Week 8 Assignments

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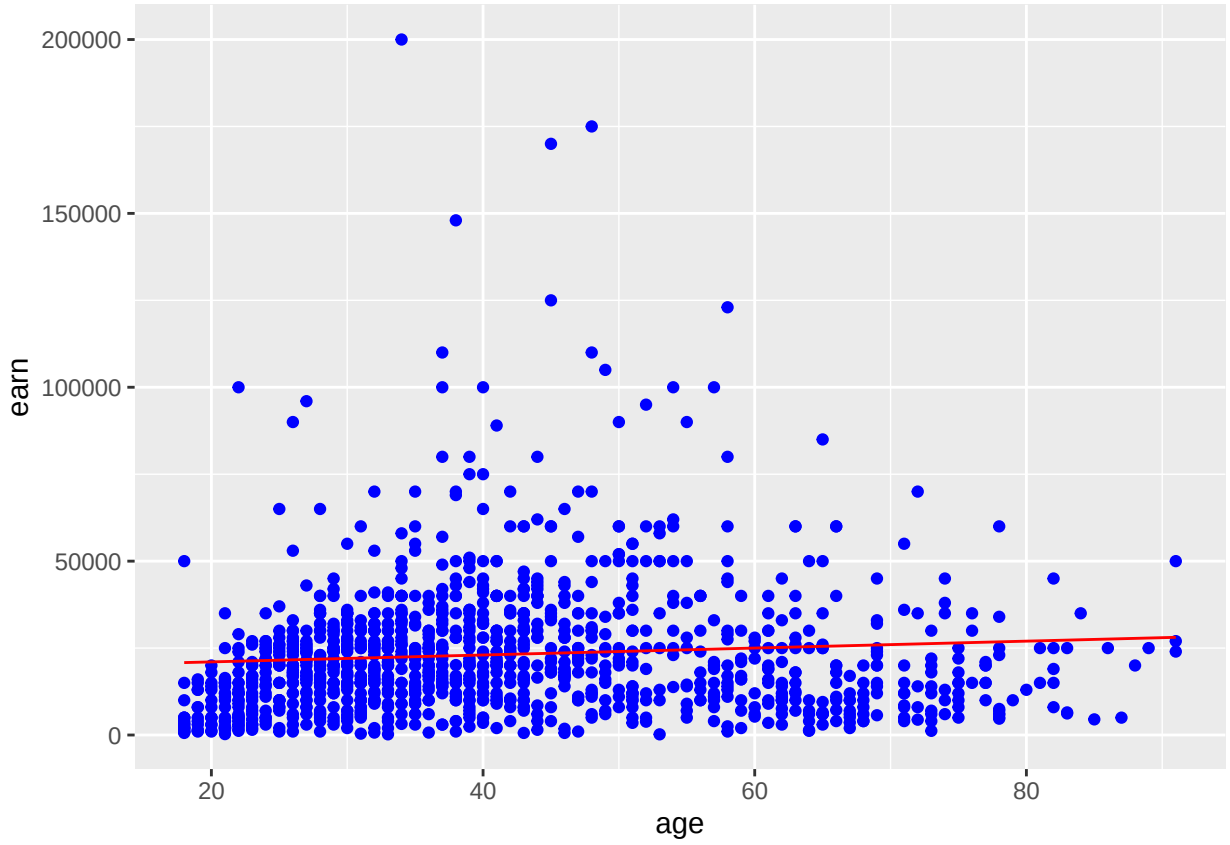
Assignment 6

```
## Set the working directory to the root of your DSC 520 directory
setwd("C:/Users/Alan Donahue/Documents/data science masters/DSC 520 Stats/GIT/dsc520")

## Load the `data/r4ds/heights.csv` to
heights_df <- read.csv("data/r4ds/heights.csv")

## Load the ggplot2 library
library(ggplot2)

## Fit a linear model using the `age` variable as the predictor and `earn` as the outcome
age_lm <- lm(earn ~ age, data = heights_df)

## View the summary of your model using `summary()`
summary(age_lm)
```

```
##
## Call:
## lm(formula = earn ~ age, data = heights_df)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -25098 -12622  -3667   6883 177579
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 19041.53    1571.26  12.119  < 2e-16 ***
## age            99.41      35.46   2.804  0.00514 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 19420 on 1190 degrees of freedom
## Multiple R-squared:  0.006561,   Adjusted R-squared:  0.005727
## F-statistic:  7.86 on 1 and 1190 DF,  p-value: 0.005137
```

```
## Creating predictions using `predict()`
age_predict_df <- data.frame(earn = predict(age_lm, heights_df), age=heights_df$age)
```

```r
## Plot the predictions against the original data
ggplot(data = heights_df, aes(y = earn, x = age)) +
  geom_point(color='blue') +
  geom_line(color='red',data = age_predict_df, aes(y=earn, x=age))
```




```r
mean_earn <- mean(heights_df$earn)
## Corrected Sum of Squares Total
sst <- sum((mean_earn - heights_df$earn)^2)
## Corrected Sum of Squares for Model
ssm <- sum((mean_earn - age_predict_df$earn)^2)
## Residuals
residuals <- heights_df$earn - age_predict_df$earn
## Sum of Squares for Error
sse <- sum(residuals^2)
## R Squared R^2 = SSM\SST
r_squared <- ssm / sst

## Number of observations
n <- 1191
## Number of regression parameters
p <- 2
## Corrected Degrees of Freedom for Model (p-1)
dfm <- p - 1
## Degrees of Freedom for Error (n-p)
dfe <- n - p
```

```r
## Corrected Degrees of Freedom Total:   DFT = n - 1
dft <- n - 1

## Mean of Squares for Model:   MSM = SSM / DFM
msm <- ssm / dfm
## Mean of Squares for Error:   MSE = SSE / DFE
mse <- sse / dfe
## Mean of Squares Total:   MST = SST / DFT
mst <- sst / dft
## F Statistic F = MSM/MSE
f_score <- msm / mse

## Adjusted R Squared R2 = 1 - (1 - R2)(n - 1) / (n - p)
adjusted_r_squared <- 1 - (1 - r_squared)*(n - 1) / (n - p)

