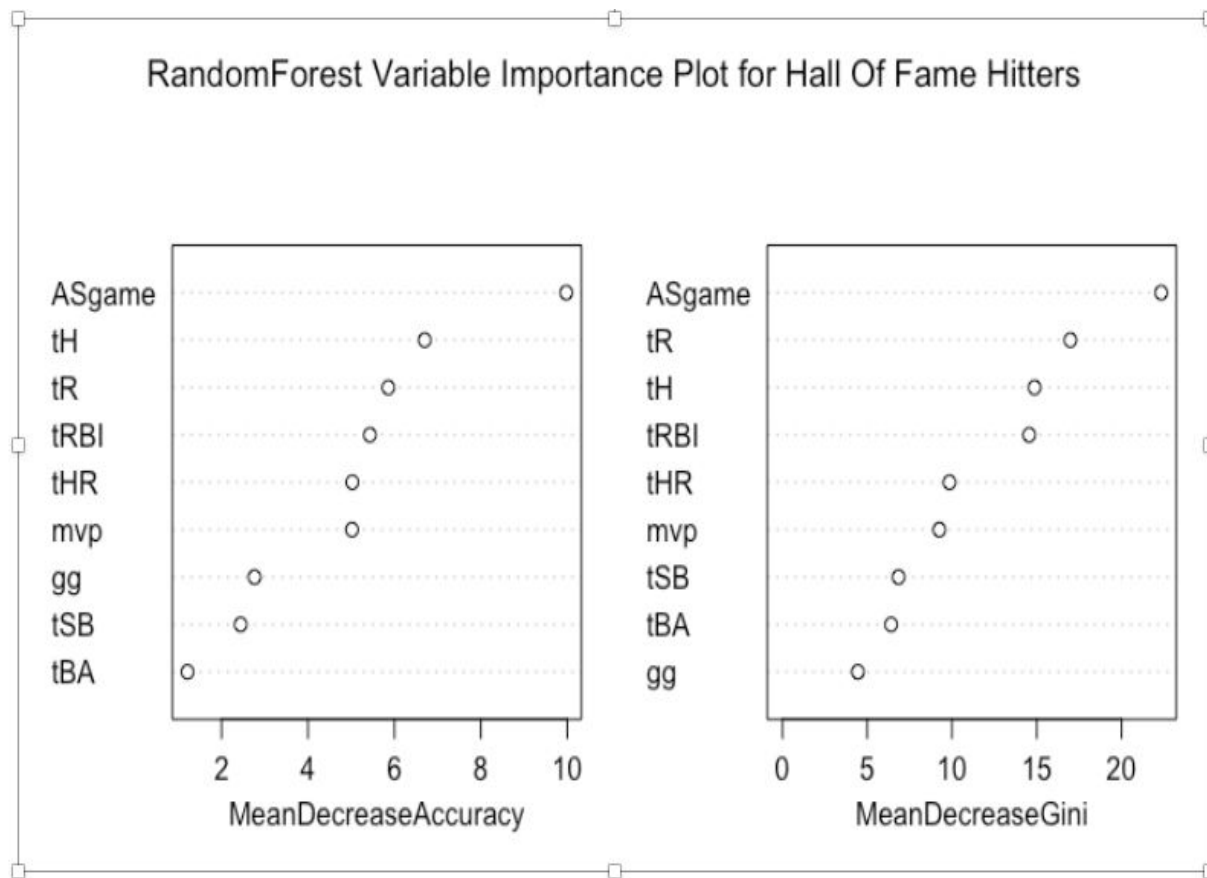
Predicting Hitters' All Star Appearances

- Calculated model accuracy by predicting values for the test data, and comparing to the actual all star appearance each year for each player
- Accuracy for this model was 0.954375
- Plotted the true positive vs true negative of the model using ROC library's `prediction` and `performance` objects
 - Looking for a curve towards high true positive and low false positive
- Calculated area under curve to be 0.8446
 - Looking for a number closer to 1 than to 0.5



RandomForest Model for Hitters HOF

- All-Star Appearance (ASgame) seem to be picking up a large portion of the variation in Hall of Fame induction for Hitters
- Hits, RBIs, and runs also are significant predictors and best than HRs
- Stolen Bases(SB) and base accepted (BA) don't have much predictive ability
- Type of random forest: classification. Number of trees;100, Variables each split: 2



Linear Model for Teams Wins

Coefficients:

