A Comprehensive Analysis of NBA Player Salaries

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Curvenote

1 Introduction

This project analyzes the factors that determine NBA player salaries during the 2024-2025 season, investigating how statistics, age, and position influence compensation. We focus particularly on the extreme salary disparity caused by superstar players who earn vastly more than average players. To understand which performance metrics teams value most, we compare traditional box score statistics against advanced all-in-one metrics. Our analysis employs multiple modeling approaches including Ordinary Least Squares regression as a baseline, Ridge and LASSO regression to handle correlated predictors, and Random Forest to capture non-linear patterns. By combining regularized linear models with ensemble methods, we provide a comprehensive examination of salary determinants in professional basketball. Ultimately, this research aims to reveal what truly drives NBA salary decisions and whether teams prioritize traditional stats or advanced analytics when compensating players.

2 Data Description

Below is a snapshot of what our data looks like. As you can see, each player is assigned to a record where the player's game statistics and salaries are recorded. The features that we look at are a mix of traditional box score statistics (Games Played, Field Goals, etc.) in addition to advanced all-in-one metrics (PER, VORP, etc.). All the data is scraped from Basketball-Reference, a third-party site that houses NBA statistics across several seasons.

We also perform some feature engineering to extract binary features based on various NBA Awards and whether a player is in their "Contract Year". A "Contract Year" means that a player is in the final year of their contract, therefore, the player will be motivated to play to the best of their ability to prove to the franchise that they are worthy of a new contract.

```
import pandas as pd
import os

data_path_2024 = os.getcwd()+'/data/final_2024_player.csv'
df = pd.read_csv(data_path_2024)
df.head()
```

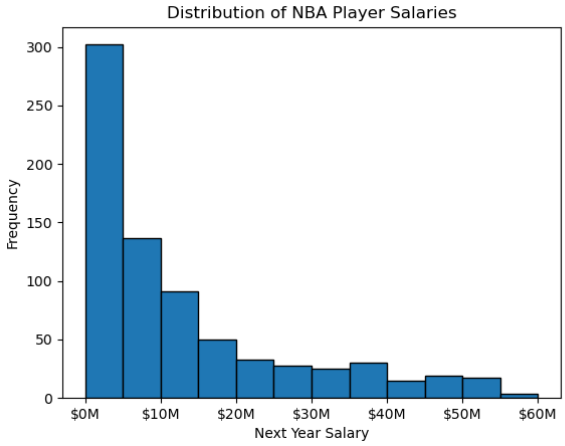
	Rk_x	Player	Age	Team	Pos	G	GS	MP	FG	FGA	...	First_Team	Second_Team	Third_Team	[illegible]	[illegible]	Salary	2023-24_contract_year	Next_Year_Salary	Guaranteed
0	363.0	A.J. Green	24.0	MIL	SG	56.0	0.0	11.0	1.5	3.5	...	0	0	0	0	0	1901769	[illegible]	2120693	2120693
1	476.0	AJ Griffin	20.0	ATL	SF	20.0	0.0	8.6	0.9	3.1	...	0	0	0	0	0	3712920	[illegible]	[illegible]	[illegible]
2	109.0	Aaron Gordon	28.0	DEN	PF	73.0	73.0	31.5	5.5	9.8	...	0	0	0	0	0	[illegible]	[illegible]	[illegible]	[illegible]
3	278.0	Aaron Holiday	27.0	HOU	PG	78.0	1.0	16.3	2.4	5.3	...	0	0	0	0	0	2019706	1	4668000	4668000
4	136.0	Aaron Nesmith	24.0	IND	SF	72.0	47.0	27.7	4.4	8.8	...	0	0	0	0	0	[illegible]	[illegible]	[illegible]	[illegible]

