Econ 1042 PS1

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Data Wrangling

```
kickers <- read_csv("kickers_v2.csv",
                    show_col_types = FALSE) %>%
  rename(., "ID" = "...1") %>%
  mutate(Grass = if_else(Grass == TRUE, 1, 0))
```

Question 1

a.)

```
min <- min(kickers$Distance)
max <- max(kickers$Distance)
mean <- round(mean(kickers$Distance),
              digits = 3)
median <- median(kickers$Distance)

sprintf("Minimum distance: %s yards.", min)
```

```
## [1] "Minimum distance: 18 yards."
```

```
sprintf("Maximum distance: %s yards.", max)
```

```
## [1] "Maximum distance: 76 yards."
```

```
sprintf("Mean distance: %s yards", mean)
```

```
## [1] "Mean distance: 36.897 yards"
```

```
sprintf("Median distance: %s yards", median)
```

```
## [1] "Median distance: 37 yards"
```

b.) The minimum distance (18 yards) isn't lower for two reasons: First, the kicker must kick the ball through the end zone (accounting for 10 yards) in addition to the distance from the ball to the goal line, and second the ball is snapped a distance of 7 yards to the holder, who holds the ball for the kicker. Therefore, an 18 yard field goal actually begins at the 1 yard line, but the total distance of the kick is 10 yards (the end zone) + 7 yards (the snap) + 1 yard (the distance to the goal line) = 18 yards.

c.)

```
max_distance_kick <- kickers %>%
  filter(Distance == max(Distance))

print(max_distance_kick)
```

```
## # A tibble: 1 x 9
##      ID Team   Year GameMinute Kicker     Distance ScoreDiff Grass Success
##   <dbl> <chr> <dbl>      <dbl> <chr>         <dbl>     <dbl> <dbl>   <dbl>
## 1  3558 OAK    2008         30 Janikowski       76        15     1       0
```

The special circumstance that explains the maximum is that it occured in the 30th minute of the game, the last minute of the 2nd quarter before halftime. Therefore, in this instance, the Oakland Raiders were forced to try to score, because the half was ending and possession is assigned based on the result of the coin toss after the 2nd quarter, and decided they had a better chance of scoring on a very long field goal rather than a hail mary.

Question 2

```
forty_to_fortyfive <- kickers %>%
  filter(Distance %in% (40:45))

forty_to_fortyfive_success <- round((mean(forty_to_fortyfive$Success) * 100),
                                    digits = 3)

over_fortyfive <- kickers %>%
  filter(Distance > 45)

over_fortyfive_success <- round((mean(over_fortyfive$Success) * 100),
                                digits = 3)

sprintf("Kicks from 40 to 45 yards made: %s percent", forty_to_fortyfive_success)
```

```
## [1] "Kicks from 40 to 45 yards made: 79.215 percent"
```

```
sprintf("Kicks over 45 yards made: %s percent", over_fortyfive_success)
```

```
## [1] "Kicks over 45 yards made: 64.448 percent"
```

Question 3

```r
grass_only <- kickers %>%
  filter(Grass == 1)

make_rate_grass <- round((mean(grass_only$Success) * 100),
                         digits = 3)

turf_only <- kickers %>%
  filter(Grass == 0)

make_rate_turf <- round((mean(turf_only$Success) * 100),
                        digits = 3)

sprintf("Make rate on grass: %s percent", make_rate_grass)
```

```
## [1] "Make rate on grass: 82.393 percent"
```

```r
sprintf("Make rate on turf: %s percent", make_rate_turf)
```

```
## [1] "Make rate on turf: 84.326 percent"
```

The make rate was slightly higher on turf.

```r
m1 <- lm(Success ~ Grass, data = kickers)
coeftest(m1, vcov = vcovHC(m1))
```

```
##
## t test of coefficients:
##
##               Estimate Std. Error  t value  Pr(>|t|)
## (Intercept)  0.8432614  0.0051154 164.8473 < 2.2e-16 ***
## Grass       -0.0193292  0.0070587  -2.7384  0.006184 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The difference is statistically significant at the 0.001 level. It could be the true effect of surface, because turf is consistantly a smoother and more solid surface, whereas grass is more imperfect with divits and inconsistencies. Therefore, in some ways, it seems like turf provides better conditions for kickers. However, there are clear counterarguments, including that grass might be better in rainy and snowy conditions, because it would be less slippery than turf.

Question 4

a.)