## Calculate the p-value from the F distribution
p_value <- pf(f_score, dfm, dft, lower.tail=F)
```

Assignment 7

```r
## Set the working directory to the root of your DSC 520 directory
setwd("C:/Users/Alan Donahue/Documents/data science masters/DSC 520 Stats/GIT/dsc520")

## Load the `data/r4ds/heights.csv` to
heights_df <- read.csv("data/r4ds/heights.csv")

# Fit a linear model
earn_lm <-  lm(earn ~ age + height + sex + ed + race, data=heights_df)

# View the summary of your model
summary(earn_lm)
```

```
##
## Call:
## lm(formula = earn ~ age + height + sex + ed + race, data = heights_df)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -39423  -9827  -2208   6157 158723
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -41478.4    12409.4  -3.342 0.000856 ***
## age            178.3       32.2   5.537 3.78e-08 ***
## height         202.5      185.6   1.091 0.275420
## sexmale      10325.6     1424.5   7.249 7.57e-13 ***
## ed            2768.4      209.9  13.190  < 2e-16 ***
## racehispanic -1414.3     2685.2  -0.527 0.598507
## raceother      371.0     3837.0   0.097 0.922983
## racewhite     2432.5     1723.9   1.411 0.158489
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 17250 on 1184 degrees of freedom
## Multiple R-squared:  0.2199, Adjusted R-squared:  0.2153
## F-statistic: 47.68 on 7 and 1184 DF,  p-value: < 2.2e-16
```

```
predicted_df <- data.frame(
  earn = predict(earn_lm, heights_df),
  ed=heights_df$ed, race=heights_df$race, height=heights_df$height,
  age=heights_df$age, sex=heights_df$sex
  )

## Compute deviation (i.e. residuals)
mean_earn <- mean(heights_df$earn)
## Corrected Sum of Squares Total
sst <- sum((mean_earn - heights_df$earn)^2)
## Corrected Sum of Squares for Model
ssm <- sum((mean_earn - predicted_df$earn)^2)
## Residuals
residuals <- heights_df$earn - predicted_df$earn
## Sum of Squares for Error
sse <- sum(residuals^2)
## R Squared
r_squared <- ssm / sst

## Number of observations
n <- 1191
## Number of regression paramaters
p <- 8
## Corrected Degrees of Freedom for Model
dfm <- p - 1
## Degrees of Freedom for Error
dfe <- n - p
## Corrected Degrees of Freedom Total:   DFT = n - 1
dft <- n - 1

## Mean of Squares for Model:   MSM = SSM / DFM
msm <- ssm / dfm
## Mean of Squares for Error:   MSE = SSE / DFE
mse <- sse / dfe
## Mean of Squares Total:   MST = SST / DFT
mst <- sst / dft
## F Statistic
f_score <- msm / mse

