

Final Project Part 3

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Introduction

The use of data science is ubiquitous across all industries' decision making in one form or another, and nowhere can data driven decision-making be better seen than in professional sports. The National Football League (NFL) is a multi-billion dollar industry in which the lowest individual value of of the thirty-two NFL teams is an incredible \$2.27 billion. The best way for a team to garner and sustain value is through winning, and naturally one would assume the greatest avenue to winning is by employing players that are the best at scoring points. With the exception of two teams, every team's individual record holder for career points scored is a placekicker. This begs an important question: is a kicker worth one of only seven precious draft picks a team gets each year? Successfully navigating the annual draft is critical for an NFL team's sustained success, thus the answer to this question is something in which all thirty-two teams should be interested. Using datasets containing draft data from 1977 through 2016 and kickers' career statistical performance, I will attempt to determine if a kicker is worth spending a draft pick upon.

Problem Statement

To determine whether a kicker is worth spending a draft pick upon the following factors must be considered: 1. What statistics reflect a kicker's value? 2. What number draft pick was used on each kicker? 3. What correlation is there between a kicker's career statistical performance and their draft pick?

Addressing the Problem Statement + (Code)

In the code below I have imported the datasets, removed non-relevant data, merged the data using player names, removed any players that were undrafted, and taken a cursory look into correlation between kicker statistical performance and draft position.

To examine the data more fully, weighted regression models and correlation tests must be performed, with draft picks being assigned a weighted value relative to their draft year and round.

```
library(tidyverse)
draft_df <- read.csv("data/draft.csv")
draft_df <- filter(draft_df, position == "K")
draft_df <- draft_df[c("draft", "round", "pick", "nameFull")]
draft_df <- draft_df[order(draft_df$nameFull),]
head(draft_df)
```

```
##      draft round pick      nameFull
## 119   2016     2   59 Aguayo, Roberto
##  77   1993     8  224  Alcorn, Daron
##  27   1982     4   86 Andersen, Morten
```

```
## 28 1982 7 171 Anderson, Gary
## 45 1985 11 298 Anderson, Ricky
## 68 1991 6 151 Andrews, Richie
```

```
fieldGoal_df <- read.csv("data/field-goal-stats.csv")
fieldGoal_df <- filter(fieldGoal_df, Year >= 1977)
fieldGoal_df <- fieldGoal_df[c("Name", "Year", "Team", "Games.Played", "FGs.Made", "FGs.Attempted", "FG.Percentage")]
fieldGoal_df <- fieldGoal_df %>% mutate_at(c("FGs.Made", "FGs.Attempted", "FG.Percentage"), as.integer)
fieldGoal_df <- aggregate(cbind(Games.Played, FGs.Made, FGs.Attempted) ~ Name, data = fieldGoal_df, sum)
fieldGoal_df$Career_FG_Percentage <- with(fieldGoal_df, (FGs.Made / FGs.Attempted) * 100)
colnames(fieldGoal_df)[1] <- "nameFull"
fieldGoal_df <- fieldGoal_df[order(fieldGoal_df$nameFull),]
head(fieldGoal_df)
```

```
##           nameFull Games.Played FGs.Made FGs.Attempted Career_FG_Percentage
## 1 Abbott, Vince           23         21          34         61.76471
## 2 Aguayo, Roberto          16         22          31         70.96774
## 3 Aguiar, Louie            16          1           2         50.00000
## 4 Akers, David           237        386         477         80.92243
## 5 Allegre, Raul           92        137         186         73.65591
## 6 Alvarez, Wilson           4          3           7         42.85714
```

```
kicker_df <- inner_join(fieldGoal_df, draft_df, by = "nameFull")
kicker_df
```

```
##           nameFull Games.Played FGs.Made FGs.Attempted
## 1 Aguayo, Roberto          16         22          31
## 2 Andersen, Morten        382        565         709
## 3 Anderson, Gary          353        538         672
## 4 Ariri, Obed              18         22          31
## 5 Bahr, Matt              235        300         415
## 6 Bullock, Randy           48         83         102
## 7 Capece, Bill             37         43          70
## 8 Chandler, Jeff           13         19          27
## 9 Crosby, Mason           160        262         326
## 10 Davis, Greg             169        224         325
## 11 DeLine, Steve            8          9          15
## 12 Edinger, Paul           96        135         180
## 13 Elam, Jason             263        436         540
## 14 Epstein, Hayden           6          5           9
## 15 Folk, Nick              150        239         294
## 16 Ford, Cole               37         45          62
## 17 Franklin, Tony          140        177         264
## 18 Gallery, Jim             17         11          25
## 19 Garcia, Eddie            7          3           9
## 20 Garcia, Teddy            28         21          38
## 21 Gostkowski, Stephen     168        303         348
## 22 Haji-Sheikh, Ali         51         76         111
## 23 Hall, Jeff               3          4           5
## 24 Hanson, Jason           327        495         601
## 25 Hopkins, Dustin          31         59          70
## 26 Igwebuike, Donald        80        108         143
## 27 Jacke, Chris            147        202         265
```