```r
distance_surface_correlation <- round(cor(kickers$Distance, kickers$Grass),
                                       digits = 3)

sprintf("Correlation between distance and surface: %s",
        distance_surface_correlation)
```

```
## [1] "Correlation between distance and surface: -0.003"
```

Coaches might be more reluctant to attempt longer kicks on grass because of its imperfect texture and also potentially because many grass fields are outdoors where wind conditions can drastically influence kicking whereas many turf fields are indoors where these conditions aren't a factor.

b.)

```r
distance_makepc_correlation <- round(cor(kickers$Distance, kickers$Success),
                                     digits = 3)

sprintf("Correlation between distance and make percentage: %s",
        distance_makepc_correlation)
```

```
## [1] "Correlation between distance and make percentage: -0.337"
```

Question 5

a.) The formula for omitted variable bias (in English) is: Short-Form Regression Coefficient = Long-Form Regression Coefficient + Omitted Variable Regression Coefficient x Correlation Between Orginal Variables.

b.) Given (a), when you add distance when estimating the effect of a kick being on grass, you would expect that the coefficient for surface would become more negative, because distance is negatively correlated with make percentage and is the omitted variable.

```r
m2 <- lm_robust(Success ~ Grass + Distance, data = kickers)
summary(m2)
```

```
##
## Call:
## lm_robust(formula = Success ~ Grass + Distance, data = kickers)
##
## Standard error type:  HC2
##
## Coefficients:
##             Estimate Std. Error t value   Pr(>|t|) CI Lower CI Upper    DF
## (Intercept)  1.29988  0.0112628 115.413  0.000e+00  1.27780  1.32195 11184
## Grass       -0.01997  0.0066494  -3.004  2.671e-03 -0.03301 -0.00694 11184
## Distance    -0.01237  0.0003322 -37.218 6.044e-286 -0.01302 -0.01171 11184
```

```
##
## Multiple R-squared:  0.1142 ,    Adjusted R-squared:  0.1141
## F-statistic: 695.7 on 2 and 11184 DF,  p-value: < 2.2e-16
```

When the regression is run with distance, the estimate for Grass becomes more negative, as expected. Specifically, it was -0.01933 (see Question 3) and now is -0.01997.

Question 6

a.)

```r
m3 <- lm_robust(Success ~ Distance + Grass + ScoreDiff + GameMinute,
                data = kickers)
summary(m3)
```

```
##
## Call:
## lm_robust(formula = Success ~ Distance + Grass + ScoreDiff +
##     GameMinute, data = kickers)
##
## Standard error type:  HC2
##
## Coefficients:
##                Estimate Std. Error  t value   Pr(>|t|)   CI Lower   CI Upper
## (Intercept)  1.29871816  0.0128000 101.4621  0.000e+00  1.2736278  1.3238085
## Distance    -0.01237181  0.0003330 -37.1581 4.484e-285 -0.0130245 -0.0117192
## Grass       -0.01997242  0.0066489  -3.0039  2.672e-03 -0.0330054 -0.0069394
## ScoreDiff   -0.00010224  0.0003593  -0.2846  7.760e-01 -0.0008064  0.0006020
## GameMinute   0.00004408  0.0001991   0.2213  8.248e-01 -0.0003463  0.0004344
##                DF
## (Intercept) 11182
## Distance    11182
## Grass       11182
## ScoreDiff   11182
## GameMinute  11182
##
## Multiple R-squared:  0.1142 ,    Adjusted R-squared:  0.1139
## F-statistic: 347.8 on 4 and 11182 DF,  p-value: < 2.2e-16
```

For every yard of distance added, the kick is roughly 1.2% less likely to be made. When the surface is grass, the kick is roughly 2% less likely to be made than if the surface was turf. For each point of score differential added, the kick is roughly 0.01% less likely to be made. And for each game minute gone by, the kick is 0.0004% more likely to be made. Therefore, it doesn't seem that kickers do better or worse late in the game and the score of the game doesn't seem to effect them, because both coefficients are so small that they are more likely to be caused by random noise.

b.)

