What Nba Players Statistics Best Predict Scoring Output.*

A Look Into The Metrics Which Best Predit Scoring Output Among NBA Players From The 2020-21 Season.

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Abstract

The NBA is the worlds largest producer of professional Basketball content. The NBA's fanbase and players include hundreds of people from many different walks of life with different charachterisitcs. As the 2020-2021 season comes to a close, O wish to analyse the significance of height on the scoring capability of NBA players. Through the use of statistical methods, it would appear that height is significant but it is not as straightforwards as you may think. .

Keywords:NBA, PTS, REB, AST, MIN, REB, FGA, AGE, X3PM

Contents

*Code and data are available at: https://github.com/adam-labas/Which-NBA-Stats-Best-Predict-Scoring-Output.

1 Introduction

The NBA has for long been a widely admired and celebrated facet of American popular culture. Every season, the average fan has the opportunity to watch the best players on the face of the earth go at each other, night after night, in nail-biting intensity. As an avid fan of the NBA, I too am a consumer of the NBA and its professional basketball content. This became foundational in my life in 2019 when my hometown Toronto Raptors had an amazing run in the playoffs and won the NBA championship. The NBA is well known for being a league full of tall players and as my data suggests, this is true. However, the Toronto Raptors team that won the NBA finals had two relatively short players: Fred VanVleet and Kyle Lowry. Being a relatively short man myself, I was mesmerized by their abilities to perform at the highest level and their abilities to score the basketball and impact the game. As such, in this Paper, I attempt to explore the true parameters which contribute to players scoring output.

As the new 2021-2022 NBA season started on October 19th 2021, it was reminiscing and was thinking about traditionally short players and their ability to score the basketball with ease. It is counter intuitive to me to think that a player that is 185 cm and 89kg like VanVleet can score with ease on a player that is much taller and heavier than him.

If a player like VanVleet, lacking in height can score the ball with ease, what are actually the qualities and traits which contribute statistically to players being able to score more points per game? In statistical terms what predictors best describe the points per game of an NBA player in the 2020-21 season? We aim to answer this question by developing a simple, yet effective and easy to understand model. I had originally decided to study the relationship between the Age, Height and Weight and the number of points scored. When plotting my data, I noticed that there was not a linear relationship between the predictor variables I chose to study and the response variable. As a result, I modified my research question to instead study the relationship between points per game (PTS) to minutes per game and assists per game as this will indirectly answer the question I had originally intended to investigate. I will be able to make this link once I find data on the positions of players and demonstrate that players with smaller heights are almost always players with positions that traditionally have a lot of assists like the Point Guard.

I think that any analysis which gives an insight on which players are prone to producing the most points is always useful and an have impacts in many fields such as the world of sports gambling and especially fantasy sports. Although I am not a gambler myself, I am an aspiring actuary and data analyst and I find pleasure in being able to bring forth simple results from large complex datasets.

2 Data

In this Data Section 2, I will provide a look into the data acquisition and processing methodology as well as a deep dive into the contents of the data. We will also touch on our exploratory data analysis as it pertains to variable selection and lastly we will discuss the reach of the data.

First of, Tables 1 and 2 give us a glimpse of the data.

Table 1: First ten rows of a dataset of shelture usage without All Population

Player	Points	Rebounds	Age	Minutes	Field Goal Attempts	3PM	Weight	Height
Aaron Gordon	12.4	5.7	25	27.7	10.0	1.2	107	203
Aaron Holiday	7.2	1.3	24	17.8	6.6	1.0	84	183
Aaron Nesmith	4.7	2.8	21	14.5	3.9	0.9	98	196
Abdel Nader	6.7	2.6	27	14.8	4.8	0.8	102	196
Adam Mokoka	1.1	0.4	22	4.0	1.4	0.1	86	193
Al Horford	14.2	6.7	35	27.9	12.9	2.0	109	206
Al-Farouq Aminu	4.4	4.8	30	18.9	4.3	0.3	97	198
Alec Burks	12.7	4.6	29	25.6	10.2	2.1	86	213
Aleksej Pokusevski	8.2	4.7	19	24.2	9.1	1.3	98	208
Alen Smailagic	1.9	1.1	20	5.6	1.8	0.3	84	193

2.1 Data Collection & Processing

All the data used in this analysis was retrieved directly from the NBA's website and used in accordance with their terms and conditions (more on this in section 5.1). The data on the NBA's website is displayed on 11 different pages each containing 50 players except for the last page which only contains 36 players. The data is available online as an HTML table. As a result, I used a Google Chrome web browser extension titled **Dowload Table as CSV** to extract the data into 11 CSV files. More information on the Google Chrome extension and the source code that makes it work can be found at the following git repository: https://github.com/arktiv/table-csv-chrome. After appending all the player data into one data frame, we now have a dataset with all the official NBA regular season data for the 2020-2021 season.

