P8106 - Final Project - NBA Players Salary Prediction

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Introduction

For any team in the National Basketball Association (NBA), a key strategy to win more games is to properly allocate their salary cap - an agreement that places a limit on the amount of money that a team can spend on players' salaries. How to evaluate the performance of each NBA player and give a suitable level of salary is a therefore complicated problem. In this project, we intend to predict the salary of NBA players in the 2021-2022 season based on their game statistics. We collected game statistics that are commonly used to evaluate players from the NBA official website, built both linear and non-linear models, including linear regression, ridge regression, lasso regression, GAM, MARS, _____, on selected feature variables, and compared these models to determine a final predictive model.

Data preprocessing

We will conduct data analysis and model construction based on two datasets on NBA players' contracted salary [1] and performance statistics per game [2] in 2021-2022. The following steps are included in our data preparation:

- Two original datasets are inner joined by players and teams
- Keep only one record with most number of games played for each of players, given a player may transfer to other teams during the session and have multiple records.
- Remove 5 variables with missing values caused by division of other existing variables.
- Convert count variables (`field_goal`, `free_throw`, etc.) to rates by dividing variable `minute`

The final cleaned dataset has 442 records and 24 variables, including 2 categorical variables, 21 numerical variables and 1 numeric response variable `salary`.

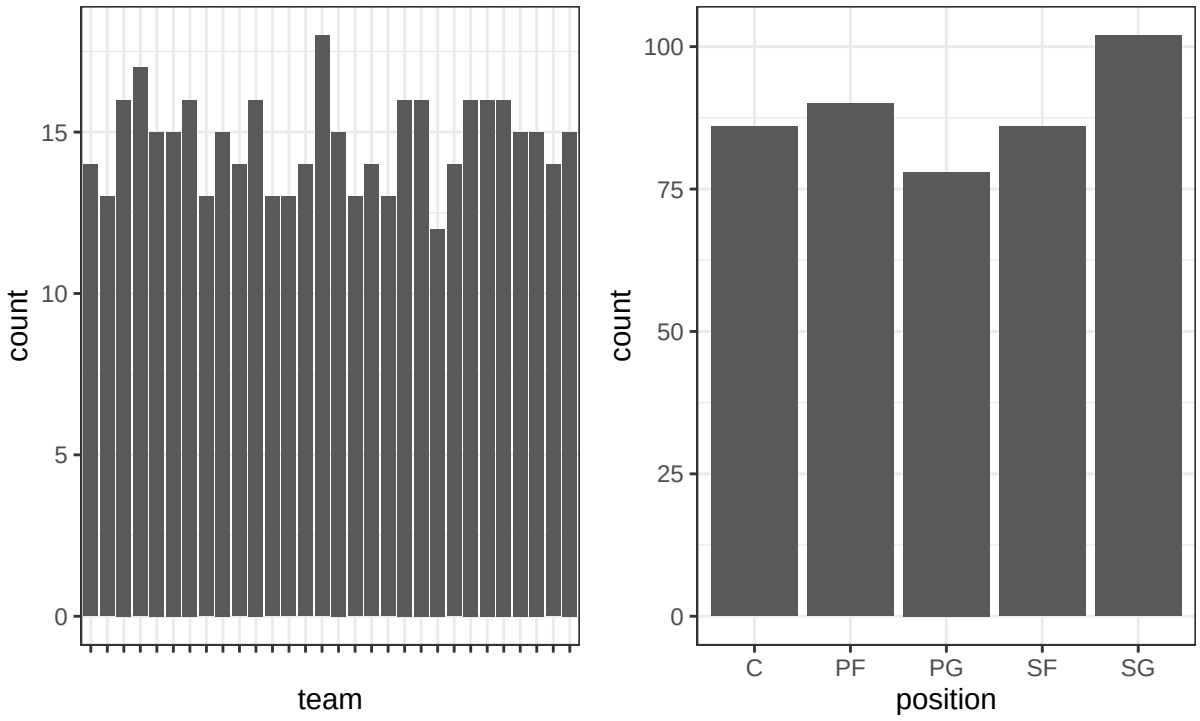
- `position` – Position of the player (5 categories)
- `age` – Player's age on February 1 of the season
- `team` – Team that the player belong to. (30 categories)
- `game` – Number of games played per minute
- `game_starting` – Number of games played as a starter per minute
- `minute` – Minutes played per game
- `field_goal` – Field goals per minute
- `fg_attempt` – Field goal attempts per minute
- `x3p` – 3-point field goals per minute

