

NHL Salary Analysis





Project Overview



Data: NHL data on players and teams.

Questions:

Can we predict player salaries based on stats?

Should teams hire superstars?

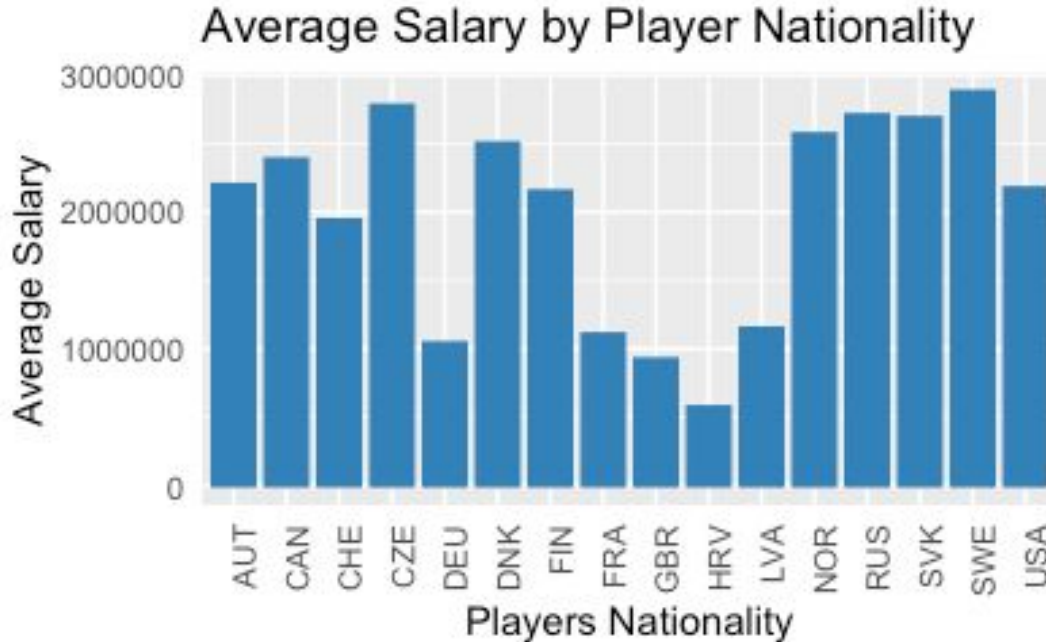
Should the Vancouver Canucks hire Quinn Hughes?

Data Cleaning



- Handling NA values
 - Providence/State
 - Draft Year, Round, and Overall
 - Average Shot Distance
 - Removal of players with high NA count
 - Replaced with mean values
- Remove Rookies
 - Matthews: 40 goals, 69 points
- Remove long-term injured players
 - Stamkos: 17 GP, \$9.5 Million