5 rows × 66 columns

3 Exploratory Data Analysis

3.1 NBA Salary Distribution

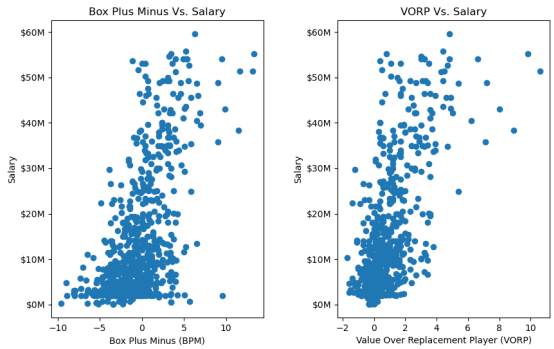
First, let's look into the distribution of NBA salaries. Getting a sense for how this is shaped is important for our later analysis and will help drive certain modeling and analysis choices made later.



The distribution of NBA salaries is clearly right skewed. Most players earn below 10 million dollars. This makes sense, because there are very few "superstars" who are deserving of large salaries above 30 million, and majority of NBA players are role players or depth pieces that aren't expected to make much relative to others in their careers. Let's take a look into how NBA stats are related to NBA salaries

3.2 Salary In Relation to Advanced Stats

Box Plus Minus (BPM) and Value Over Replacement Player (VORP) are two popular advanced stats metrics calculated for NBA players. BPM measures a player's contribution to their team's point differential per 100 possessions. VORP estimates how much added value a player brings to a team in comparison to an average "replacement player". Intuitively, one would expect that players with higher BPM or VORP metrics would have higher salaries, as better players should be paid more. Let's take a look at this relationship.

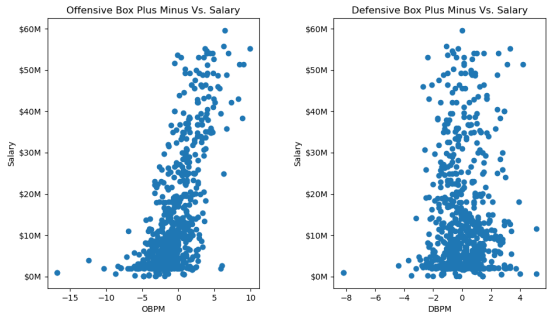


As expected, there is a moderately strong positive correlation between BPM and VORP and salaries. When calculating the correlation coefficients, VORP

showed a slightly stronger correlation at around 0.67, while BPM had a correlation coefficient of 0.57.

3.3 Offensive Metrics vs. Defensive Metrics and Their Impacts on Salaries

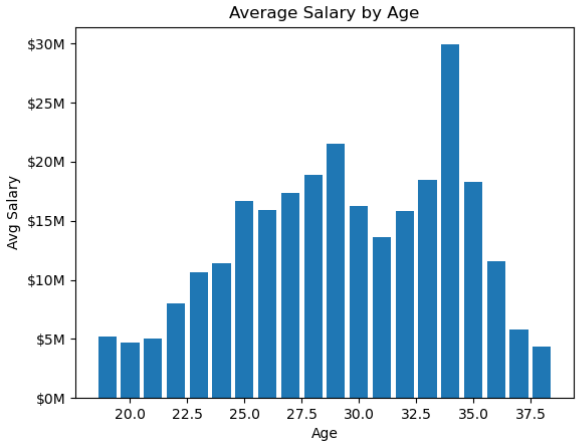
BPM and VORP combine offensive and defensive efficiency into one metric. As a result, they don't show whether offense or defense is more valued in evaluating a player's salary potential. Fortunately, BPM can be broken down into two other stats: Offensive Box Plus Minus (OBPM) and Defensive Box Plus Minus (DBPM). As their names suggest, they separate offensive and defensive performance from each other. By plotting these two against salaries, we can see if one has a stronger relationship with NBA salaries.



The correlation coefficient between OBPM and Salary is around 0.64, while the correlation coefficient between DBPM and Salary is around 0.06. As the plots and correlation coefficients show, there is a much stronger relationship between OBPM and Salary compared to that between DBPM and salary. An interpretation for this is that an offensively superior player could average expect to receive a higher salary than a defensively superior player. This is most probably because basketball, at its core, is a highly offensive sport, so a player being able to contribute more to their team's scoring would be highly valuable.

