

# NBA Player Salary & Metrics

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# Process

## Identify scope

Using player metrics as a predictor of player salary

## Variable selection

LASSO regression and Stepwise

## Analysis

Compared usefulness and accuracy of models

## Create all data frames

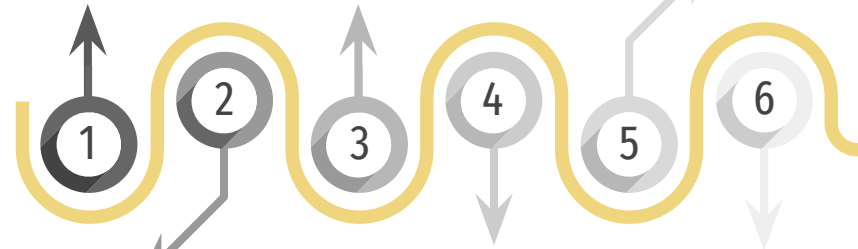
Grouped by positions, age, and no grouping

## Models & prediction

Variety of models used, including regression, random forests, boosting

## Interpretation

What did we conclude, and why does this matter?



Identify scope



Data frame creation



Variable selection



Models/Analysis



Interpretation

# Data Wrangling

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## CSVs

- ☐ NBA Salary: 1985-2017
- ☐ NBA Salary Cap: 1985-2017
- ☐ Advanced NBA Player Metrics: 1985-2017

## Manipulation

- ☐ Traded Players
  - ☐ Summarized Stats per Season
- ☐ Time Frame
  - ☐ 2010-2017

## Final Dataframe

- ☐ 3028 Observations
- ☐ 50 Predictors
  - ☐ PTS
  - ☐ TS%
  - ☐ OWS
- ☐ Response Variable
  - ☐ Player Salary % Salary Cap

