Project Description

Pipe it Up! will use the Kaggle dataset "Social Power NBA" to explore the following research question: Is there a relationship between measures of basketball success (such as win percentage and offensive/defensive ratings) and Internet popularity, measured in the number of Twitter followers? If we find that there is a relationship between measures of basketball success and social media popularity, we plan to conduct further analysis to determine which of these measures is the best predictor of Internet popularity. Our hypothesis regarding this question is that there will be at least a weak positive correlation between basketball success (which will be discussed in the following paragraph) and the number of Twitter followers; in other words, players with relatively high offensive and defensive ratings will tend to also have more Twitter followers. We also predict that salary, points scored, and offensive rating will be particularly strong predictors of Twitter popularity.

Recently, researchers from many different fields have begun using data science techniques to extract information from social media data. One 2019 journal found that academics in the United States alone have published 7548 papers that use social media data, analyzed via big data techniques, as evidence of their claims (Esfahani et al., 2019). Our desire to explore these questions stems from the increasing relevance of social media in today's hyper-connected world. Social media gives a platform to people's stories and opinions, and influential people, like athletes, can have considerable sway over large segments of the population. Additionally, the NBA is a star-driven league due to its small team size and increasing popularity, so social media presence is significant for basketball players. The original creator of our Kaggle dataset, UC Davis and Northwestern professor Noah Gift, did analyses to determine what social media and internet popularity could predict. He searched for correlations between those factors and a number of response variables, including arena attendance, endorsements, salary, and NBA performance. Our team was fascinated by the statistician's conclusions, but we wanted to take the reverse approach and determine what kinds of factors can predict the social media popularity that he claims is so important.

The dataset we wish to explore includes on-court performance data for NBA players in the 2016-2017 season, along with their salary, Twitter engagement, and Wikipedia traffic data. Because we are examining the relationship between player stats and the number of Twitter followers, we also filtered for players who had an active Twitter account, by filtering for values where TWITTER_HANDLE is not n/a. After filtering, we have 95 observations. The data was originally collected from ESPN, Basketball-Reference, Twitter, Five-ThirtyEight, and Wikipedia. We assume that basketball players in the dataset were not chosen randomly because while the creators did not specify how they chose which players to include, many big name basketball players are in the dataset. We assume the creators chose the best basketball players and the rest, other random smaller name basketball players. However, the players in the dataset are not all from the same team and the data set includes players from 30 different teams, suggesting that at least one player is from each NBA team. While the sample was not collected randomly, there is a sufficiently large sample size and all groups are represented with no team dominating the sample. The dataset has independent observations, so the number of Twitter followers of one player does not affect the number of Twitter followers of another player. The dataset also has independent groups, so the number of Twitter followers of a player from one team does not affect the number of Twitter followers of a player from another team. We will examine independence after choosing the initial variables for our model.

More information about the data set can be found at this link: https://www.kaggle.com/noahgift/social-power-nba

While the dataset has 63 variables, we chose to only use 15 by selecting stats we thought were indicative and all-encompassing of a player's performance and Twitter followers because our research question attempts to predict the number of Twitter followers. We ignored variables like rank because they are discrete numerical variables, and chose continuous numerical variables like percentage ratios because they are more indicative of a player's skill. Below, we've listed the variable we're planning to use and a general description of the variables:

PLAYER_NAME: Player's name (categorical) TEAM_ABBREVIATION: Abbreviation for the team the player is on (categorical) AGE: Player age (quantitative) W_PCT: Percentage of games played won (quantitative) OFF_RATING: Player offensive rating calculated using the formula - Offensive Production Rating = (Points Produced / Individual Possessions) x OAPOW × PPG + FTM/FT * 3pt% + FG% (quantitative) DEF_RATING: Player defensive rating - Defensive Player Rating = (Players Steals*Blocks) + Opponents Differential= 1/5 of possessions - Times blown by + Deflections* OAPDW(Official Adjusted Players Defensive Withstand) (quantitative) NET_RATING: Average of the offensive/defensive rating (quantitative) AST_RATIO: Assists-to-turnovers ratio (quantitative) REB_PCT: Total rebounds (quantitative) USG_PCT: Usage percentage, an estimate of how often a player makes team plays (quantitative) PIE Player impact factor, a statistic roughly measuring a player's impact on the games that they play that's used by nba.com (quantitative) SALARY_MILLIONS: Salary in millions (quantitative) TWITTER_FOLLOWER_COUNT_MILLIONS: Number of Twitter followers (quantitative) TWITTER_HANDLE: Twitter handle (categorical) PTS: Points scored (quantitative)