```r
m4 <- lm_robust(Success ~ Distance + Grass + ScoreDiff + GameMinute + Kicker,
                data = kickers)
summary(m4)
```

```
##
## Call:
## lm_robust(formula = Success ~ Distance + Grass + ScoreDiff +
##     GameMinute + Kicker, data = kickers)
##
## Standard error type:  HC2
##
## Coefficients:
##                      Estimate Std. Error t value Pr(>|t|) CI Lower CI Upper
## (Intercept)        1.26592530        NaN     NaN      NaN      NaN      NaN
## Distance          -0.01245612        NaN     NaN      NaN      NaN      NaN
## Grass             -0.02455670        NaN     NaN      NaN      NaN      NaN
## ScoreDiff         -0.00003034        NaN     NaN      NaN      NaN      NaN
## GameMinute         0.00004117        NaN     NaN      NaN      NaN      NaN
## KickerAndersen     0.04381603        NaN     NaN      NaN      NaN      NaN
## KickerAndrus      -0.36643808        NaN     NaN      NaN      NaN      NaN
## KickerBailey       0.11159334        NaN     NaN      NaN      NaN      NaN
## KickerBarth        0.07745615        NaN     NaN      NaN      NaN      NaN
## KickerBironas      0.07604501        NaN     NaN      NaN      NaN      NaN
## KickerBoswell      0.12479251        NaN     NaN      NaN      NaN      NaN
## KickerBrien       -0.45973686        NaN     NaN      NaN      NaN      NaN
## KickerBrindza     -0.23718359        NaN     NaN      NaN      NaN      NaN
## KickerBrown        0.03112579        NaN     NaN      NaN      NaN      NaN
## KickerBryant       0.05718160        NaN     NaN      NaN      NaN      NaN
## KickerBuehler     -0.03196493        NaN     NaN      NaN      NaN      NaN
## KickerBullock      0.03495995        NaN     NaN      NaN      NaN      NaN
## KickerCarney       0.00371087        NaN     NaN      NaN      NaN      NaN
## KickerCarpenter    0.06895324        NaN     NaN      NaN      NaN      NaN
## KickerCatanzaro    0.09253760        NaN     NaN      NaN      NaN      NaN
## KickerCoons        0.06276277        NaN     NaN      NaN      NaN      NaN
## KickerCortez      -0.11747215        NaN     NaN      NaN      NaN      NaN
## KickerCoutu       -0.70642277        NaN     NaN      NaN      NaN      NaN
## KickerCrosby       0.01127434        NaN     NaN      NaN      NaN      NaN
## KickerCundiff     -0.03312640        NaN     NaN      NaN      NaN      NaN
## KickerDawson       0.06070381        NaN     NaN      NaN      NaN      NaN
## KickerEdinger     -0.07194958        NaN     NaN      NaN      NaN      NaN
## KickerElam         0.03501133        NaN     NaN      NaN      NaN      NaN
## KickerElling      -0.59504591        NaN     NaN      NaN      NaN      NaN
## KickerFeely        0.04762822        NaN     NaN      NaN      NaN      NaN
## KickerFolk         0.01124171        NaN     NaN      NaN      NaN      NaN
## KickerForbath      0.05426925        NaN     NaN      NaN      NaN      NaN
## KickerFrance      -0.04723015        NaN     NaN      NaN      NaN      NaN
## KickerFranks       0.03612936        NaN     NaN      NaN      NaN      NaN
## KickerFreese      -0.35621015        NaN     NaN      NaN      NaN      NaN
## KickerGano         0.01730043        NaN     NaN      NaN      NaN      NaN
## KickerGostkowski   0.06009622        NaN     NaN      NaN      NaN      NaN
## KickerGould        0.06640870        NaN     NaN      NaN      NaN      NaN
## KickerGraham       0.03744593        NaN     NaN      NaN      NaN      NaN
## KickerGramatica    0.01663024        NaN     NaN      NaN      NaN      NaN
```