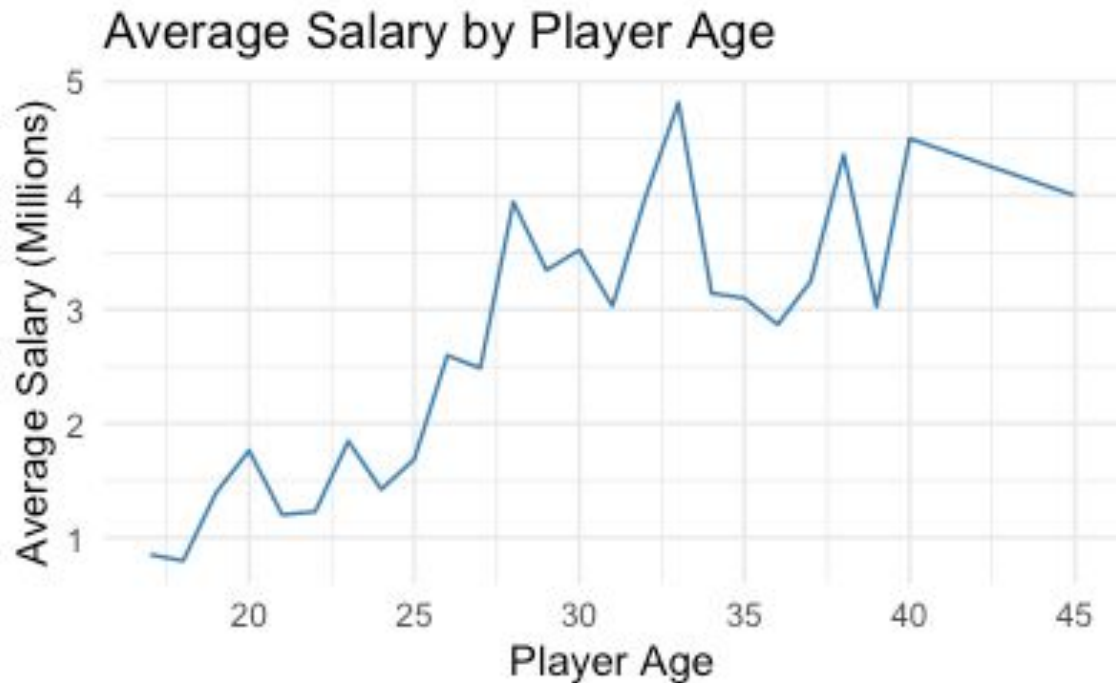
Exploratory- Nationality



- The United State does not produce the highest paid Hockey players
- Highest paid players come from Europe
- USA/Canada are the only North American countries



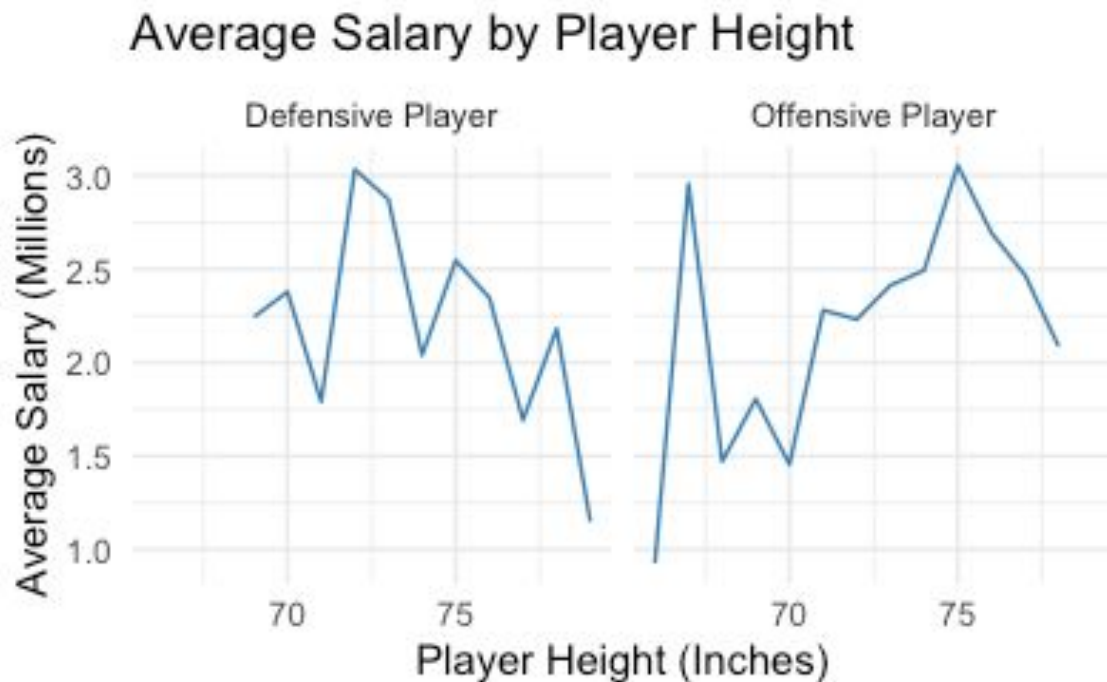
Exploratory- Age



- A player's salary is likely to increase until their early 30's
- No dramatic dip in salary as age increases
- Peaks at age 33



Exploratory - Height



- Any two-way player is classified as an offensive player
- Offensive players can get away with being shorter
- Defensive players average salary peaks at a shorter height