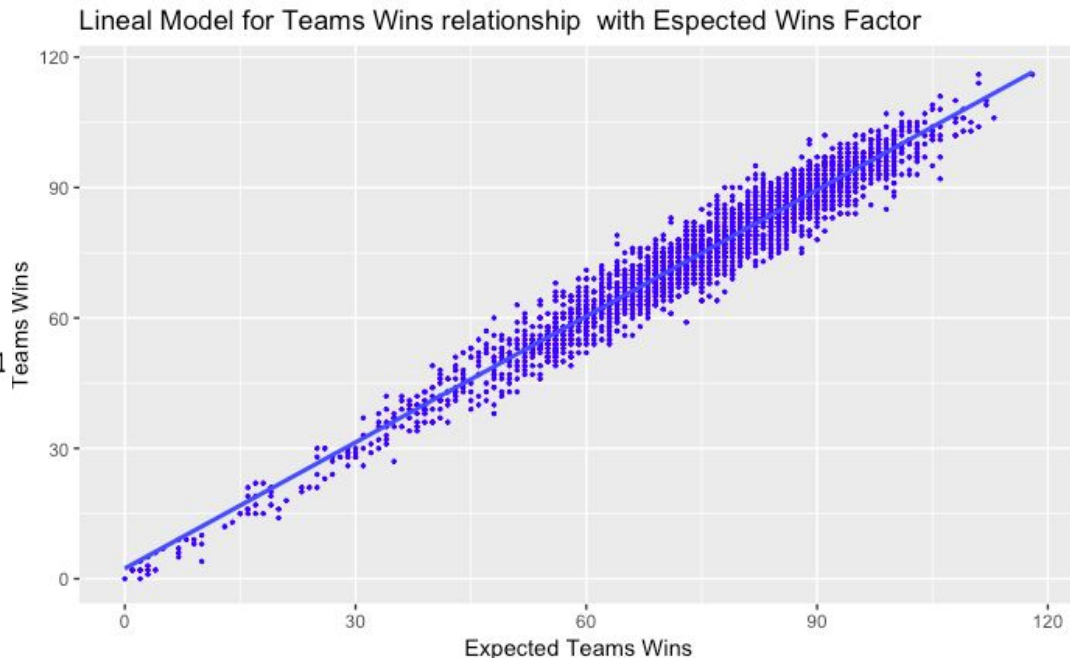
	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	2.353917	0.328461	7.167	9.77e-13 ***
Expwin	0.967597	0.004269	226.681	< 2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 4.022 on 2833 degrees of freedom

Multiple R-squared: 0.9477, Adjusted R-squared: 0.9477

F-statistic: 5.138e+04 on 1 and 2833 DF, p-value: < 2.2e-16



Salary Importance using RF

```
> allSalary.rf
```

Call:

```
randomForest(formula = salary ~ teamID + G + AB + R + H + HR +  
              Type of random forest: regression  
              Number of trees: 100  
              No. of variables tried at each split: 2  
              RBI, data = allSalary, ntree = 100, mtry = 2)
```

```
Mean of squared residuals: 9.390217e+12  
% Var explained: 19.27
```

```
> importance(allSalary.rf)
```

	IncNodePurity
teamID	5.265702e+16
G	3.413666e+16
AB	3.644148e+16
R	2.491169e+16
H	2.589516e+16
HR	2.346352e+16
RBI	2.734937e+16

- Used RF to identify factors that may lead to a higher salary
- The model identified team as the most important factor to high salaries followed by at bats and games played
- Teams make sense in baseball as there is no salary cap and teams with more money and known for overpaying players (Yankees, Red Sox, Cubs)

World Series Wins - Importance using LM

- Used `lm()` to look at the total list of World Series winners to determine what factors throughout the season influenced their win
- The model confirmed that in order to be great throughout the season and win a World Series, you need to score runs, and not let the opposition score
- It would confirm the theory that if you score more runs than the other team, you will win 100% of the time

Call:

```
lm(formula = W ~ R + H + X2B + X3B + HR + AB + BB + SO + SB +  
    RA + ER + ERA + attendance, data = WSWinners)
```

Residuals:

Min	1Q	Median	3Q	Max
-6.7459	-2.3395	-0.2046	2.2947	7.6467

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	1.058e+02	2.313e+01	4.573	1.53e-05	***
R	9.640e-02	1.505e-02	6.403	6.75e-09	***
H	-1.630e-02	1.101e-02	-1.480	0.142241	
X2B	-1.935e-02	1.279e-02	-1.513	0.133824	
X3B	-2.326e-02	3.350e-02	-0.694	0.489268	
HR	-2.653e-02	1.759e-02	-1.508	0.134994	
AB	-5.511e-04	5.471e-03	-0.101	0.919981	
BB	-8.345e-03	7.003e-03	-1.192	0.236530	
SO	-2.803e-03	3.074e-03	-0.912	0.364353	
SB	-8.770e-03	9.447e-03	-0.928	0.355723	
RA	-6.917e-02	2.071e-02	-3.340	0.001220	**
ER	2.439e-01	6.237e-02	3.911	0.000178	***
ERA	-3.802e+01	8.372e+00	-4.541	1.73e-05	***
attendance	5.009e-07	5.782e-07	0.866	0.388578	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 3.176 on 90 degrees of freedom

(13 observations deleted due to missingness)

Multiple R-squared: 0.8129, Adjusted R-squared: 0.7859

F-statistic: 30.08 on 13 and 90 DF, p-value: < 2.2e-16

Next Steps...

- Look at pitching and defensive statistics
- Plotting coordinate heatmaps of hit and homerun locations
- Plotting coordinate heatmaps of pitch locations
- Finding correlation with players pre-MLB history to their MLB performance (college, nationality, minor league, etc.)
- SVM model to predict players' future salaries