```
## KickerHall         0.02865402         NaN      NaN       NaN       NaN       NaN
## KickerHanson       0.06731450         NaN      NaN       NaN       NaN       NaN
## KickerHartley      0.01052404         NaN      NaN       NaN       NaN       NaN
## KickerHauschka     0.07433508         NaN      NaN       NaN       NaN       NaN
## KickerHenery       0.01834460         NaN      NaN       NaN       NaN       NaN
## KickerHocker      -0.09164184         NaN      NaN       NaN       NaN       NaN
## KickerHopkins      0.10415283         NaN      NaN       NaN       NaN       NaN
## KickerJanikowski   0.05137517         NaN      NaN       NaN       NaN       NaN
## KickerKaeding      0.04316970         NaN      NaN       NaN       NaN       NaN
## KickerKasay        0.06534438         NaN      NaN       NaN       NaN       NaN
## KickerKoenen      -0.41151939         NaN      NaN       NaN       NaN       NaN
## KickerLambo        0.07430028         NaN      NaN       NaN       NaN       NaN
## KickerLindell      0.03251634         NaN      NaN       NaN       NaN       NaN
## KickerLongwell     0.04079047         NaN      NaN       NaN       NaN       NaN
## KickerMare        -0.00996415         NaN      NaN       NaN       NaN       NaN
## KickerMcManus      0.06306189         NaN      NaN       NaN       NaN       NaN
## KickerMedlock     -0.14234608         NaN      NaN       NaN       NaN       NaN
## KickerMehlhaff    -0.10266952         NaN      NaN       NaN       NaN       NaN
## KickerMurray       0.10034741         NaN      NaN       NaN       NaN       NaN
## KickerMyers        0.06213240         NaN      NaN       NaN       NaN       NaN
## KickerNedney       0.07429009         NaN      NaN       NaN       NaN       NaN
## KickerNovak        0.03247871         NaN      NaN       NaN       NaN       NaN
## KickerNugent       0.00830262         NaN      NaN       NaN       NaN       NaN
## KickerParkey       0.06655629         NaN      NaN       NaN       NaN       NaN
## KickerPeterson     0.05376993         NaN      NaN       NaN       NaN       NaN
## KickerPettrey     -0.40343016         NaN      NaN       NaN       NaN       NaN
## KickerPotter      -0.06651648         NaN      NaN       NaN       NaN       NaN
## KickerPrater       0.05309480         NaN      NaN       NaN       NaN       NaN
## KickerRackers      0.05314020         NaN      NaN       NaN       NaN       NaN
## KickerRayner      -0.06415445         NaN      NaN       NaN       NaN       NaN
## KickerReed         0.02355016         NaN      NaN       NaN       NaN       NaN
## KickerSantos       0.05739172         NaN      NaN       NaN       NaN       NaN
## KickerSchmitt     -0.16049987         NaN      NaN       NaN       NaN       NaN
## KickerScifres      0.25472643         NaN      NaN       NaN       NaN       NaN
## KickerScobee       0.03290450         NaN      NaN       NaN       NaN       NaN
## KickerStitser     -0.00925080         NaN      NaN       NaN       NaN       NaN
## KickerStover       0.04534670         NaN      NaN       NaN       NaN       NaN
## KickerSturgis      0.00799754         NaN      NaN       NaN       NaN       NaN
## KickerSuccop       0.04197136         NaN      NaN       NaN       NaN       NaN
## KickerSuisham      0.02981151         NaN      NaN       NaN       NaN       NaN
## KickerTucker       0.10472919         NaN      NaN       NaN       NaN       NaN
## KickerTynes       -0.01301411         NaN      NaN       NaN       NaN       NaN
## KickerVanderjagt  -0.02027932         NaN      NaN       NaN       NaN       NaN
## KickerVinatieri    0.06188170         NaN      NaN       NaN       NaN       NaN
## KickerWalsh        0.07112426         NaN      NaN       NaN       NaN       NaN
## KickerWilkins      0.04380249         NaN      NaN       NaN       NaN       NaN
## KickerZuerlein     0.02767417         NaN      NaN       NaN       NaN       NaN
##                      DF
## (Intercept)       11100
## Distance          11100
## Grass             11100
## ScoreDiff         11100
## GameMinute        11100
## KickerAndersen    11100
```