Building the Model

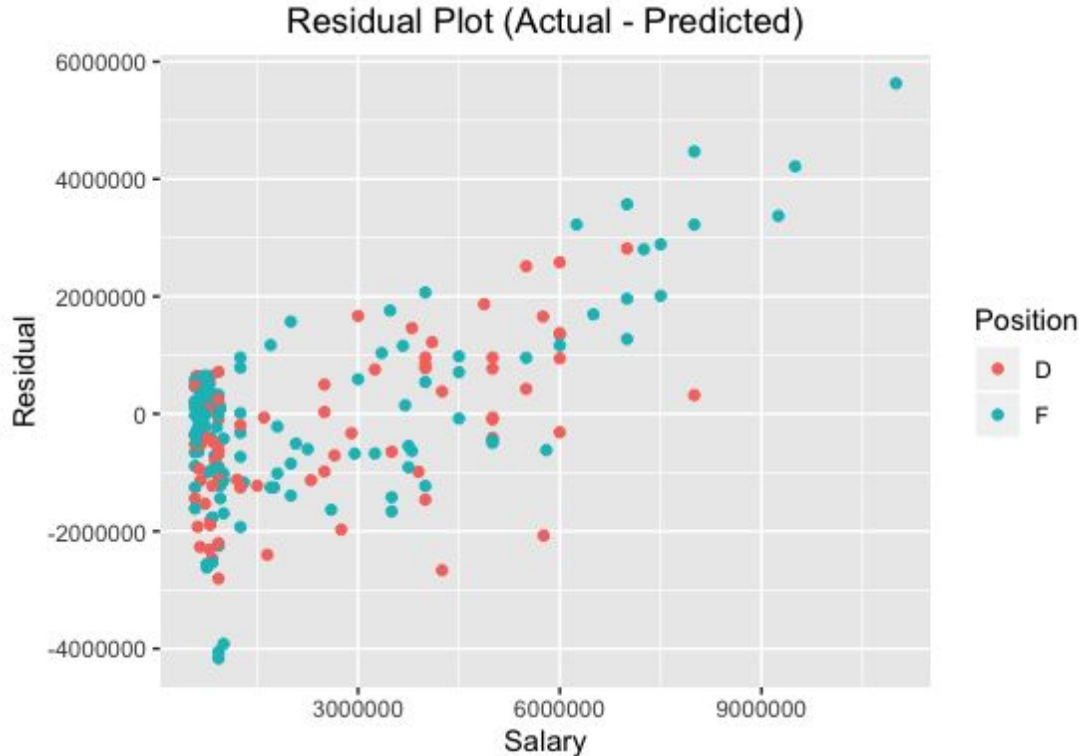
```
set.seed(45)
cv_5 = trainControl(method = "cv", 5)

best_elastic_regression = train(
  form = Salary ~ .,
  data = stat_trn,
  method = "glmnet",
  trControl = cv_5,
  tuneLength = 10
)
```

- Additional Data Cleaning
 - Categorical Data: Last Name, Country, City, etc
 - Face-Off Statistics
 - Double-counted statistics
 - Position → D and F only
- Penalized Regression
- Transformations attempted
 - Log, cube root, etc
- Lowest RMSE achieved:

\$1,436,393

Using the Model



Quinn Hughes
Predicted Salary:

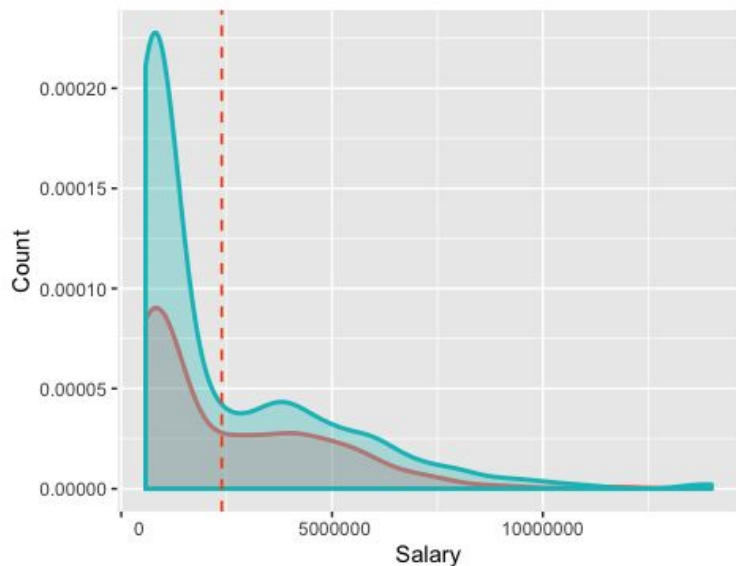
\$2,967,417

(We believe this is a huge underestimate)