- `x3p_attempt` – 3-point field goal attempts per minute
- `x2p` – 2-point field goals per minute
- `x2p_attempt` – 2-point field goal attempts per minute
- `free_throw` – Free throws per minute
- `ft_attempt` – Free throw attempts per minute
- `offensive_rb` – Offensive rebounds per minute
- `defenssive_rb` – Defensive rebounds per minute
- `total_rb` – Total rebounds per minute
- `assistance` – Assists per minute
- `steal` – Steals per minute
- `block` – Blocks per minute
- `turnover` – Turnovers per minute
- `personal_foul` – Personal fouls per minute
- `point` – Points per minute
- `salary` – Salary of the player in million

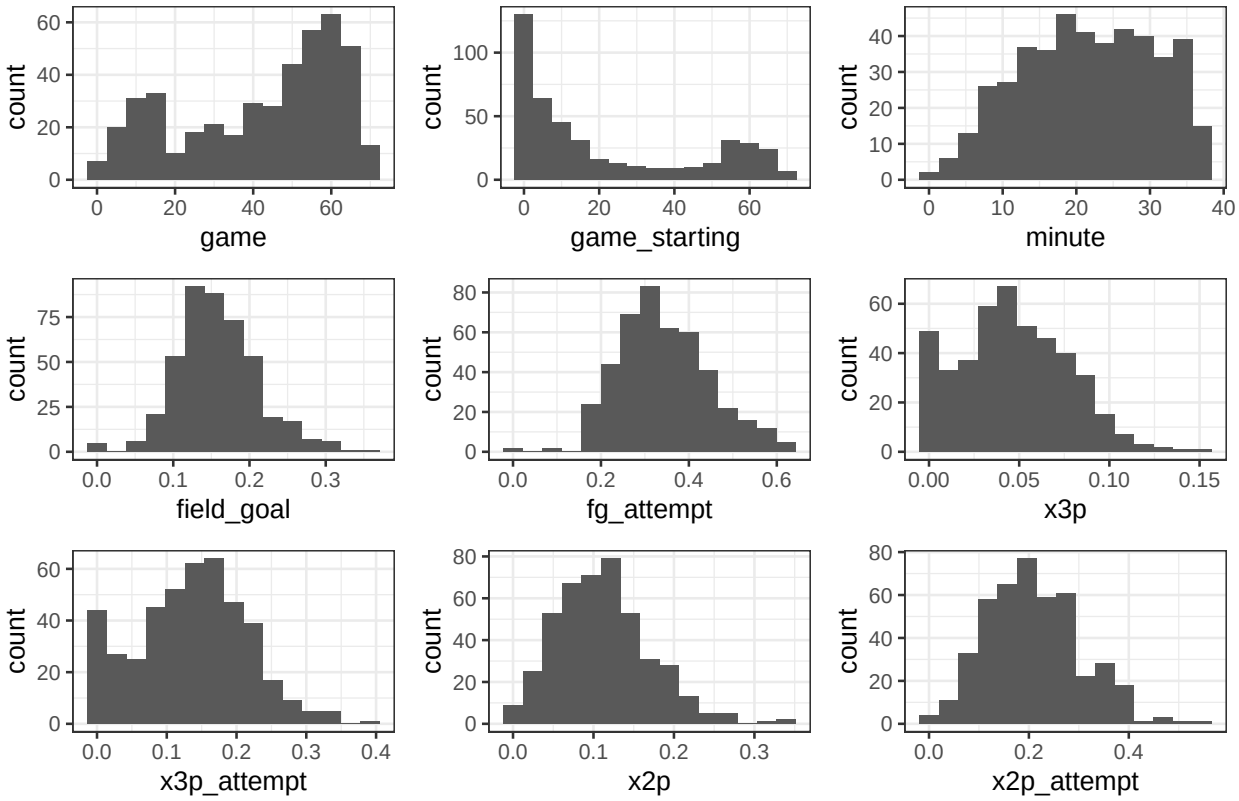
Exploratory Analysis

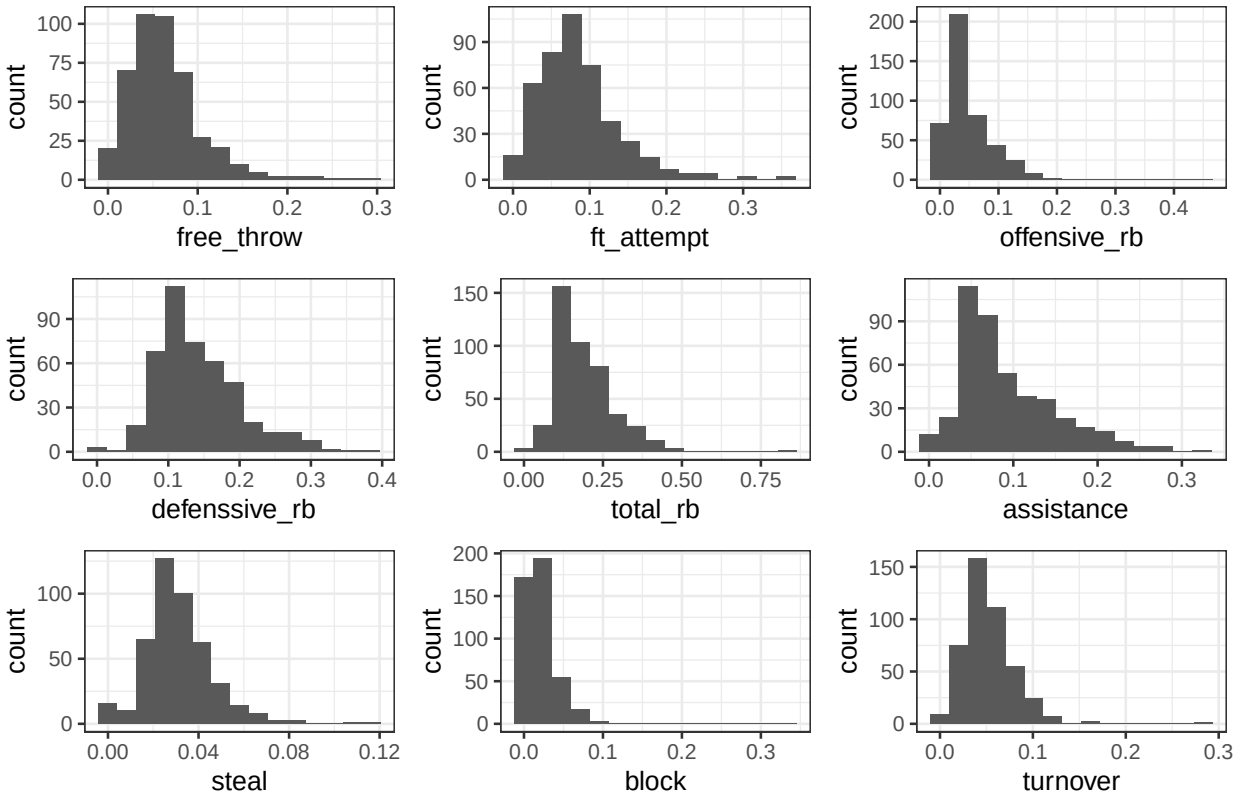
Univariate Analysis

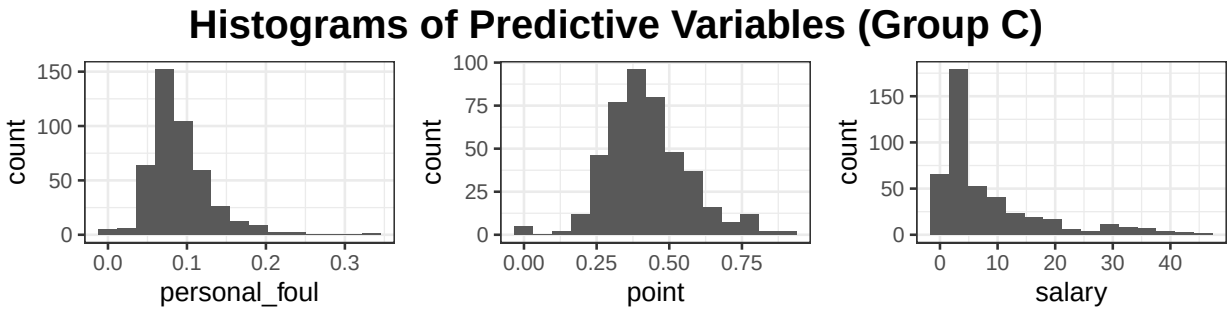
The following plots show distribution of each univariable. For categorical variables `team` and `position`, they are dsitributed quite evenly. There are 30 unique values in `team`, which may result in too many dummy variables in the model. Therefore, we may consider exclude `team` or cluster it into fewer classes in selected models.