```
## KickerAndrus      11100
## KickerBailey      11100
## KickerBarth       11100
## KickerBironas     11100
## KickerBoswell     11100
## KickerBrien       11100
## KickerBrindza     11100
## KickerBrown       11100
## KickerBryant      11100
## KickerBuehler     11100
## KickerBullock     11100
## KickerCarney      11100
## KickerCarpenter   11100
## KickerCatanzaro   11100
## KickerCoons       11100
## KickerCortez      11100
## KickerCoutu       11100
## KickerCrosby      11100
## KickerCundiff     11100
## KickerDawson      11100
## KickerEdinger     11100
## KickerElam        11100
## KickerElling      11100
## KickerFeely       11100
## KickerFolk        11100
## KickerForbath     11100
## KickerFrance      11100
## KickerFranks      11100
## KickerFreese      11100
## KickerGano        11100
## KickerGostkowski  11100
## KickerGould       11100
## KickerGraham      11100
## KickerGramatica   11100
## KickerHall        11100
## KickerHanson      11100
## KickerHartley     11100
## KickerHauschka    11100
## KickerHenery      11100
## KickerHocker      11100
## KickerHopkins     11100
## KickerJanikowski  11100
## KickerKaeding     11100
## KickerKasay       11100
## KickerKoenen      11100
## KickerLambo       11100
## KickerLindell     11100
## KickerLongwell    11100
## KickerMare        11100
## KickerMcManus     11100
## KickerMedlock     11100
## KickerMehlhaff    11100
## KickerMurray      11100
## KickerMyers       11100
```

```
## KickerNedney     11100
## KickerNovak      11100
## KickerNugent     11100
## KickerParkey     11100
## KickerPeterson   11100
## KickerPettrey    11100
## KickerPotter     11100
## KickerPrater     11100
## KickerRackers    11100
## KickerRayner     11100
## KickerReed       11100
## KickerSantos     11100
## KickerSchmitt    11100
## KickerScifres    11100
## KickerScobee     11100
## KickerStitser    11100
## KickerStover     11100
## KickerSturgis    11100
## KickerSuccop     11100
## KickerSuisham    11100
## KickerTucker     11100
## KickerTynes      11100
## KickerVanderjagt 11100
## KickerVinatieri  11100
## KickerWalsh      11100
## KickerWilkins    11100
## KickerZuerlein   11100
##
## Multiple R-squared:  0.1273 ,    Adjusted R-squared:  0.1205
## F-statistic:    NA on 86 and 11100 DF,  p-value: NA
```

Kicker fixed effects corrects for the skill of each individual kicker. Adjusted R-squared increases from 0.1139 to 0.1205, which makes sense because this is a more complex model and seems to be better fitted.

Question 7

a.)

```
new_data <- kickers %>%
  filter(Kicker == "Tucker",
         ScoreDiff == -11,
         Year == 2015,
         GameMinute == 30)

tucker_lm_predict <- round((predict(m4, newdata = new_data) * 100),
                           digits = 3)

sprintf("Probability of Justin Tucker making specified kick: %s percent",
        tucker_lm_predict)
```

```
## [1] "Probability of Justin Tucker making specified kick: 99.854 percent"
```

b.)