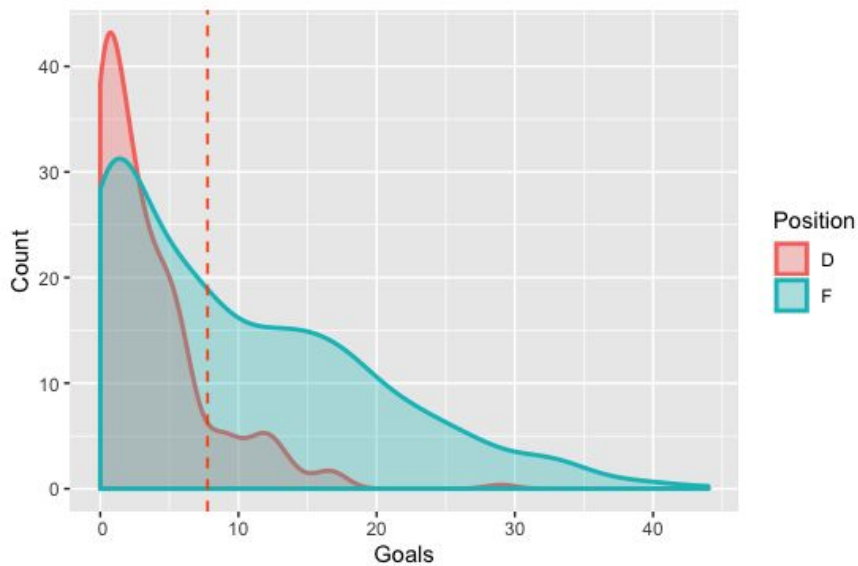


Reasons for Shortfall - Skewed Data

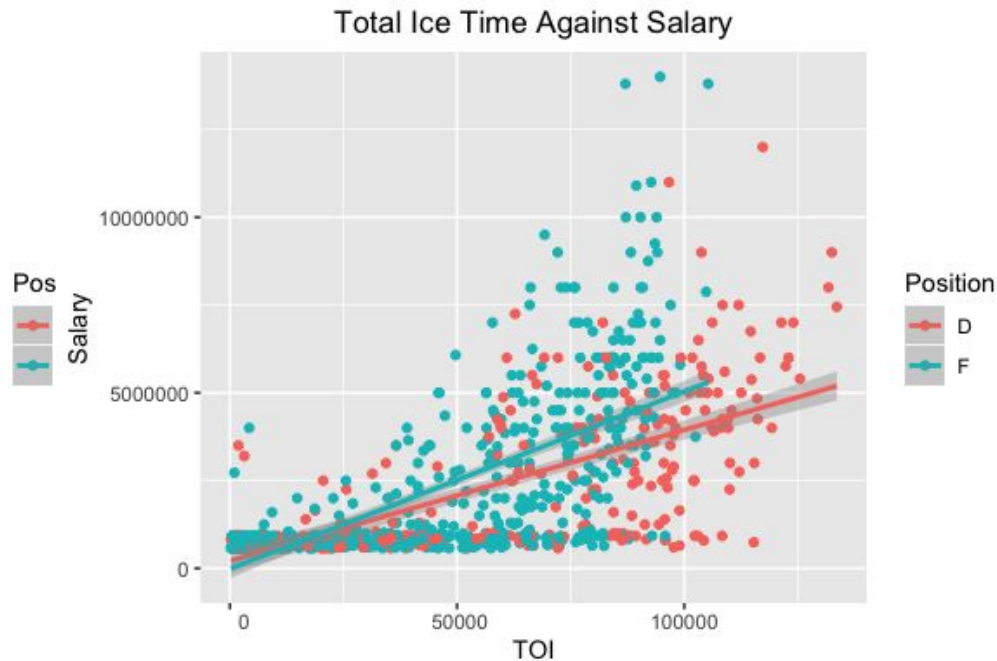
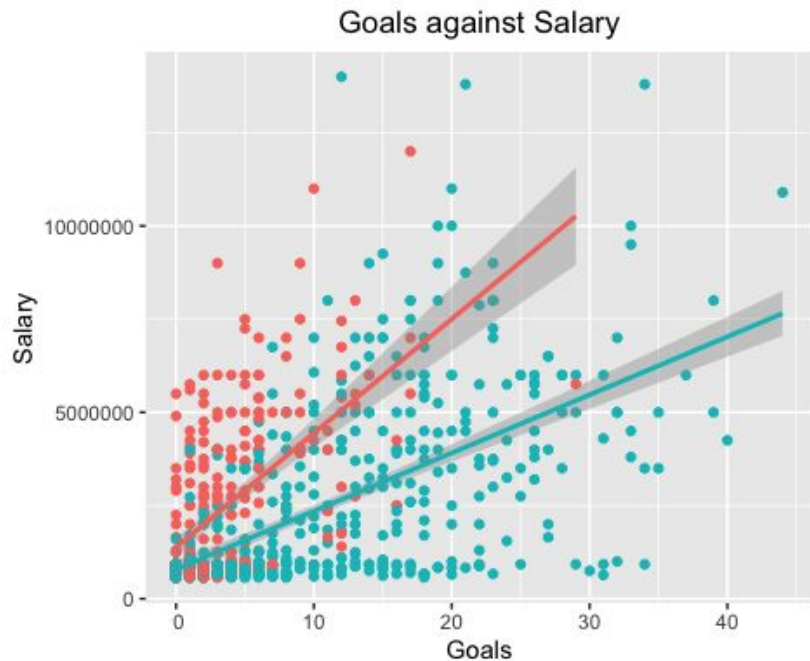
Salary Density Plot



Goal Density Plot



Reasons for Shortfall - Noisy Data