For numeric variables, some of them (`gs`, `ft`, `orb`,`blk`), including response `salary` are skewed, with some players have extremely high salary. Visualization for all variables are enclosed in Appendix A.

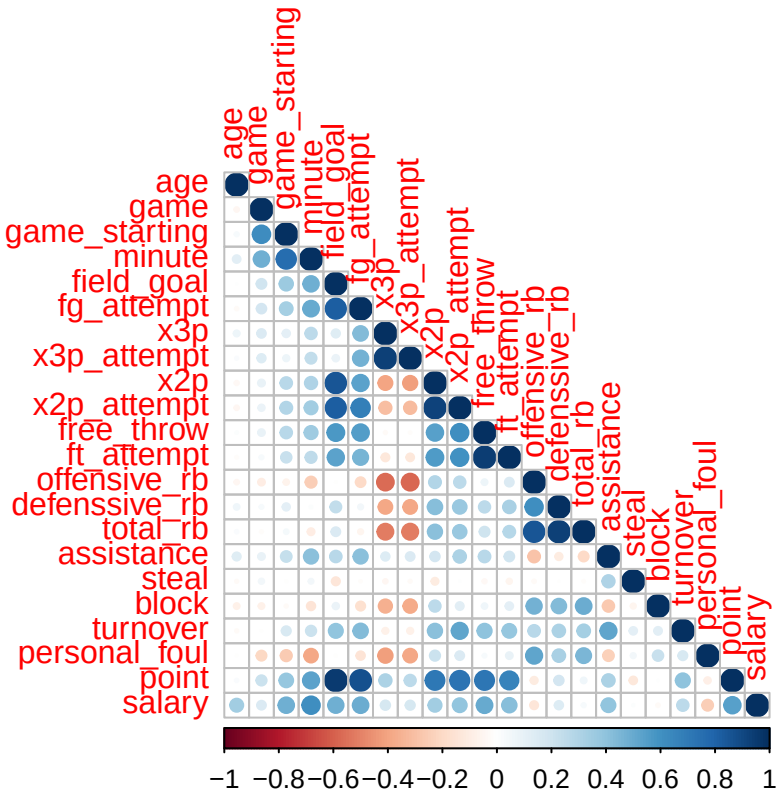

Histograms of Selected Variables (Group A)
count
game
game_starting
minute
field_goal
fg_attempt
x3p
x3p_attempt
x2p
x2p_attempt