```
new_data
```

```
## # A tibble: 1 x 9
##      ID Team   Year GameMinute Kicker Distance ScoreDiff Grass Success
##   <dbl> <chr> <dbl>      <dbl> <chr>     <dbl>     <dbl> <dbl>   <dbl>
## 1 11082 BAL    2015         30 Tucker       30       -11     0       1
```

The distance of the kick was only 30 yards and Justin Tucker is one of the best kickers in NFL history, so that prediction does seem reasonable to me.

```
average_lm_predict <- round((tucker_lm_predict - 0.10472919),
                            digits = 3)

sprintf("Probability of an average kicker making specified kick: %s percent",
        average_lm_predict)
```

```
## [1] "Probability of an average kicker making specified kick: 99.749 percent"
```

Question 8

a.)

```
m5 <- glm(Success ~ Distance + Grass + ScoreDiff + GameMinute + Kicker,
          family = binomial(),
          data = kickers)

tucker_glm_predict <- round((predict(m5, newdata = new_data,
                                     type = "response") * 100),
                           digits = 3)

sprintf("Probability of Justin Tucker making specified kick: %s percent",
        tucker_glm_predict)
```

```
## [1] "Probability of Justin Tucker making specified kick: 97.063 percent"
```

b.) The coefficients look so different for the logistic regression versus the OLS regression, because coefficients in logistic regressions show a value of log odds whereas coefficients in OLS regressions show how each interval of one variable changes the other variable (Source: "Interpreting Coefficients in Linear and Logistic Regression" by Jonathan Benton).

Question 9

a.)

```r
kickers %>%
  group_by(Kicker) %>%
  summarise(make_rate = mean(Success),
            total_makes = sum(Success)) %>%
  arrange(desc(make_rate)) %>%
  filter(total_makes > 200) %>%
  head(1)
```

```
## # A tibble: 1 x 3
##   Kicker     make_rate total_makes
##   <chr>          <dbl>       <dbl>
## 1 Gostkowski     0.877         300
```

According to this analysis, Stephen Gostkowski was the best kicker in the NFL over this period. Gostkowski had the highest make percentage among kickers with at least 200 total makes in the dataset. In other words, he was consistently a high percentage kicker, and as a New England Patriots fan, this feels very right!

```r
kickers %>%
  filter(Distance > 45) %>%
  group_by(Kicker) %>%
  summarise(total_makes = sum(Success),
            over_fortyfive_percentage = mean(Success)) %>%
  filter(total_makes > 50) %>%
  arrange(desc(over_fortyfive_percentage)) %>%
  head(1)
```

```
## # A tibble: 1 x 3
##   Kicker    total_makes over_fortyfive_percentage
##   <chr>           <dbl>                     <dbl>
## 1 Vinatieri          67                     0.770
```

According to this analysis, Adam Vinatieri was the best kicker in the NFL over this period. Vinatieri had the highest make percentage of attempts over 45 yeards among kickers with at least 50 total makes above 45 yards in the dataset. In other words, Vinatieri was consistantly a high percentage kicker from long range, and once again, as a Patriots fan, this feels right!

b.)

```r
kickers %>%
  filter(Kicker == "Gostkowski") %>%
  group_by(Year) %>%
  summarise(make_rate = mean(Success))
```

```
## # A tibble: 10 x 2
##     Year make_rate
```

```
##    <dbl>     <dbl>
##  1  2006     0.824
##  2  2007     0.846
##  3  2008     0.9
##  4  2009     0.812
##  5  2010     0.769
##  6  2011     0.868
##  7  2012     0.846
##  8  2013     0.929
##  9  2014     0.947
## 10  2015     0.925
```

Overall, Gostkowki's make rate is fairly stable over time. There are some ebbs and flows, but generally he's hovering around the low 80% range to low 90% range.