The data collected is listed as *Traditional Stats* on the NBA website. In total, there are 31 variables. The type of data that the NBA considers traditional are the data categories which are simple and straight forward to understand. These variables include but are not limited to player name, team, the points per game, games played, number of wins and losses, minutes played, field goals made, field goals attempted, number of 3 points made and rebounds per game. Some variables like the latter are also further broken down into sub-categories like offensive rebounds and defensive rebounds. In Section 2.2, I will elaborate on the exploratory data analysis, the driving factor which contributed to variable selection.

As far as data processing goes, we began by loading all the necessary libraries like haven (Zhu 2021) into R (R Core Team 2020). Additionally, we used a wide variety of libraries like knitr (Xie 2021), tidyverse (Wickham et al. 2019), tidyr (Wickham 2021), janitor (Firke 2021), patchwork (Pedersen 2020), readr (Wickham, Hester, and Bryan 2021),dplyr (Wickham 2021) as well as tinytex (Xie 2022) at some points in the process for data processing and pdf document generation. Packages like kableExtra (Zhu 2021) and equatiomatic (Anderson, Heiss, and Sumners 2022) where also used to produce tables and LaTex formulas of the models. We removed the unwanted columns as discussed in Section 2.2 and then rearranged them for purely aesthetic purposes. Lastly, we created two new data: the training and test data. This will help us extensively in Section 3 when we are creating the parsimonious model we desire. To do this, we used the initial_split function to determine the proportion of data that would be in the training and test data. There are a few decisions which needed to be made at this step. The first being the seed and the second being the proportion. I decided to set the seed with a value of 866 which are simply the last three digits of

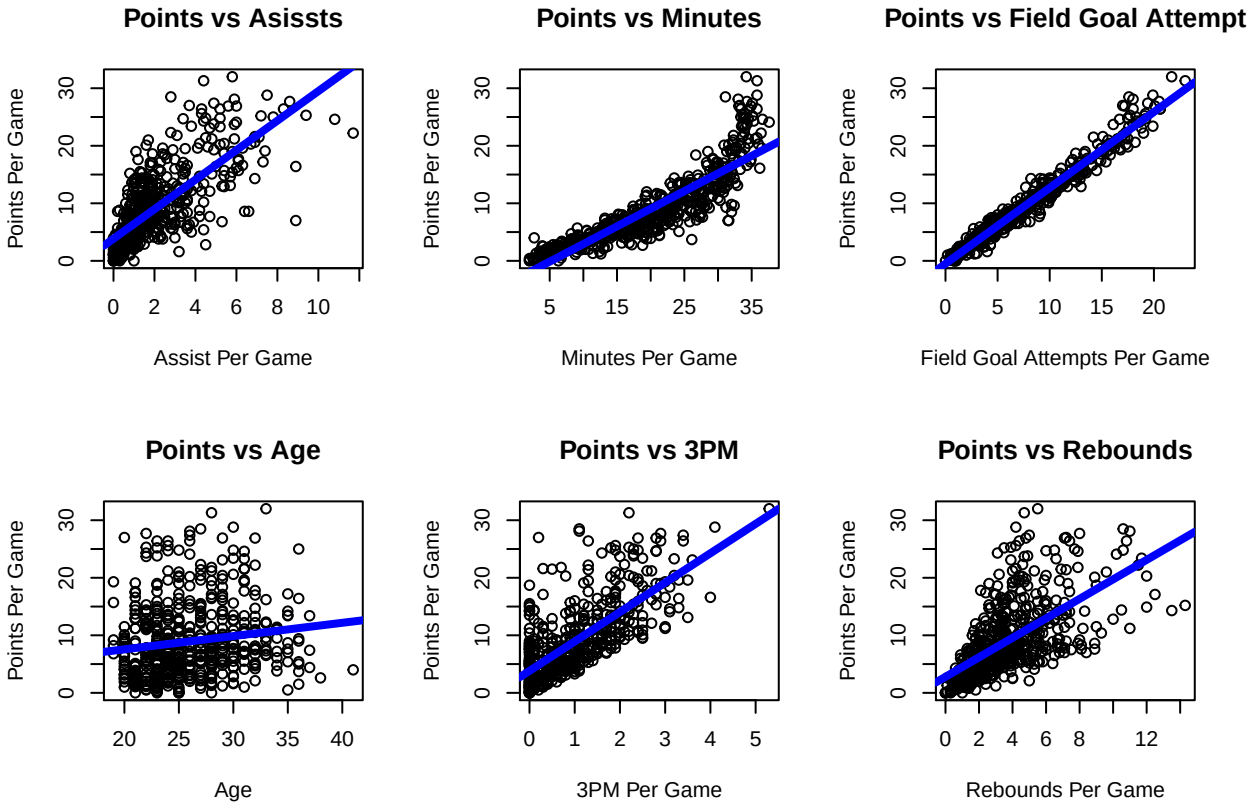
my university student number and hold no other meaning within the analysis. For the proportion, I decided on a 80:20 test to training split. There was no math involved in this decision; I simply wanted to give the training model enough data to produce healthy estimates for the model coefficients.

The Appendix (Section .1) contains a datasheet which was produced to provide more information on the data collected.