Identify scope



**Data frame creation**



Variable selection



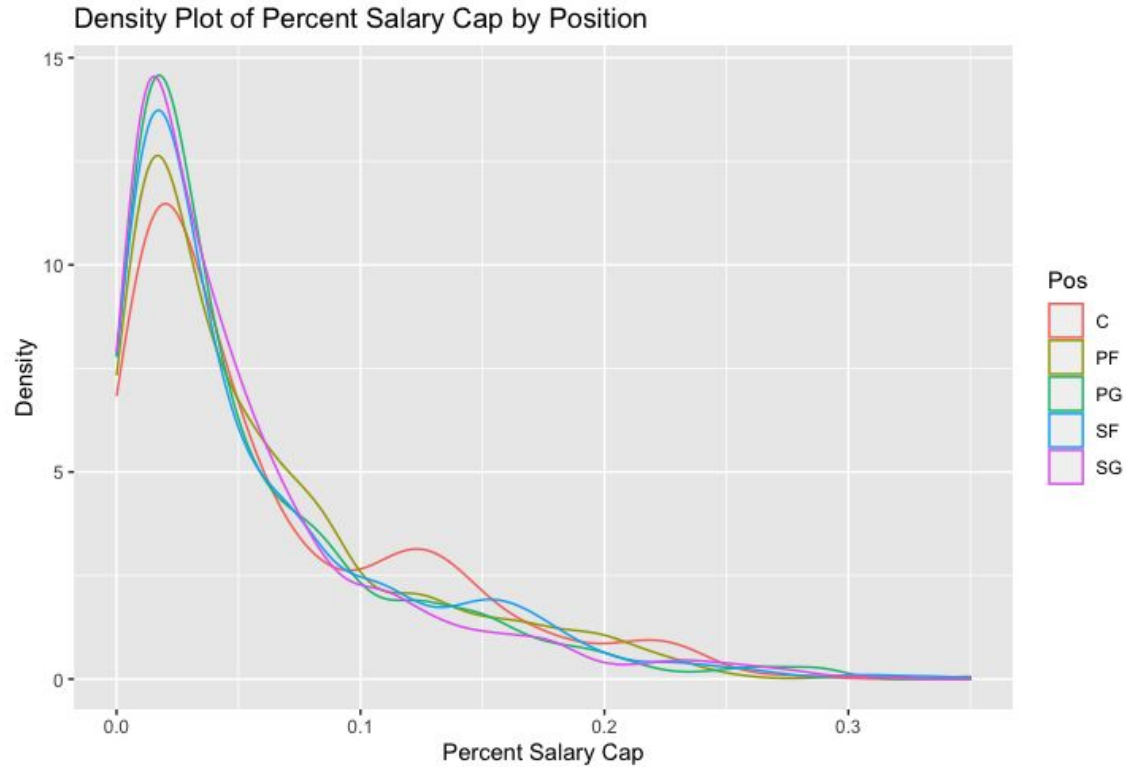
Models/Analysis



Interpretation

# Analysis of Data

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Identify scope



**Data frame creation**



Variable selection

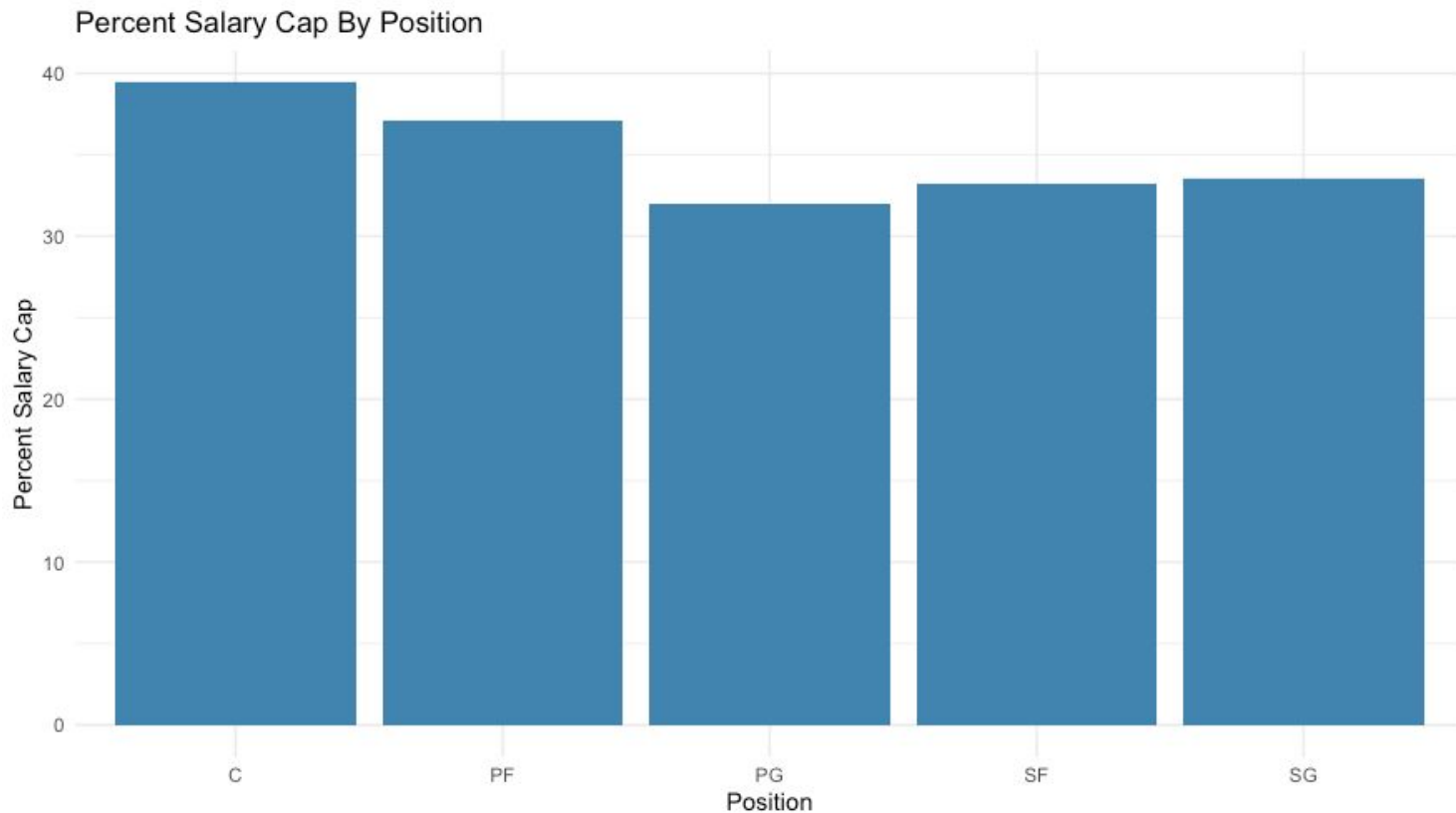


Models/Analysis



Interpretation

# Analysis of Data



Identify scope



**Data frame creation**



Variable selection



Models/Analysis



Interpretation

# Model Subsetting

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## Complete

- Complete salary and metric data frame

## Position

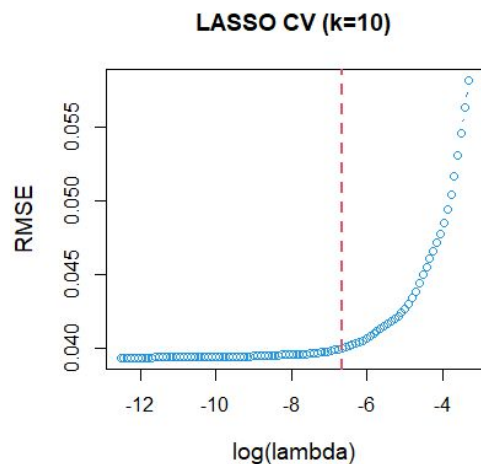
- Shooting guard; Center; Power Forward; Small Forward; Point Guard
- Position indicates different value placed on metrics

## Age

- 18-22; 23-26; 27-30; 31-35; >35
- Age indicates experience and reputation



# Variable Selection



ex. (3/20 coefficients)

Intercept	0.058
Age	0.01
G	-0.01

ex. (5/19 coefficients)

Coefs	Estimate	p-value
Age	2.58e-3	<2e-16
G	-4.38e-4	1.57e-13
DRB	5.62e-5	5.51e-7
PF	-9.3e-5	1.14e-4
TSA	4.227e-5	9.35e-16

LASSO RMSE: 0.04001212 % salary cap  
(3.96 \$million)  
LASSO  $\text{adj}R^2 = 0.535$

Stepwise RMSE: 0.03 % salary cap  
(3.1 \$million)  
Stepwise  $\text{adj}R^2 = 0.537$

Identify scope



Data frame creation



**Variable selection**



Models/Analysis



Interpretation

## Model Comparison (Out-Of-Sample RMSE)

(in \$millions)	No Grouping	Shooting Guard	Center	Power Forward	Small Forward	Point Guard
Multiple Linear Regression	3.06	3.58	4.04	2.29	3.58	3.62
Random Forest	3.08	3.34	3.93	2.23	3.63	3.37
Boosting	2.85	3.19	3.88	2.14	3.50	3.02