Directions for Improvement

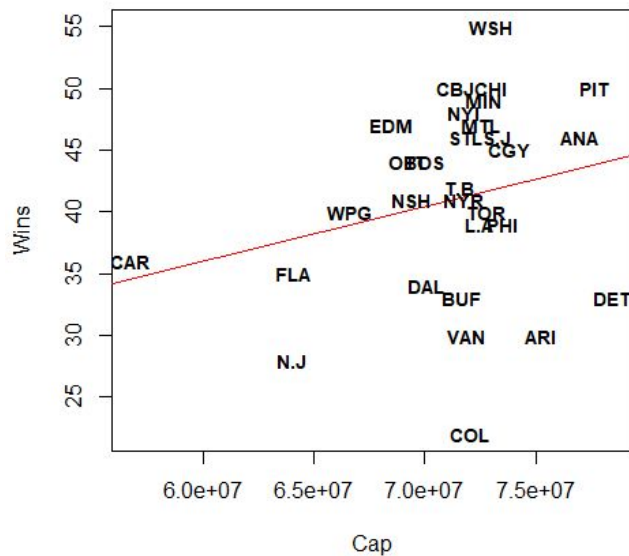


- Increase Sample Size to multiple seasons
- Split data into baskets of similar playing styles
- Explore non-linear relationships further