2.2 EDA: Exploratory Data Analysis

As was stated in the Introduction Section 1, the aim of this analysis is to find a parsimonious model which can predict the scoring output of NBA players in the relevant season. It was very clear to me from the beginning of this analysis that a model with 31 variables is far from parsimonious and had that many variables would have to be eliminated from inclusion in the final model. Ultimately, I decided on 8 predictors, those in the final_raw_data dataset. These variables are age, minutes, field goal attempts, number of three points made, rebounds, assists, weight and height. These predictors in my opinion will cover a lot of ground and will explain a reasonable amount of the variance in the data.

Below are a few graphs which demonstrate that there is a clear linear correlation between points and many of the selected variables.



Clearly, we can see that for all the variables plotted above with the exception of age, there is a strong positive linear correlation between the variables and points. For this reason, we have decided that in section **??** when we discuss the model that we come up with, we elected to solely use simple linear models.

2.3 Population, Frame or Sample

It is important to discuss the reach of our data as this will have an effect on the generalizability of our Model. As previously stated, the data we have gathered is of all 540 players which were listed on any teams roster for the 2020-2021 season. As a result, I put forth the claim that the findings of this analysis will have strong generalizability and the model should be reliable to predict the scoring output of any player.

3 Model

In this section, we will go through the process of sifting through the remaining variables to simplify our model slightly and come up with the final model. As we mentioned previously, we have split our data into two datasets: the training set and the test set. The first thing we wish to do is compare the two using summary statistics to see if we can observe any abnormalities or extreme differences between the data. Because we segregated the total data using a set seed, the process was absolutely random and thus we expect to see little to no difference between the two datasets. Below is a table displaying summary statistics for both datasets.

Table 2: Some summary data for the training and test data.

Variable	Mean (Standard Deviation) In Training	Mean (Standard Deviation) In Test
PTS	9.0162 (6.4557)	8.64722 (6.61758)
AGE	26.00926 (4.09174)	25.93519 (4.27834)
MIN	20.01968 (9.12071)	19.03519 (10.01606)
FGA	7.2294 (4.82537)	6.89537 (4.86414)
X3PM	1.01181 (0.91524)	0.96574 (0.86556)
REB	3.68819 (2.39793)	3.42222 (2.36873)
AST	1.99699 (1.88067)	1.95 (1.80878)
KG	98.49537 (11.36323)	97.23148 (10.79253)
CM	199.1088 (8.38542)	198.43519 (9.04844)

As we can see from Table 2, the values for both the mean and the standard deviation of all the predictors are almost identical and there is little to no difference as expected.Now, to create a baseline for our model, lets create a model with all of the predictors. We call this model mod_full.

$$\begin{aligned} \text{PTS} = \alpha &+ \beta_1(\text{AGE}) + \beta_2(\text{MIN}) + \beta_3(\text{FGA}) + \\ &\beta_4(\text{X3PM}) + \beta_5(\text{REB}) + \beta_6(\text{AST}) + \beta_7(\text{KG}) + \\ &\beta_8(\text{CM}) + \epsilon \end{aligned} \tag{1}$$

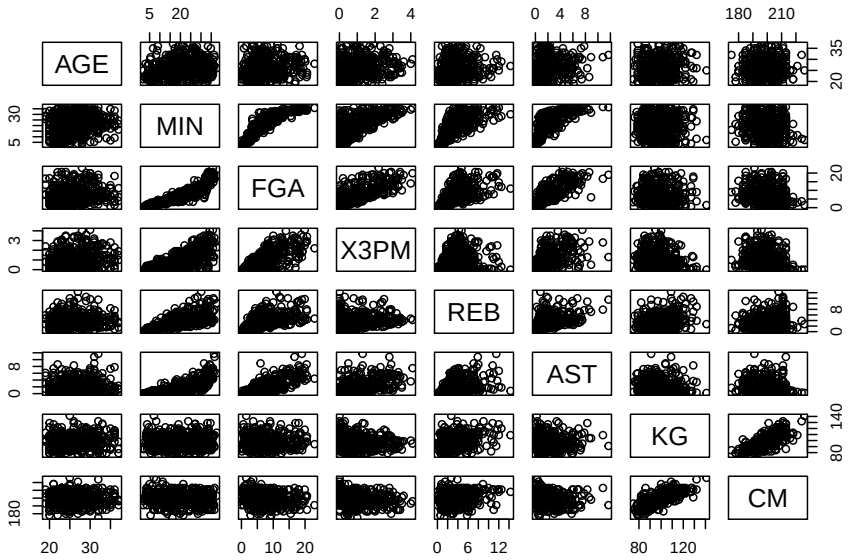
When we run a summary of this mod_full, we can extract the R squared and the adjusted R squared. The adjusted R Squared is the value we will primarily be looking at as we know that when comparing simple linear models with different numbers of predictors, the adjusted R squared is the desired quantity and the simple R^2 will not provide valuable information.