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



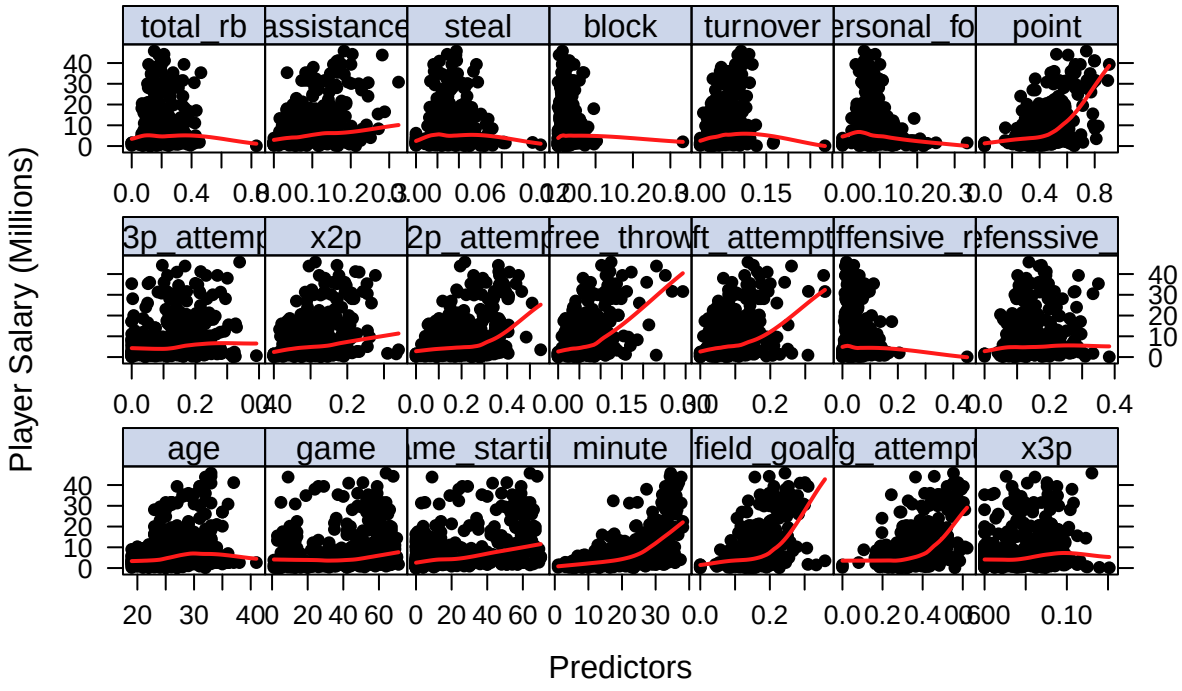
Correlation Analysis

From the correlation heat map, it is obvious that multicolinearity could be a problem, which we may consider using penalized models (ridge, lasso) or ensembled models (random forest, boosting, neural network) to fix.

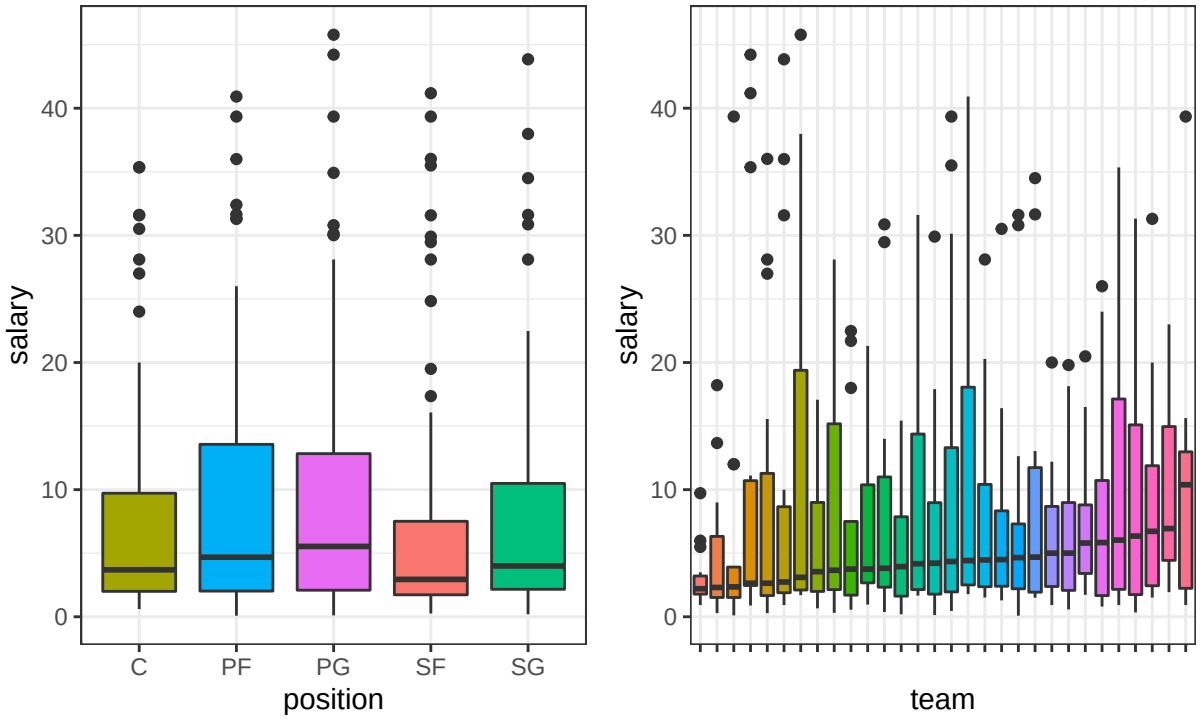


Analyzing trends in data

The feature maps demonstrated that some correlations are non-linear, which we may consider using GAM or MARS to address.