Identify scope



Data frame creation



Variable selection



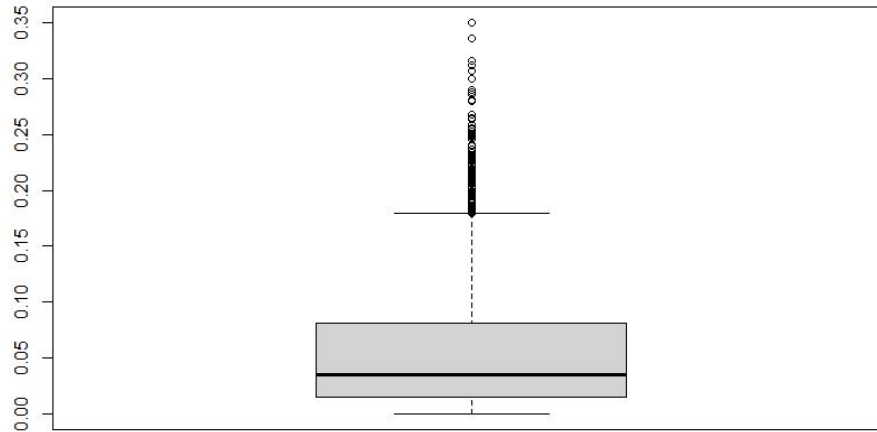
**Models/Analysis**



Interpretation



# Salary % of Salary Cap Boxplot

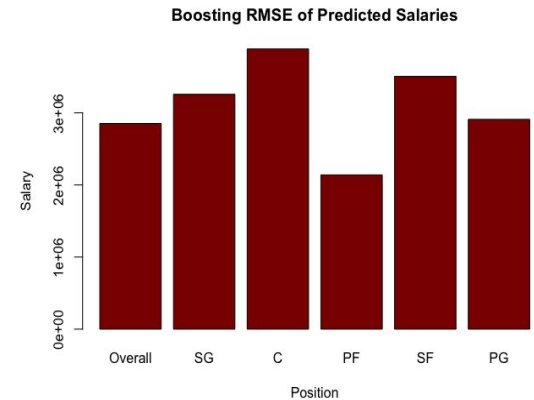
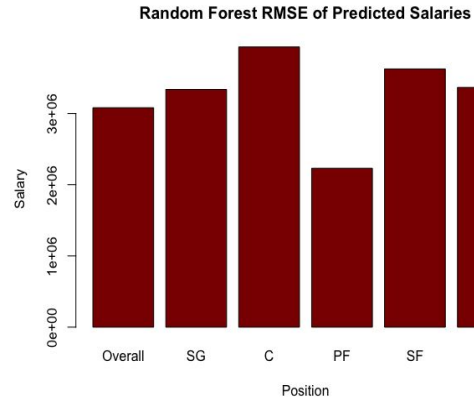
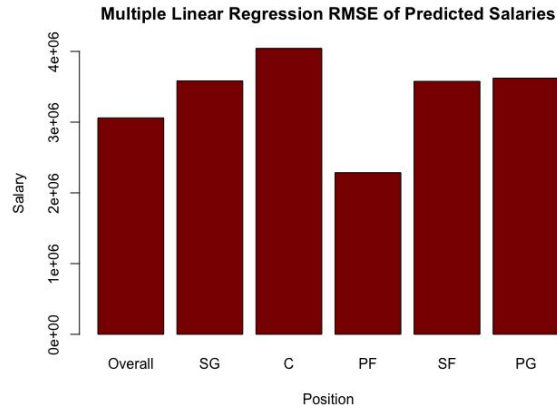


## Boxplot Summary

- Min: 0.0000748
- 1st Q: 0.0148
- Median: 0.035
- 3rd Q: 0.081
- Max: 0.35



# RMSE Graphs



Identify scope



Data frame creation



Variable selection



**Models/Analysis**



Interpretation

## Model Comparison (Adj R<sup>2</sup>)

(adjR <sup>2</sup> )	No Grouping	Shooting Guard	Center	Power Forward	Small Forward	Point Guard
Multiple Linear Regression	0.5373	0.5271	0.5277	0.6025	0.5461	0.5436
Random Forest	0.5466	0.2336	0.1175	0.4179	0.2719	0.4397
Boosting	0.6131	0.3022	0.1444	0.4635	0.3181	0.5495

Identify scope



Data frame creation



Variable selection



**Models/Analysis**



Interpretation

# Test Case

(Boosting – Pos Grouping [Center])

**Clint Capela**



Predicted \$6,750,428.20

Actual \$2,334,520.00

Difference Attributable To:

- ☐ Young Player (First Contract)

Identify scope



Data frame creation



Variable selection



Models/Analysis



**Interpretation**

# What's the Point?

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- Player salary possibly based on more than performance than outside factors
- Really about the GM's bottom line - revenue, endorsements, etc.
- Position doesn't matter in the long run

Identify scope



Data frame creation



Variable selection



Models/Analysis



**Interpretation**