Model Name	R Squared	Adjusted R Squared
mod_full	0.9722968	0.9717729

We see that the adjusted R squared is equal to 97.18%. This is a very high number and after simplifying the model from 31 variables to only 8 variables, we did not lose much information.

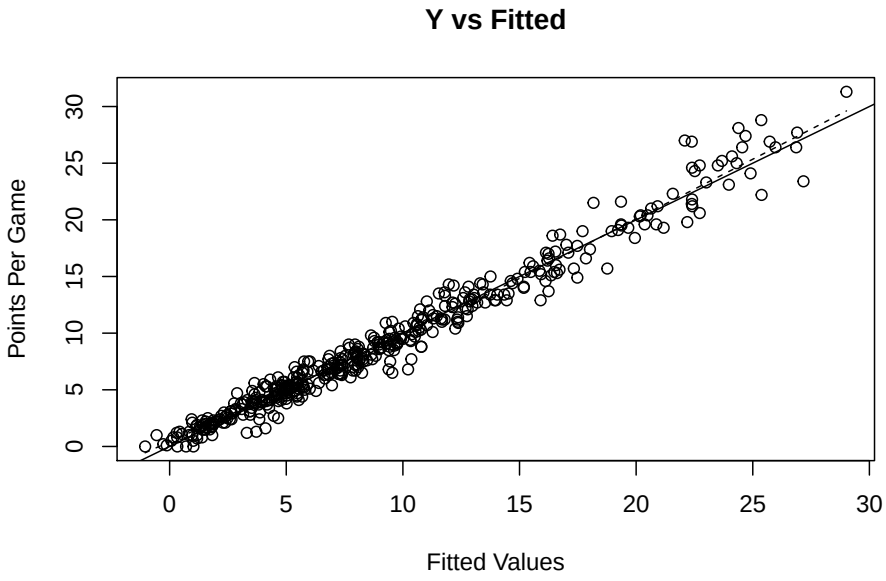
3.1 Checking for Model Violations

The next thing we will do is look for possible model violations. first, lets plot pairwise plots of the predictors and look for any possible evidence of colinearity.



We see very clearly that there is a strong colinearity between minutes played and field goal attempts and between weight and height. We can also see that there is no significant linear relationship between the other pairs of variables.

Lets conduct another test to determine if we will need to transform our data (response and/or predictors).



We see that the points of the Y versus Y hat (fitted values) graph follow very closely to the line of function f(x) = x.

With all the information gathered in the previous steps, we have come to our final model, mod_final:

$$\text{PTS} = \alpha + \beta_1(\text{FGA}) + \beta_2(\text{REB}) + \beta_3(\text{KG}) + \epsilon \tag{2}$$

Model Name	R Squared	Adjusted R Squared
mod_final	0.9718567	0.9716594

4 Results

In this Section 4, we we look at the information gathered in Section 3 and we will objectively describe the events that transpired.

Our first result from Section 3 is the fact that when we plotted the summaries in Table 2, there was little to no difference between the values of the means and standard deviations for the training and test dataset. This is what we expect. If we take a closer look into it, we see that the biggest different between two values from the training and test datasets is a value of the means of weight which differ by 1.26389 KG.

We proceeded by plotting the relationship between points per game and many variables. Bellow is the plot of Points vs Minutes.

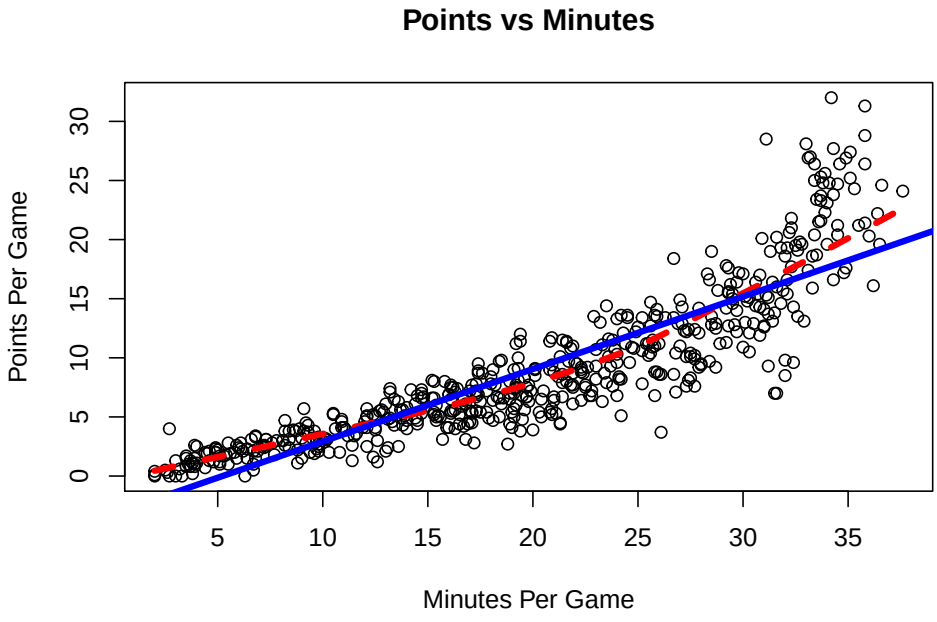


Figure 1: Seemingly exponential elationship between Points and Minutes

In the above graph, we have a red and blue line. The blue line is a linear line fitted to the model using simple linear regression. The red line is not linear and follows more closely the trend in the data. It would appear as if the plot of Points Per Game to Minutes might follow an exponential trend.