## 28	Jacobs, Dave	12	12	26
## 29	Jaeger, Jeff	165	229	309
## 30	Janikowski, Sebastian	268	414	515
## 31	Johansson, Ove	2	1	4
## 32	Kaeding, Nate	114	181	210
## 33	Kasay, John	301	461	563
## 34	Lansford, Mike	124	158	217
## 35	Leavitt, Allan	8	5	10
## 36	Lee, John	11	8	13
## 37	Nelson, Chuck	63	63	93
## 38	O'Donoghue, Neil	110	112	189
## 39	Pelfrey, Doug	111	153	198
## 40	Peterson, Todd	159	235	296
## 41	Rackers, Neil	180	264	330
## 42	Rayner, Dave	57	65	90
## 43	Reveiz, Fuad	147	188	250
## 44	Scobee, Josh	172	241	301
## 45	Septien, Rafael	151	180	256
## 46	Sturgis, Caleb	61	108	134
## 47	Succop, Ryan	128	174	209
## 48	Vitiello, Sandro	2	0	2
## 49	von Schamann, Uwe	89	101	149
## 50	Walsh, Blair	73	133	158
## 51	Zendejas, Max	27	34	49
## 52	Zuerlein, Greg	78	112	141
##	Career_FG_Percentage	draft	round	pick
## 1	70.96774	2016	2	59
## 2	79.68970	1982	4	86
## 3	80.05952	1982	7	171
## 4	70.96774	1981	7	178
## 5	72.28916	1979	6	165
## 6	81.37255	2012	5	161
## 7	61.42857	1981	12	324
## 8	70.37037	2002	4	102
## 9	80.36810	2007	6	193
## 10	68.92308	1987	9	246
## 11	60.00000	1987	7	189
## 12	75.00000	2000	6	174
## 13	80.74074	1993	3	70
## 14	55.55556	2002	7	247
## 15	81.29252	2007	6	178
## 16	72.58065	1995	7	247
## 17	67.04545	1979	3	74
## 18	44.00000	1984	10	254
## 19	33.33333	1982	10	264
## 20	55.26316	1988	4	100
## 21	87.06897	2006	4	118
## 22	68.46847	1983	9	237
## 23	80.00000	1999	6	181
## 24	82.36273	1992	2	56
## 25	84.28571	2013	6	177
## 26	75.52448	1985	10	260
## 27	76.22642	1989	6	142
## 28	46.15385	1979	12	325

```
## 29          74.11003 1987      3    82
## 30          80.38835 2000      1    17
## 31          25.00000 1977     12   316
## 32          86.19048 2004      3    65
## 33          81.88277 1991      4    98
## 34          72.81106 1980     12   312
## 35          50.00000 1977      4    89
## 36          61.53846 1986      2    32
## 37          67.74194 1983      4    87
## 38          59.25926 1977      5   127
## 39          77.27273 1993      8   202
## 40          79.39189 1993      7   177
## 41          80.00000 2000      6   169
## 42          72.22222 2005      6   202
## 43          75.20000 1985      7   195
## 44          80.06645 2004      5   137
## 45          70.31250 1977     10   258
## 46          80.59701 2013      5   166
## 47          83.25359 2009      7   256
## 48           0.00000 1980     10   252
## 49          67.78523 1979      7   189
## 50          84.17722 2012      6   175
## 51          69.38776 1986      4   100
## 52          79.43262 2012      6   171
```

```
summary(kicker_df)
```