The Data

```r
library(tidyverse)
library(broom)
library(stringr)
library(knitr)
```

```r
nba_social_power <- read_csv("data/nba_2016_2017_100.csv")
```

```
## Parsed with column specification:
## cols(
##   .default = col_integer(),
##   PLAYER_NAME = col_character(),
##   TEAM_ABBREVIATION = col_character(),
##   W_PCT = col_double(),
##   MIN = col_double(),
##   OFF_RATING = col_double(),
##   DEF_RATING = col_double(),
##   NET_RATING = col_double(),
##   AST_PCT = col_double(),
##   AST_TO = col_double(),
##   AST_RATIO = col_double(),
##   OREB_PCT = col_double(),
##   DREB_PCT = col_double(),
##   REB_PCT = col_double(),
##   TM_TOV_PCT = col_double(),
##   EFG_PCT = col_double(),
##   TS_PCT = col_double(),
##   USG_PCT = col_double(),
##   PACE = col_double(),
##   PIE = col_double(),
##   FGM_PG = col_double()
##   # ... with 8 more columns
## )
```

```
## See spec(...) for full column specifications.
```

Finally, we will examine the relevant variables in the dataset after removing players without Twitter handles (since social power cannot be measured):

```r
nba_social_power_mod <- nba_social_power %>%
  filter(TWITTER_HANDLE != "0") %>%
```

```r
  select(PLAYER_NAME,
         TEAM_ABBREVIATION,
         AGE,
         W_PCT,
         OFF_RATING,
         DEF_RATING,
         NET_RATING,
         AST_RATIO,
         REB_PCT,
         USG_PCT,
         PIE,
         SALARY_MILLIONS,
         ACTIVE_TWITTER_LAST_YEAR,
         TWITTER_FOLLOWER_COUNT_MILLIONS,
         PTS)

glimpse(nba_social_power_mod) # examine modified dataset for analysis
```

```
## Observations: 95
## Variables: 15
## $ PLAYER_NAME                     <chr> "Russell Westbrook", "Demetriu...
## $ TEAM_ABBREVIATION               <chr> "OKC", "BOS", "NOP", "HOU", "G...
## $ AGE                             <int> 28, 22, 24, 27, 28, 32, 32, 26...
## $ W_PCT                           <dbl> 0.568, 0.200, 0.413, 0.667, 0....
## $ OFF_RATING                      <dbl> 107.9, 124.2, 104.2, 113.6, 11...
## $ DEF_RATING                      <dbl> 104.6, 117.8, 102.5, 107.3, 10...
## $ NET_RATING                      <dbl> 3.3, 6.3, 1.7, 6.3, 16.0, 7.7,...
## $ AST_RATIO                       <dbl> 23.4, 31.1, 7.3, 27.6, 18.4, 2...
## $ REB_PCT                         <dbl> 0.167, 0.103, 0.170, 0.123, 0....
## $ USG_PCT                         <dbl> 0.408, 0.172, 0.326, 0.341, 0....
## $ PIE                             <dbl> 0.230, 0.194, 0.192, 0.190, 0....
## $ SALARY_MILLIONS                 <dbl> 26.54, 1.45, 22.12, 26.50, 26....
## $ ACTIVE_TWITTER_LAST_YEAR        <int> 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, ...
## $ TWITTER_FOLLOWER_COUNT_MILLIONS <dbl> 4.500, 0.049, 1.220, 4.470, 16...
## $ PTS                             <dbl> 31.6, 2.0, 28.0, 29.1, 25.1, 2...
```

Because we are concerned with satisfying the independence assumption, we will fit a multiple linear regression model predicting the number of Twitter followers based on the 15 predictor variables we chose:

```r
model <- lm(TWITTER_FOLLOWER_COUNT_MILLIONS ~ AGE + OFF_RATING + DEF_RATING + PIE + REB_PCT + USG_PCT +
            data = nba_social_power_mod)
tidy(model)
```

```
## # A tibble: 10 x 5
##    term                     estimate std.error statistic p.value
##    <chr>                       <dbl>     <dbl>     <dbl>   <dbl>
##  1 (Intercept)              -36.4      16.0      -2.27    0.0257
##  2 AGE                        0.205     0.119     1.72    0.0889
##  3 OFF_RATING                 0.103     0.0980    1.05    0.299
##  4 DEF_RATING                 0.0918    0.122     0.751   0.455
##  5 PIE                       35.6      25.2       1.41    0.161
##  6 REB_PCT                    2.12      8.62      0.247   0.806
##  7 USG_PCT                   -0.984    10.3      -0.0960  0.924
##  8 SALARY_MILLIONS            0.145     0.0577    2.50    0.0142
##  9 W_PCT                      3.04      3.50      0.868   0.388
```