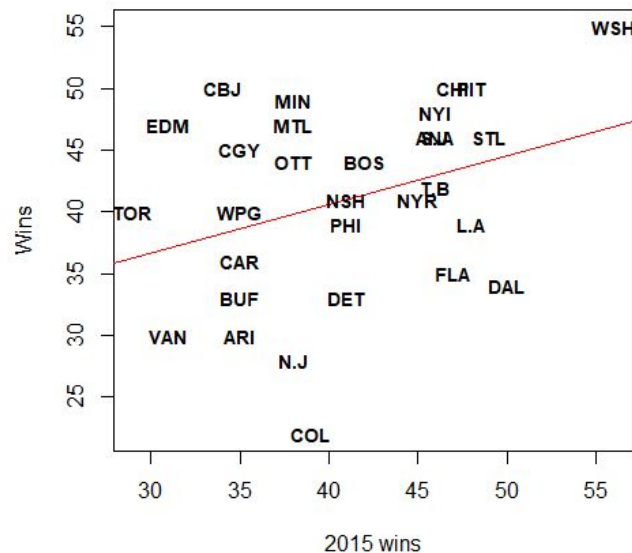


Team Analysis

Salary Cap versus wins



2015 wins versus wins





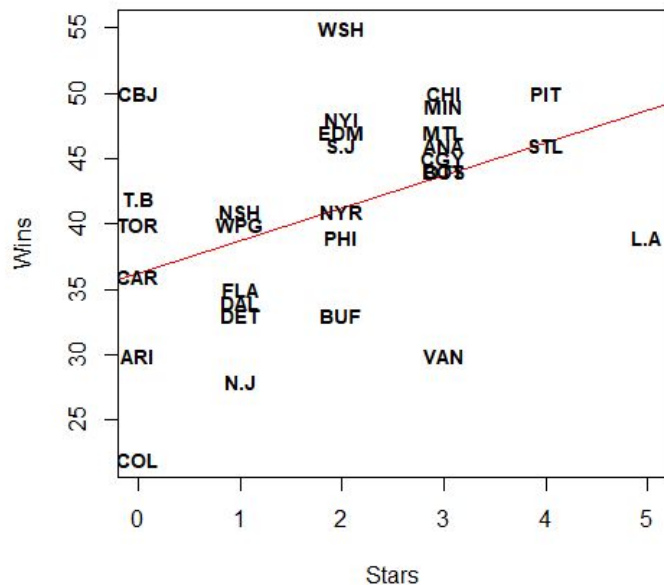
Regression

These two variables explain about 10-15 percent of the variance between teams.

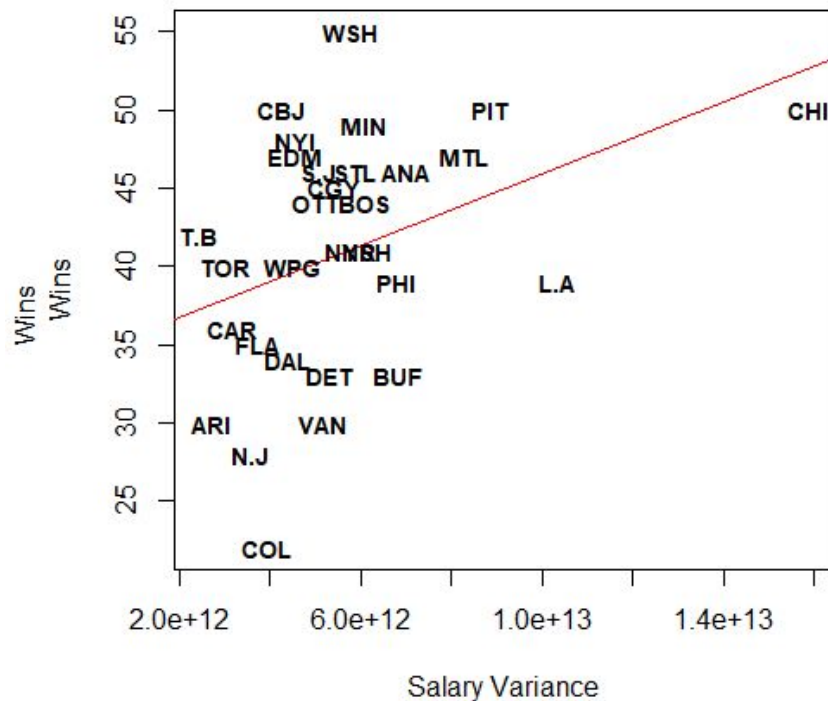


Team Analysis

Superstar count versus wins



Salary Variance versus wins





Regression

Bringing in these additional variables we are able to explain around 15-25 percent of the variance.

Each additional superstar is associated with 1.5 more wins.



Quinn Hughes



Difficulties and improvements

- Data Wrangling
- Time series
- Weaknesses in data



Questions?