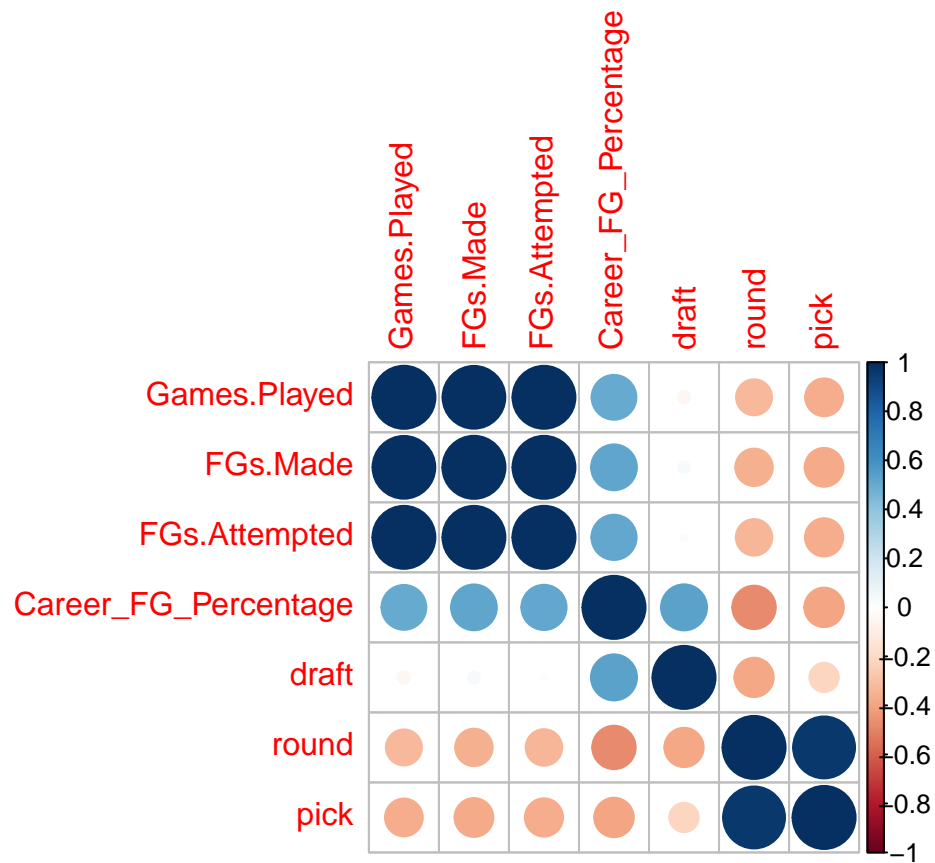
```
##      nameFull      Games.Played      FGs.Made      FGs.Attempted
## Length:52      Min.   : 2.00      Min.   : 0.0      Min.   : 2.00
## Class :character 1st Qu.: 24.75      1st Qu.: 22.0      1st Qu.: 36.25
## Mode  :character Median : 84.50      Median :112.0      Median :153.50
##              Mean  :107.75      Mean  :154.6      Mean  :199.98
##              3rd Qu.:159.25      3rd Qu.:230.5      3rd Qu.:297.25
##              Max.   :382.00      Max.   :565.0      Max.   :709.00
## Career_FG_Percentage draft      round      pick
## Min.   : 0.00      Min.   :1977      Min.   : 1.000      Min.   : 17.0
## 1st Qu.:67.57      1st Qu.:1982      1st Qu.: 4.000      1st Qu.:100.0
## Median :73.46      Median :1988      Median : 6.000      Median :174.5
## Mean   :69.60      Mean   :1992      Mean   : 6.231      Mean   :170.2
## 3rd Qu.:80.14      3rd Qu.:2002      3rd Qu.: 7.000      3rd Qu.:239.2
## Max.   :87.07      Max.   :2016      Max.   :12.000      Max.   :325.0
```

```
cor_df <- cor(kicker_df[sapply(kicker_df, is.numeric)])
cor_df
```

```
##      Games.Played      FGs.Made FGs.Attempted
## Games.Played      1.00000000 0.99093514 0.9966439
## FGs.Made          0.99093514 1.00000000 0.9967767
## FGs.Attempted     0.99664394 0.99677669 1.0000000
## Career_FG_Percentage 0.50632575 0.52796337 0.5143671
## draft             -0.04007157 0.03495371 -0.0109467
## round             -0.32616544 -0.35304613 -0.3359135
## pick              -0.36000405 -0.37995705 -0.3679589
```

```
##           Career_FG_Percentage      draft      round      pick
## Games.Played      0.5063257 -0.04007157 -0.3261654 -0.3600041
## FGs.Made          0.5279634  0.03495371 -0.3530461 -0.3799571
## FGs.Attempted     0.5143671 -0.01094670 -0.3359135 -0.3679589
## Career_FG_Percentage 1.0000000  0.53325321 -0.4745624 -0.3923629
## draft             0.5332532  1.00000000 -0.3885474 -0.2164457
## round            -0.4745624 -0.38854740  1.0000000  0.9650050
## pick             -0.3923629 -0.21644573  0.9650050  1.0000000
```

```
library(corrplot)
corrplot(cor_df)
```



```
kicker_lm <- lm(pick ~ FGs.Made + Games.Played + FGs.Attempted, data = kicker_df)
summary(kicker_lm)
```

```
##
## Call:
## lm(formula = pick ~ FGs.Made + Games.Played + FGs.Attempted,
##     data = kicker_df)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -163.214  -35.582   -2.697   52.523  132.351
##
## Coefficients:
```

```
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)   193.7800    16.2953  11.892 6.48e-16 ***
## FGs.Made      -1.0109     0.9275  -1.090   0.281
## Games.Played   0.2238     1.3929   0.161   0.873
## FGs.Attempted  0.5430     1.2331   0.440   0.662
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 73.99 on 48 degrees of freedom
## Multiple R-squared:  0.1629, Adjusted R-squared:  0.1105
## F-statistic: 3.112 on 3 and 48 DF,  p-value: 0.03481
```