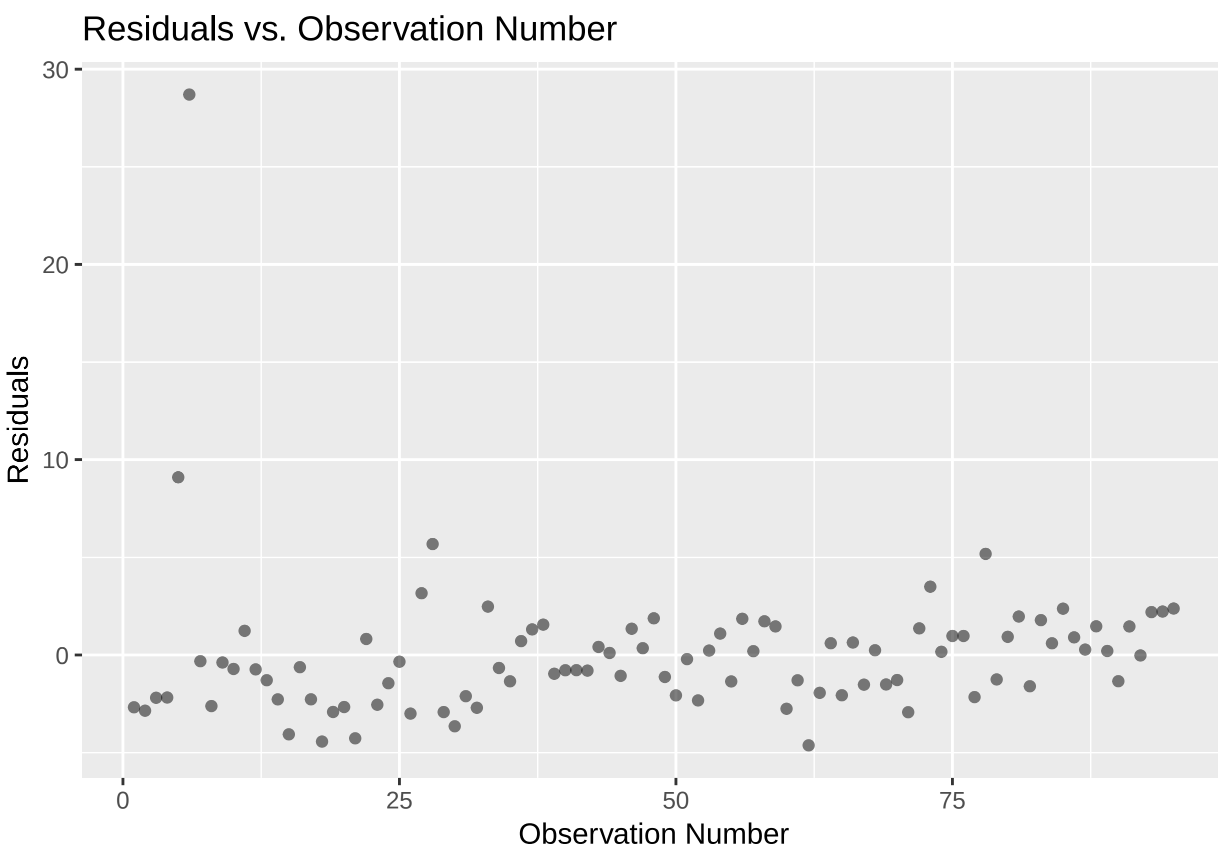
```
## 10 ACTIVE_TWITTER_LAST_YEAR   3.47      2.84      1.22    0.225
```

The linear model is: -36.407 + 0.205 * `AGE` + 0.103 * `OFF_RATING` + 0.092 * `DEF_RATING` + 35.618 * `PIE` + 2.125 * `REB_PCT` - 0.984 * `USG_PCT` + 0.145 * `SALARY_MILLIONS` + 3.037 * `W_PCT` + 3.472 * `ACTIVE_TWITTER_LAST_YEAR`.

Now, we will look at a residual plot of observation number:

```
model_aug <- augment(model)
model_aug <- model_aug %>%
  mutate(obs_num = 1:nrow(model_aug))

ggplot(data = model_aug, aes(x = obs_num, y = .resid)) +
  geom_point(alpha = 0.5) +
  labs(x = "Observation Number",
       y = "Residuals",
       title = "Residuals vs. Observation Number")
```



It is clear, based on the plot displayed above, that there are some deviations from independence because the residuals are not "randomly" distributed.

References

Esfahani, H. J., Tavasoli, K., & Jabbarzadeh, A. (2019). Big data and social media: A scientometrics analysis. International Journal of Data and Network Science, 145–164. doi: 10.5267/j.ijdns.2019.2.007