3.4 Salary vs. Age

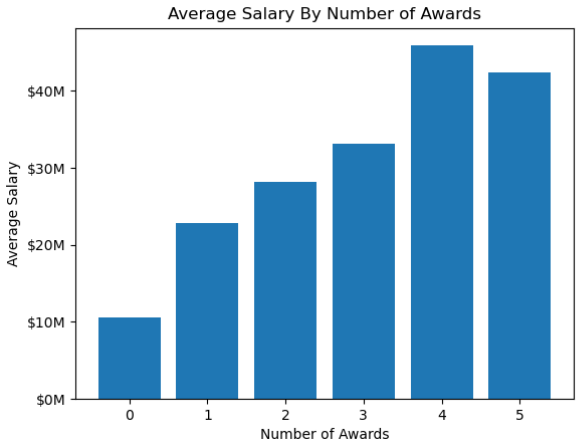
An important relationship is that between salary and age. Younger players are typically on rookie contracts which are valued a lot lower than the average NBA salary. After a couple years of development and experience, NBA players typically reach their prime around their late twenties, so we can expect to see a mode around here. On the other hand, much older players towards the end of their careers are not as physically gifted anymore and are more valued for their basketball IQ and leadership. Yet, they are still paid a lot less than the average salary, because they don't contribute much to an offense.



Suprisingly, players at age 34 show the highest average salary, while players at age 29 show the second highest average salary. However, players in their early to mid thirties are still physically able to produce at an elite level for teams. The only players to remain in the league at that age, however, are typically those who have been elite throughout their careers. As a result, it does make sense that they show such high average salaries. As expected, there is another mode for players in their late 20s, when they are typically in their primes.

3.5 Salary In Relation to Number of Awards

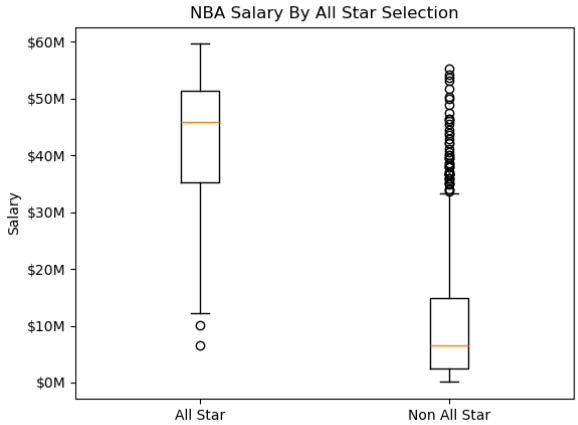
NBA awards are an easy way to distinguish elite players from average players. Intuitively, one would expect that players with any awards are better than players without any awards, and would expect to see higher salaries than their average counterparts.



The plot follows exactly as we had thought. Players with more awards have

a higher salary on average, as these awards are good ways to identify the best players in the league, who would obviously earn the highest salaries.

Another important accolade is all star selection. Each year, there are around 24 players selected for the All Star accolade. These are essentially the 24 best NBA players in a certain year.



The side by side boxplot shows that All Star Players do earn much more than those who aren't. However, there are a lot of non All Star players as outliers who make about the same as All Star players. This is because All Star nominations are extremely selective, as there is only a certain amount of players each year who can be selected. As a result, there are many extremely talented players who are left off of the All Star roster.

3.6 Multicollinearity and VIF Analysis

After a thorough VIF analysis, we limit our dataset to the following columns: Age, MP_x, PF, TS%, TRB%, AST%, STL%, BLK%, TOV%, USG%, BPM, NumOfAwards, All-Star, AwardWinner, FirstTeam, SecondTeam, ThirdTeam, DefTeam1, DefTeam2. All of these columns have VIF scores lower than 10.