Analysis

Based solely upon the above results, there appears to be little evidence that a kicker is worth spending a draft pick upon. Neither the number of points scored by a kicker (FGs.Made) nor their career length (Games.Played) show any statistically significant correlation with their draft pick. If using a properly weighted multiple regression model or correlation test the results may differ, however there is such a low correlation shown that even if the results differ, the variables could remain statistically insignificant.

Implications

The lack of statistically significant evidence implies that not only is a kicker not worth using a high value draft pick upon, it is unlikely that a kicker will ever perform well enough to justify using any draft pick on them. Instead, the above results indicate that teams would receive better value by waiting until after the yearly draft to offer employment to kickers that went undrafted.

Limitations

The most impactful limitation on this project is my own lack of knowledge regarding weighted regression models and correlation tests. With that knowledge one could more fully examine the data as the value of draft picks changes both over time and by round. Another limitation is the availability of data on team specific values. Each NFL team applies a different strategy in their pursuit of winning, and as such each team has different valuation for different positions. Without insight into each team's closely guarded valuation of the kicker position, whether or not their valuation is accurate, we are limited to only examining a kickers value against a draft pick on an objective scale, while the true value of each is skewed by teams' subjective valuation.

Concluding Remarks

While the true valuation of a kicker vs draft pick is reliant upon a team's subjective valuation, the results shown above do indicate that the best value at the kicker position can be found in the pool of undrafted players post-draft. As draft pick position shows little implication that a kickers performance or career length can be expected to be any better or worse, one can then conclude (without weighted pick values) that where a kicker is drafted will rarely impact a team's success.