Next, we collected data for mod_full. We notice that the adjusted R squared fro mod_full is very high at 97.18%. If we run a summary for mod_full, we can see that rebounds and field goal attempts are two of the predictors with the three asterisk beside them. This means that they are being listed as having statistically significant p-values. This contributed to the two variables being implemented in the final model.

When we moved on to looking at the potential model violations, we started by examining the pairwise plots of the predictors. We notice that there is a strong linear correlation between minutes played and field goal attempts and between weight and height, as seen in the plots below.

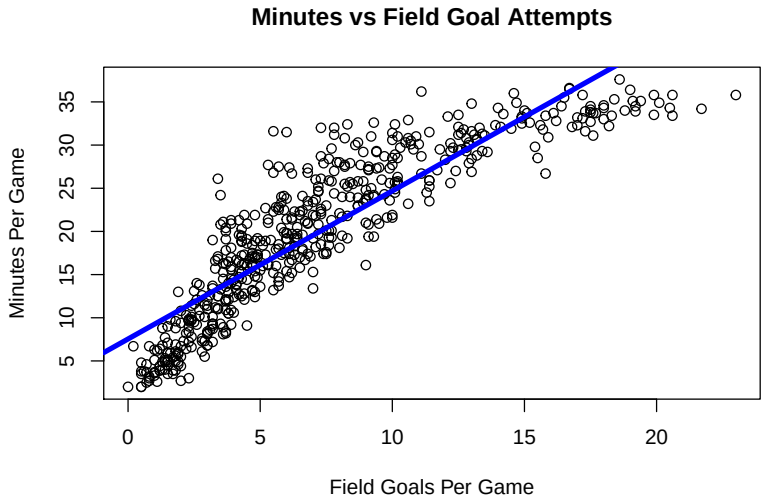


Figure 2: Some examples of collinearity in the data.

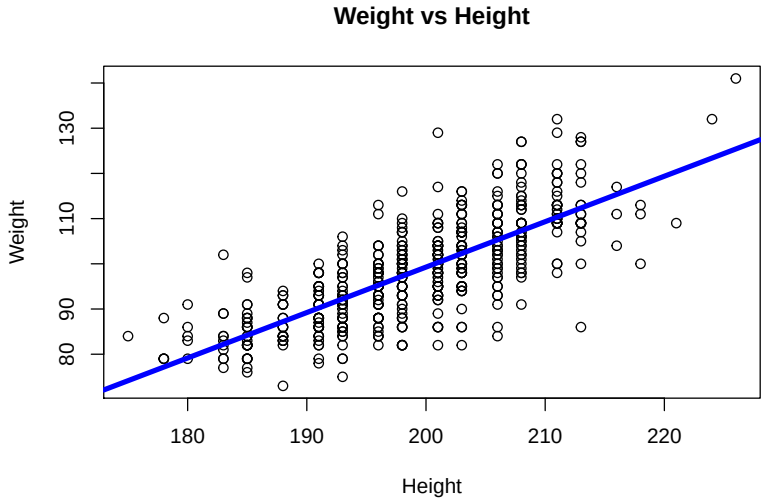


Figure 3: Some examples of collinearity in the data.

Another thing we notice is that there is some fanning effect in some of the plots. This is often associated with a potential violation of constant error variance. This is known as a violation of homoscedasticity. This can be observed in a lot of the plots such as the one between minutes and 3 points made, minutes and rebounds, minutes and assists and others. Below are examples of possible violations of homoscedasticity:

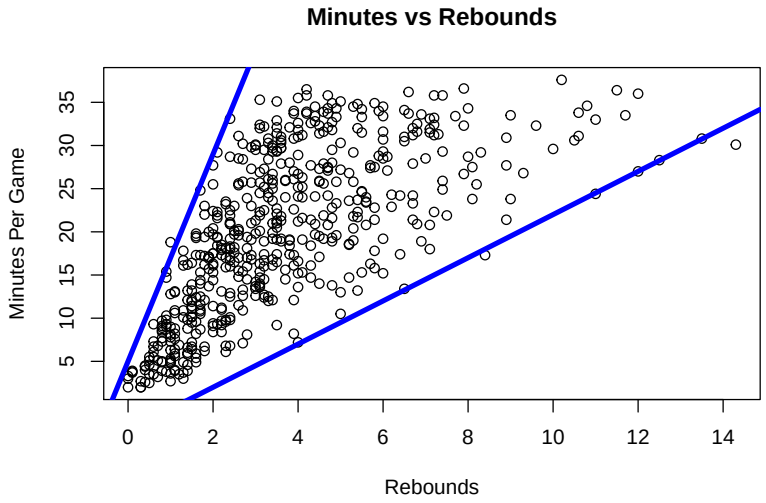


Figure 4: An example of a potential violations of homoscedasticity in the data.