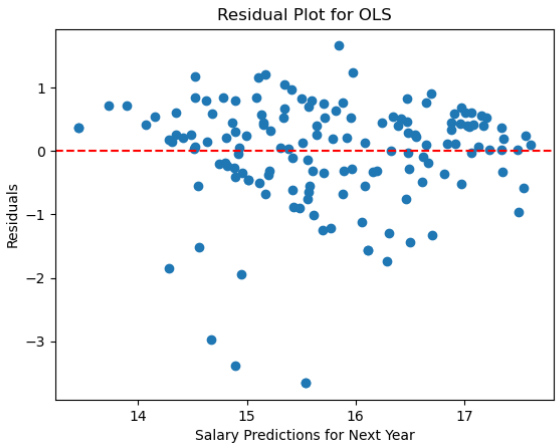
It's expected that there aren't many quantitative performance statistics, as most of these statistics are just linear combinations of other statistics, which is responsible for the data's original high VIF scores.

4 Model Building and Evaluation

4.1 Ordinary Least Squares

Once, we've split our data into the predictors set and the target data (NBA Salaries), we're ready to start fitting models. First, we fit an Ordinary Least Squares (OLS) regression model to our training data. After predicting the NBA

salaries in our testing data, we achieve a mean square error (MSE) of around 0.76. We then plot the residuals to analyze.

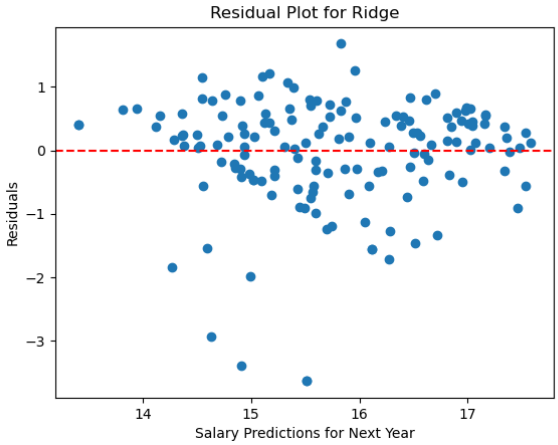


Looking at the residual plot above, we see that the residuals are not entirely randomly scattered but are generally within the [-2, 2] range, which suggests there may be a better model for this dataset. There is a slight linear pattern of residuals that can be seen so a nonlinear model may be a better fit.

4.2 Ridge Regression

One downside of the OLS model is that it may overfit, especially when noise or multicollinearity exists in the dataset. To prevent overfitting, we will now use ridge regression to regularize the model by limiting the model's complexity.

After we've standardized the data, we fit our ridge regression model on the training dataset and make predictions on the test set. This results in a MSE of around 0.76, which is about the same as the MSE from OLS. Plotting, the residuals, we notice the following:

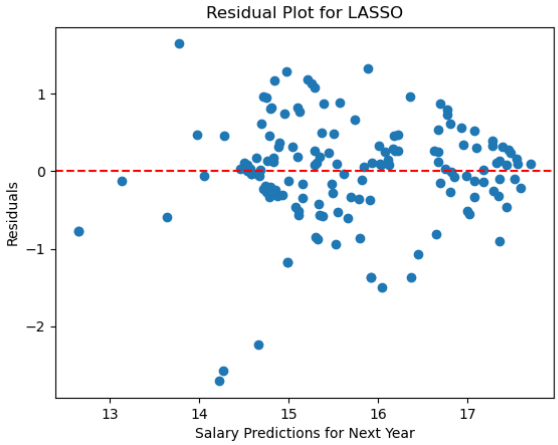


Looking at the residual plot above, we see that it resembles the residual plot for OLS, where there the residuals between [14,16] are not randomly scattered. Therefore, a nonlinear model may be a better fit. Both ridge regression and OLS showed subpar results on our data, so we'll go in a different direction.