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



Model Construction

- What predictor variables did you include?
- What technique did you use? What assumptions, if any, are being made by using this technique?
- If there were tuning parameters, how did you pick their values?
- Discuss the training/test performance if you have a test data set.
- Which variables play important roles in predicting the response?
- **Explain/visualize the final model you select.**
- What are the limitations of the models you used (if there are any)? Are the models flexible enough to capture the underlying truth?

Conclusion

- What were your findings? Are they what you expect? What insights into the data can you make?

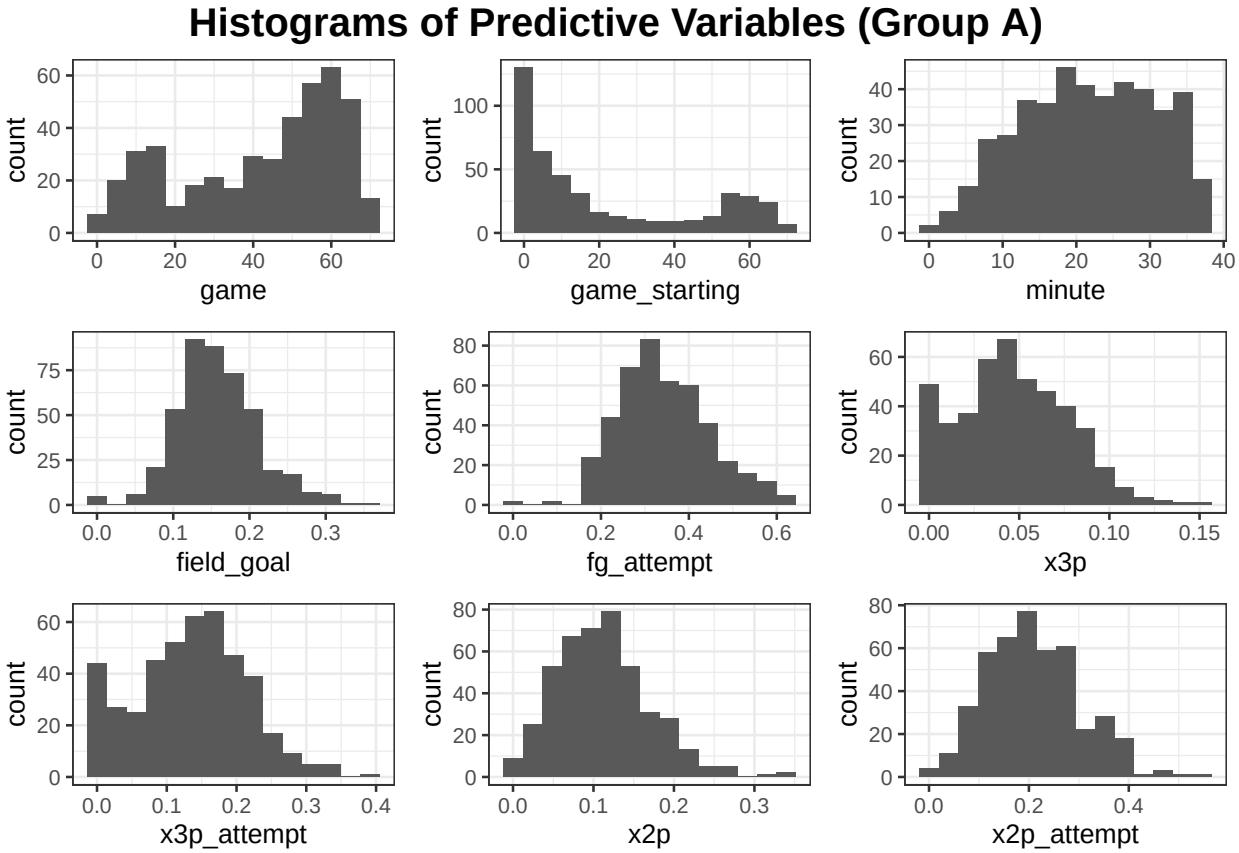
References

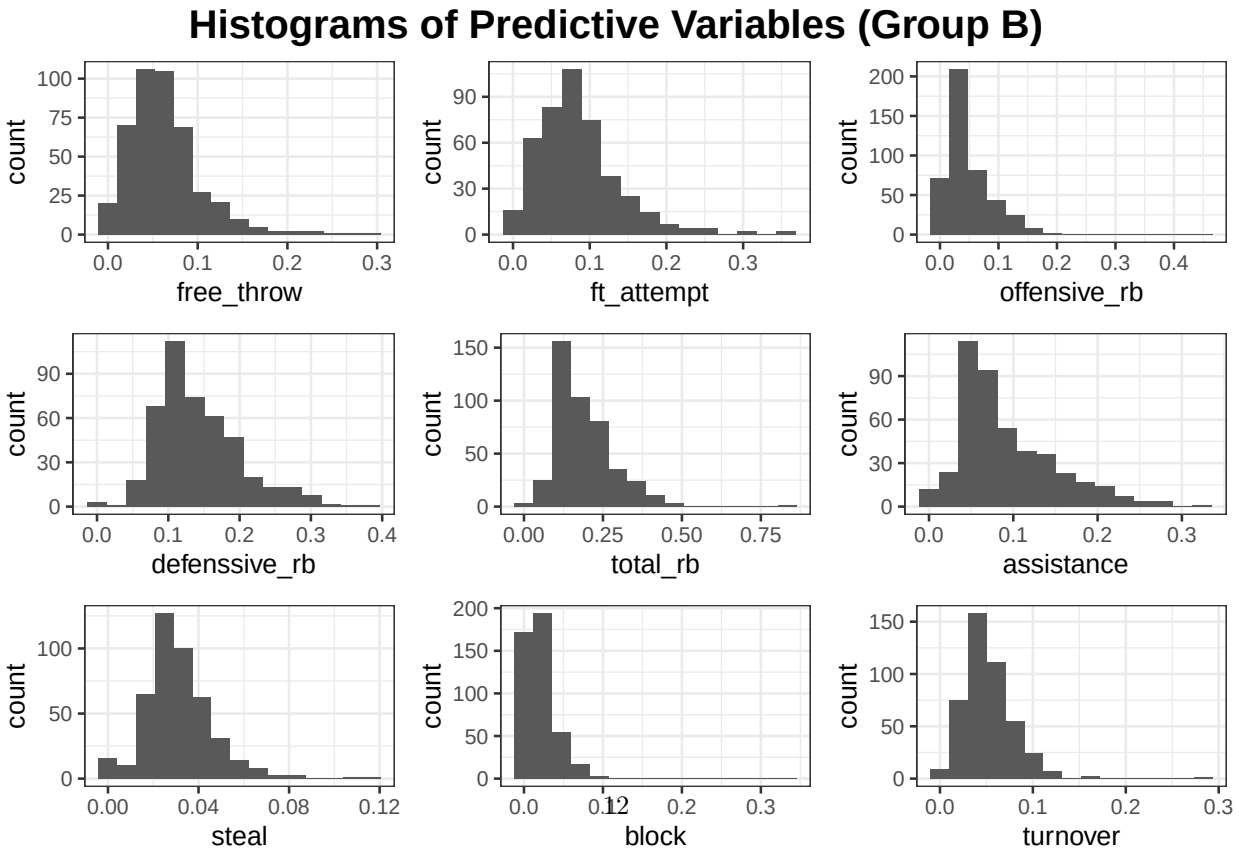
[1]https://www.basketball-reference.com/contracts/players.html

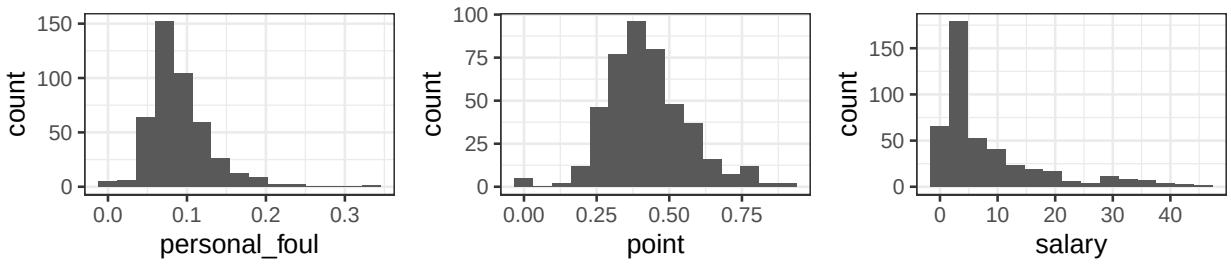
[2]https://www.basketball-reference.com/leagues/NBA_2022_per_game.html

Appendices

Appendix A - Numeric Variable Distribution






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