We can see a fanning effect with the points getting further away from eachother as the number of rebounds increase.

Lastly, we compare the plot of of Y vs the fitted values with the function f(x) = x. We notice a very pure trend and the values follow very closely to the function f(x). This brings us to the establishment of the final model, mod_final. We conclude that the final model is that in equation (2). The parameters in mod_final are as follows:

$$\alpha = -2.661466$$

$$beta1 = 1.266497$$

$$\beta_2 = 0.177978$$

$$\beta_3 = 0.018937$$

5 Discussion

When we have a look at the results from the later Section 4, we notice that a lot can be done to further the analysis. The following is my personal explanation and speculation for why many of the observations were observed as well as some discussion on the limitations and weaknesses of this analysis and finally some next steps that can be taken to improve the analysis in a future iteration.

We started this analysis because we wanted to determine weather or not height was a reliable predictor for determining the scoring production of NBA players. At surface value, if we simply look at the final model which we produced, we notice that height is not a predictor and one could leave it at that, close the door and simply state that height is not a relevant predictor. This would of course be a gross over-simplification and as I will demonstrate right now, it is untrue. The first thing which tips us off to this is the fact that although height might not be a predictor in the final model, the weight of the players is and this is relevant. As we saw in Figure 3 weight and height and clearly have a strong positive linear correlation. As a result, we would expect to see on average, that when weight increases, we also see height increase. This is fairly intuitive.

As far as the model is concerned, there are a few things we should discuss as it pertains to model violations and validation. The first is that many assumptions needed to be very loosely regulated in order to achieve our final model. I will explain what I mean by this with the help of a few examples. First off, we know that one of the assumptions for using a linear model is obviously having a linear relationship in the data. Although this is true for a lot of the variables we stated our model off with, we can clearly see that in the case of minutes, there appeared to be a exponential trend. This does make sense. In the NBA, when a player is playing well, he playes more minutes. However, if a player is playing exceptionally, often the team will allow them to play even more minutes that they usually do as the player is simply shooting the lights out and appears to make every shot attempt they take. Another potential model violation is that of homoscedasticity that we saw in Figure 4.

5.1 Limitations

As far as limitations, I think that our analysis is held back by the lack of rigor which is partially a fault of myself as the data analyst but ambiguity is also somewhat embedded within simple linear regression. It is fro this reason that simple linear regression is often referred to as an art rather than science: there is a lot of subjective analysis and decisions made.

One more limitation is that according to the NBA's terms of Service on the data, we are only allowed to use the data on the condition that it is not for commercial use. This prevents a large scale independent analysis of the data that can provide clarity and guidance for sports betters and what players are more likely to hit scoring targets on a nightly basis.

5.2 Weaknesses and Next Steps

There are many weaknesses in the analysis and next steps that we can take to improve it. For instance, one weakness is the lack of true model validation. In another iteration of the analysis, we could use values like the AIC, VIF, BIC and things like Cook's distance to analyze for outliers or influential points in the data. This will allow us to bettwe compare models and come to the best conclusion.

It would also be interesting to see how our model changes potentially if we only include players that meet a certain threshold. For example, instead of using all players, only looking players who have played a minimum of 15 games or shoot at least 5 times per game.

Appendix

.1 DataSheet

Below is a datasheet for the data which provides additional information on various topics pertaining to the data.

Motivation

1. *For what purpose was the data set created? Was there a specific task in mind? Was there a specific gap that needed to be filled? Please provide a description.*
    - The NBA has a financial incentive to track data and player statistics as it is a bargaining tool used by players, general managers and player representatives when they are negotiating contracts. It is also a good engagement tool for fans (the consumer of the NBA)to engage with the sport and keep track of historical acheivements.
2. *Who created the dataset (for example, which team, research group) and on behalf of which entity (for example, company, institution, organization)?*
    - The NBA has signed multi-year, multi-million dollar deals with companies Second Spectrum and Sportradar (later purchased by Genius Sports Group). These are big data analytics companies which work on behalf of the NBA and other sports organizations to collect sports data using elite technologies and computing powers to provide long term data for the NBA but also live metrics and statistics which can be displayed during games.
3. *Who funded the creation of the dataset? If there is an associated grant, please provide the name of the grantor and the grant name and number.*
    - The NBA.
4. *Any other comments?*
    - No.

