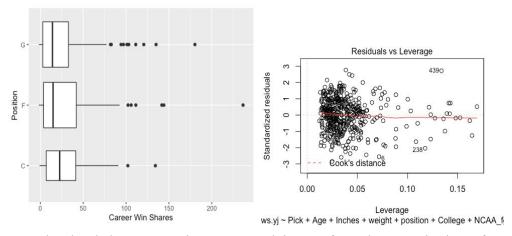
Exploratory Data Analysis Report

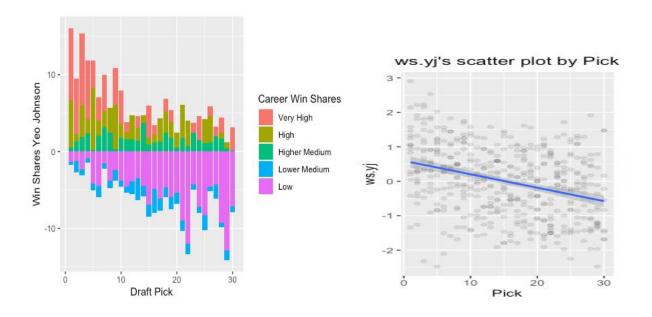
Micaleb Johnson, Elias Cheleuitte, Morgan Williams

Data Cleaning and Aim Assessment:

From our merged dataset, we found that certain players had a missing value for the variable 3pt percentage. Upon further investigation this was due to these players having never attempted 3 pointers, thus we decided to fill in the missing values with 0. The variable measuring player height required some adjustment because the original height format wouldn't have been usable in R programs, thereby we converted it from the format (6,8) to height in inches (80). The format for the college and position variable would have also been difficult for an R program to accurately interpret, thus we turned each variable into a factor with 3 levels. The college factor is broken down into 3 factors, 1 being high school, 2 being international, and 3 being NCAA college. Some higher outliers were present in the win shares variable, which is the metric we are using to measure the success of a player's NBA career. After running a preliminary regression model, with all players included, we didn't see any player who had an abnormally high Cook's distance or leverage. This indicated to us that these players simply had very successful careers and shouldn't be removed from our dataset.

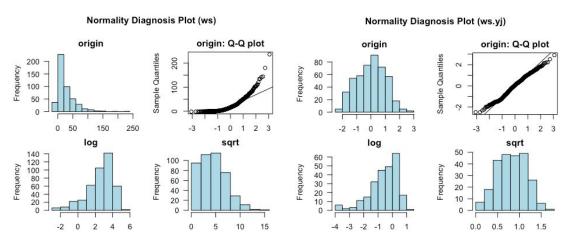


From the plots below, we see that as expected the transformed career win shares for a player decreases as draft pick increases. This thought is reinforced from our initial linear regression model predicting win shares, providing a coefficient of -.029267 for the pick variable. The plot on the lower left also shows that super star NBA players are more likely to be drafted in the early picks and players who produce very little in the NBA are more frequently drafted with higher picks. For instance, players in the 90th percentile of our data set for career win shares (indicated by the "Very High" label) are very prevalent in the top 5 picks but then greatly decrease in frequency as the pick numbers get higher. Players in the bottom quartile (labelled as "Low") of our data for win shares see a large increase in frequency of being picked as the picks increase. One interesting note is that it appears players who have decent careers (labelled as "Higher Medium") have a pick frequency that stays approximately the same throughout all the 1st round picks. From these plots, it seems that pick value will be much greater for the top 5 picks and that after that pick value will have a steep drop off and then gradually decline as each pick increases.

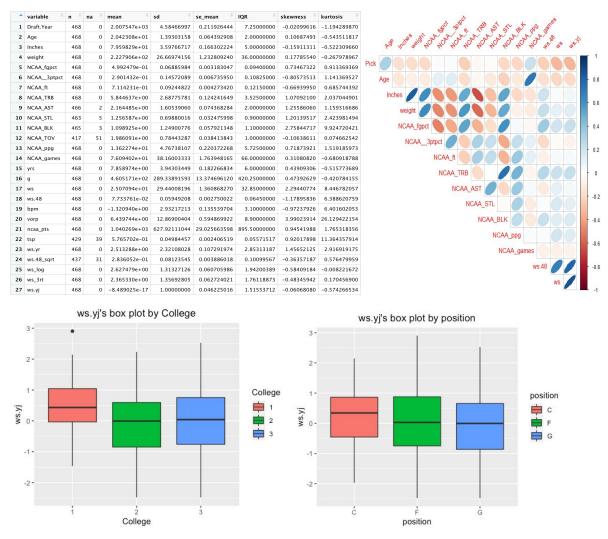


Variable Characteristics and Associations:

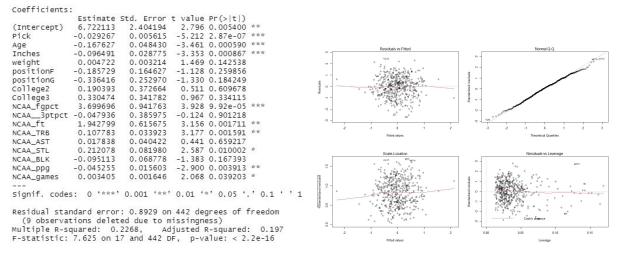
As we began working towards a linear model to predict win share totals from our statistics before being drafted, we noted that our win shares were not normally distributed. In order to normalize the distribution of win share totals as best we can, we performed a yeo-johnson transformation due to some negative win share totals.



The win share totals had to be split into factors due to the different distribution of win share totals from different positions (Guard, Forward, or Center), and also the win share distributions from where they were drafted (highschool, NCAA, or international).



Our linear model using all the NCAA stats before they were drafted using position and college as indicator variables and our win shares transformed as the response came out to:



References: bestNormalize- yeo-johnson transformation, dlookr - Variable structure, associations and Normality testing, ggplot2 and Dplyr - Plotting and Data Cleaning