```
kickers %>%
  filter(Distance > 45,
         Kicker == "Vinatieri") %>%
  group_by(Year) %>%
  summarise(over_fortyfive_percentage = mean(Success))
```

```
## # A tibble: 11 x 2
##     Year over_fortyfive_percentage
##    <dbl>                     <dbl>
##  1  2005                     0.5
##  2  2006                     0.8
##  3  2007                     0.333
##  4  2008                     0.667
##  5  2009                     0.5
##  6  2010                     0.875
##  7  2011                     0.857
##  8  2012                     0.714
##  9  2013                     0.846
## 10  2014                     0.818
## 11  2015                     0.889
```

Vinatieri's make rate of attempts over 45 yards isn't stable over time. Specifically, between 2005-2009, Vinatieri's make rate for attempts over 45 yards falls below his rate for the whole dataset in 4 of 5 years, and between 2010-2014, his make rate is above his rate for the whole dataset in 4 of 5 years. Altogether, this shows that Vinatieri's make rate of attempts over 45 yards rose with more experience.

Question 10

```
simple <- kickers %>%
  mutate(kick = 1) %>%
  group_by(Kicker) %>%
  summarise(make_rate = mean(Success),
            total_kicks = sum(kick)) %>%
```

```r
  arrange(desc(make_rate)) %>%
  mutate(total_kicks_squared = (total_kicks)^2)

m6 <- lm_robust(make_rate ~ total_kicks,
                data = simple)
summary(m6)
```

```
##
## Call:
## lm_robust(formula = make_rate ~ total_kicks, data = simple)
##
## Standard error type:  HC2
##
## Coefficients:
##              Estimate Std. Error t value  Pr(>|t|)  CI Lower  CI Upper DF
## (Intercept) 0.7007075  0.0398416   17.59 2.172e-29 0.6214353 0.7799797 81
## total_kicks 0.0005596  0.0001732    3.23 1.787e-03 0.0002149 0.0009043 81
##
## Multiple R-squared:  0.1393 ,    Adjusted R-squared:  0.1287
## F-statistic: 10.44 on 1 and 81 DF,  p-value: 0.001787
```

```r
m7 <- lm_robust(make_rate ~ total_kicks + total_kicks_squared,
                data = simple)
summary(m7)
```

```
##
## Call:
## lm_robust(formula = make_rate ~ total_kicks + total_kicks_squared,
##     data = simple)
##
## Standard error type:  HC2
##
## Coefficients:
##                       Estimate  Std. Error t value  Pr(>|t|)     CI Lower
## (Intercept)          0.650982968 0.052265287  12.455 2.030e-20  0.546971733
## total_kicks          0.001774469 0.000612362   2.898 4.847e-03  0.000555829
## total_kicks_squared -0.000003588 0.000001642  -2.185 3.181e-02 -0.000006855
##                        CI Upper DF
## (Intercept)          0.7549942039 80
## total_kicks          0.0029931091 80
## total_kicks_squared -0.0000003201 80
##
## Multiple R-squared:  0.2227 ,    Adjusted R-squared:  0.2033
## F-statistic: 6.423 on 2 and 80 DF,  p-value: 0.002588
```

The regression with a linear specification shows some support to the conjecture that kickers get better with experience in this dataset, as for ever additional kick a kicker performs, their make rate slightly increases. The regression with a quadratic specification shows similar support at first, but eventually, shows that kickers performance would decline. A way to interpret this is that kickers get better with experience at first, but their performance eventually declines with age. With this being said, these estimates certainly aren't perfect, as they don't consider many potential confounding variables and don't study how kickers' make rates change throughout this specific dataset.

Question 11

1. Precipitation? - Precipitation would negatively bias the kicker, because it's harder to kick in rainy or snowy conditions.

2. Centered Spot? - A centered spot would positively bias the kicker, because it's more of a straight shot for the kicker to make the attempt.

3. Blocked? - A blocked kick would negatively bias the kicker, because even though the attempt wasn't made, it wasn't the kicker's fault (it was the lineman's fault).

Note: I worked with Ty Thabit on this problem set.