Composition

1. *What do the instances that comprise the dataset represent (for example, documents, photos, people, countries)? Are there multiple types of instances (for example, movies, users, and ratings; people and interactions between them; nodes and edges)? Please provide a description.*
    - Each row of the dataset is an individual NBA Player and all the *traditional stats* associated with him.
2. *How many instances are there in total (of each type, if appropriate)?*
    - 540
3. *Does the dataset contain all possible instances or is it a sample (not necessarily random) of instances from a larger set? If the dataset is a sample, then what is the larger set? Is the sample representative of the larger set (for example, geographic coverage)? If so, please describe how this representativeness was validated/verified. If it is not representative of the larger set, please describe why not (for example, to cover a more diverse range of instances, because instances were withheld or unavailable).*
    - Contains all instances (ie. all NBA players from the 2020-2021 regular season).
4. *What data does each instance consist of? "Raw" data (for example, unprocessed text or images) or features? In either case, please provide a description.*
    - Each instance consists of the Players Name, Team, and 29 numerical fields of Basketball variables.

5. *Is there a label or target associated with each instance? If so, please provide a description.*
    - The players name.
6. *Is any information missing from individual instances? If so, please provide a description, explaining why this information is missing (for example, because it was unavailable). This does not include intentionally removed information, but might include, for example, redacted text.*
    - No.
7. *Are relationships between individual instances made explicit (for example, users' movie ratings, social network links)? If so, please describe how these relationships are made explicit.*
    - If players are on the same team, they both have the same information in the team column. There is no other form of relationship between instances.
8. *Are there recommended data splits (for example, training, development/validation, testing)? If so, please provide a description of these splits, explaining the rationale behind them.*
    - No.
9. *Are there any errors, sources of noise, or redundancies in the dataset? If so, please provide a description.*
    - No.
10. *Is the dataset self-contained, or does it link to or otherwise rely on external resources (for example, websites, tweets, other datasets)? If it links to or relies on external resources, a) are there guarantees that they will exist, and remain constant, over time; b) are there official archival versions of the complete dataset (that is, including the external resources as they existed at the time the dataset was created); c) are there any restrictions (for example, licenses, fees) associated with any of the external resources that might apply to a dataset consumer? Please provide descriptions of all external resources and any restrictions associated with them, as well as links or other access points, as appropriate.*
    - The dataset is self-contained but each player name is a link to their individual player profile.
11. *Does the dataset contain data that might be considered confidential (for example, data that is protected by legal privilege or by doctor-patient confidentiality, data that includes the content of individuals' non-public communications)? If so, please provide a description.*
    - No.
12. *Does the dataset contain data that, if viewed directly, might be offensive, insulting, threatening, or might otherwise cause anxiety? If so, please describe why.*
    - No.
13. *Does the dataset identify any sub-populations (for example, by age, gender)? If so, please describe how these subpopulations are identified and provide a description of their respective distributions within the dataset.*
    - Yes, age.
14. *Is it possible to identify individuals (that is, one or more natural persons), either directly or indirectly (that is, in combination with other data) from the dataset? If so, please describe how.*
    - Yes, individuals are listed by their name.
15. *Does the dataset contain data that might be considered sensitive in any way (for example, data that reveals race or ethnic origins, sexual orientations, religious beliefs, political opinions or union memberships, or locations; financial or health data; biometric or genetic data; forms of government identification, such as social security numbers; criminal history)? If so, please provide a description.*
    - No.

16. *Any other comments?*
    - No.

Collection process

1. *How was the data associated with each instance acquired? Was the data directly observable (for example, raw text, movie ratings), reported by subjects (for example, survey responses), or indirectly inferred/derived from other data (for example, part-of-speech tags, model-based guesses for age or language)? If the data was reported by subjects or indirectly inferred/derived from other data, was the data validated/verified? If so, please describe how.*
    - The data is directly observable during NBA games.
2. *What mechanisms or procedures were used to collect the data (for example, hardware apparatuses or sensors, manual human curation, software programs, software APIs)? How were these mechanisms or procedures validated?*
    - Many different kinds of cameras and recording equipement. Computing and tracking capabilities.
3. *If the dataset is a sample from a larger set, what was the sampling strategy (for example, deterministic, probabilistic with specific sampling probabilities)?*
    - The data is self-contained.
4. *Who was involved in the data collection process (for example, students, crowdworkers, contractors) and how were they compensated (for example, how much were crowdworkers paid)?*
    - Contractors. Two companies by the names Second Spectrum and Sportradar (later purchased by Genius Sports Group)
5. *Over what timeframe was the data collected? Does this timeframe match the creation timeframe of the data associated with the instances (for example, recent crawl of old news articles)? If not, please describe the timeframe in which the data associated with the instances was created.*
    - The 2020-2021 NBA regular season.
6. *Were any ethical review processes conducted (for example, by an institutional review board)? If so, please provide a description of these review processes, including the outcomes, as well as a link or other access point to any supporting documentation.*
    - Not sure.
7. *Did you collect the data from the individuals in question directly, or obtain it via third parties or other sources (for example, websites)?*
    - Directly from the NBA.
8. *Were the individuals in question notified about the data collection? If so, please describe (or show with screenshots or other information) how notice was provided, and provide a link or other access point to, or otherwise reproduce, the exact language of the notification itself.*
    - Yes.
9. *Did the individuals in question consent to the collection and use of their data? If so, please describe (or show with screenshots or other information) how consent was requested and provided, and provide a link or other access point to, or otherwise reproduce, the exact language to which the individuals consented.*
    - Yes.
10. *If consent was obtained, were the consenting individuals provided with a mechanism to revoke their consent in the future or for certain uses? If so, please provide a description, as well as a link or other access point to the mechanism (if appropriate).*

- Not sure. It is their contractual obligation to allow to have their statistics tracked.