4.3 Lasso + Random Forest

Compared to ridge regression, LASSO will only retain features with great prediction power by shrinking the coefficients of irrelevant features to zero. This results in a model that is simpler in complexity, which additionally prevents overfitting. Since the residuals plots for OLS and ridge suggested that a nonlinear model may be better suited for this dataset, we will then use a random forest model to model the nonlinear relationship between the features selected by LASSO and salary.

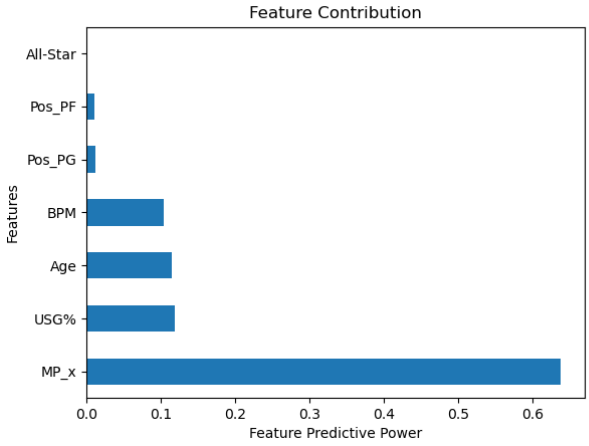
Lasso ended up simplifying our set of predictors to 7 predictors. These are: MP_x, USG%, Age, BPM, Pos_PG, Pos_PF, and All-Star. Then, after fitting the random forest model, we see the following residual plot.



Comparing this residual plot to the residual plots for OLS or ridge, we see that the residuals in this plot are slightly more randomly scattered. The outliers present in the other residual plots are no longer present in this plot as LASSO removes features that have low predictive power/noise.

4.4 Feature Importance

Now that we have a solid predictive model and have restricted our set of predictors to only 7 predictors, we can finally answer our question of what factors are most important in determining an NBA player's salary. We can achieve this by observing the feature importance amongst these 7 remaining features.



Looking at the bar plot above, we see that out of the 7 features above, the players' minutes played per game was the most predictive of their next year's salary. Minutes played per game contributed to about 60% of the prediction while BPM and age were the 2nd and 3rd more predictive features, contributing

about 11% and 7.5% resepectively. LASSO ignores the other 17 features for its predictions while ridge and OLS take all 24 features into account when predicting salary. Since LASSO + random forest resulted in the lowest MSE, we can conclude that a non-linear model using a subset of all the features to predict next year's salary is the best fit.

5 Results and Conclusion

Overall, NBA salaries are heavily skewed, with a small number of star players earning very large contracts while most players earn far less. Salaries tend to increase with overall on-the-court impact, as advanced metrics like BPM and VORP show strong positive relationships with pay, indicating that teams are willing to compensate players who consistently contribute to winning.

When breaking performance into offense and defense, offensive impact plays a much larger role in determining salary. Offensive Box Plus Minus is strongly related to pay, while defensive impact shows little relationship, suggesting that scoring ability and offensive creation are valued more highly than defensive contributions in the NBA. Salary also varies with age in a nonlinear way, with players generally earning the most during their prime years in their late twenties and early thirties, while the highest salaries among older players are largely driven by a small group of elite veterans who remain productive later in their careers.

From a modeling perspective, simpler linear models were not able to fully capture the patterns in the data. A nonlinear approach using feature selection and a random forest model produced the strongest results and showed that only a small number of factors are needed to explain salary differences. Among these, minutes played per game emerged as the most important predictor, highlighting that consistent availability and sustained playing time are often more important for future salary than individual efficiency statistics alone.

```
# Author Contributions
 - **Brian Fernando:** Brian worked on scraping the data. Brian also worked on feature engi
 - **Sharona Yang:** Sharona worked on the modeling section of the analysis. Sharona also he
 - **Aarush Maddela:** Aarush worked on the EDA section of the project, sifting through the
 - **Nixon Tan:** Nixon worked on the Makefile and running the tests. Nixon also helped crea
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