11. *Has an analysis of the potential impact of the dataset and its use on data subjects (for example, a data protection impact analysis) been conducted? If so, please provide a description of this analysis, including the outcomes, as well as a link or other access point to any supporting documentation.*
    - Not sure.
12. *Any other comments?*
    - No.

Preprocessing/cleaning/labeling

1. *Was any preprocessing/cleaning/labeling of the data done (for example, discretization or bucketing, tokenization, part-of-speech tagging, SIFT feature extraction, removal of instances, processing of missing values)? If so, please provide a description. If not, you may skip the remaining questions in this section.*
    - Yes cleaning of the data was done.
2. *Was the "raw" data saved in addition to the preprocessed/cleaned/labeled data (for example, to support unanticipated future uses)? If so, please provide a link or other access point to the "raw" data.*
    - Yes.https://www.nba.com/stats/players/traditional/?sort=PLAYER_NAME&dir=-1&Season=2020-21&SeasonType=Regular%20Season
3. *Is the software that was used to preprocess/clean/label the data available? If so, please provide a link or other access point.*
    - R was used.
4. *Any other comments?*
    - No.

Uses

1. *Has the dataset been used for any tasks already? If so, please provide a description.*
    - Yes. Many analysis have been conducted using NBA data.
2. *Is there a repository that links to any or all papers or systems that use the dataset? If so, please provide a link or other access point.*
    - No.
3. *What (other) tasks could the dataset be used for?*
    - Analyzing another NBA related question.
4. *Is there anything about the composition of the dataset or the way it was collected and preprocessed/cleaned/labeled that might impact future uses? For example, is there anything that a dataset consumer might need to know to avoid uses that could result in unfair treatment of individuals or groups (for example, stereotyping, quality of service issues) or other risks or harms (for example, legal risks, financial harms)? If so, please provide a description. Is there anything a dataset consumer could do to mitigate these risks or harms?*
    - No.
5. *Are there tasks for which the dataset should not be used? If so, please provide a description.*
    - No.

6. *Any other comments?*
    - No.

Distribution

1. *Will the dataset be distributed to third parties outside of the entity (for example, company, institution, organization) on behalf of which the dataset was created? If so, please provide a description.*
    - Not without the written consent of the NBA per the Terms of Service.
2. *How will the dataset be distributed (for example, tarball on website, API, GitHub)? Does the dataset have a digital object identifier (DOI)?*
    - GitGub.
3. *When will the dataset be distributed?*
    - The dataset is available now.
4. *Will the dataset be distributed under a copyright or other intellectual property (IP) license, and/or under applicable terms of use (ToU)? If so, please describe this license and/ or ToU, and provide a link or other access point to, or otherwise reproduce, any relevant licensing terms or ToU, as well as any fees associated with these restrictions.*
    - No. MIT license.
5. *Have any third parties imposed IP-based or other restrictions on the data associated with the instances? If so, please describe these restrictions, and provide a link or other access point to, or otherwise reproduce, any relevant licensing terms, as well as any fees associated with these restrictions.*
    - No.
6. *Do any export controls or other regulatory restrictions apply to the dataset or to individual instances? If so, please describe these restrictions, and provide a link or other access point to, or otherwise reproduce, any supporting documentation.*
    - No.
7. *Any other comments?*
    - No.

Maintenance

1. *Who will be supporting/hosting/maintaining the dataset?*
    - The dataset will no longer be changed considering that the NBA data from the 2020-2021 season is locked in time.
2. *How can the owner/curator/manager of the dataset be contacted (for example, email address)?*
    - Through NBA contacts.
3. *Is there an erratum? If so, please provide a link or other access point.*
    - No.
4. *Will the dataset be updated (for example, to correct labeling errors, add new instances, delete instances)? If so, please describe how often, by whom, and how updates will be communicated to dataset consumers (for example, mailing list, GitHub)?*
    - No.

5. *If the dataset relates to people, are there applicable limits on the retention of the data associated with the instances (for example, were the individuals in question told that their data would be retained for a fixed period of time and then deleted)? If so, please describe these limits and explain how they will be enforced.*

    - No.

6. *Will older versions of the dataset continue to be supported/hosted/maintained? If so, please describe how. If not, please describe how its obsolescence will be communicated to dataset consumers.*

    - There is no older version of the data.

7. *If others want to extend/augment/build on/contribute to the dataset, is there a mechanism for them to do so? If so, please provide a description. Will these contributions be validated/verified? If so, please describe how. If not, why not? Is there a process for communicating/distributing these contributions to dataset consumers? If so, please provide a description.*

    - No.

8. *Any other comments?*

    - No.

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