## Adjusted R Squared R2 = 1 - (1 - R2)(n - 1) / (n - p)
adjusted_r_squared <- 1 - (1-r_squared)*(n - 1) / (n - p)
```

Housing Data

Question 1

```
library(car)
```

```
## Loading required package: carData
```

```
#setting the working directory
setwd("C:/Users/Alan Donahue/Documents/data science masters/DSC 520 Stats/GIT/dsc520")

#load the data
housing_df <- read.csv("data/week-6-housing.csv")

summary(housing_df)
```

```
##   Sale.Date           Sale.Price       sale_reason    sale_instrument
##  Length:12865       Min.   :    698   Min.   : 0.00   Min.   : 0.000
##  Class :character   1st Qu.: 460000   1st Qu.: 1.00   1st Qu.: 3.000
##  Mode  :character   Median : 593000   Median : 1.00   Median : 3.000
##                     Mean   : 660738   Mean   : 1.55   Mean   : 3.678
##                     3rd Qu.: 750000   3rd Qu.: 1.00   3rd Qu.: 3.000
##                     Max.   :4400000   Max.   :19.00   Max.   :27.000
##  sale_warning         sitetype          addr_full              zip5
##  Length:12865       Length:12865       Length:12865       Min.   :98052
##  Class :character   Class :character   Class :character   1st Qu.:98052
##  Mode  :character   Mode  :character   Mode  :character   Median :98052
##                                                           Mean   :98053
##                                                           3rd Qu.:98053
##                                                           Max.   :98074
##    ctyname           postalctyn             lon              lat
##  Length:12865       Length:12865       Min.   :-122.2   Min.   :47.46
##  Class :character   Class :character   1st Qu.:-122.1   1st Qu.:47.67
##  Mode  :character   Mode  :character   Median :-122.1   Median :47.69
##                                        Mean   :-122.1   Mean   :47.68
##                                        3rd Qu.:-122.0   3rd Qu.:47.70
##                                        Max.   :-121.9   Max.   :47.73
##  building_grade  square_feet_total_living    bedrooms      bath_full_count
##  Min.   : 2.00   Min.   :  240            Min.   : 0.000   Min.   : 0.000
##  1st Qu.: 8.00   1st Qu.: 1820            1st Qu.: 3.000   1st Qu.: 1.000
##  Median : 8.00   Median : 2420            Median : 4.000   Median : 2.000
##  Mean   : 8.24   Mean   : 2540            Mean   : 3.479   Mean   : 1.798
##  3rd Qu.: 9.00   3rd Qu.: 3110            3rd Qu.: 4.000   3rd Qu.: 2.000
##  Max.   :13.00   Max.   :13540            Max.   :11.000   Max.   :23.000
##  bath_half_count  bath_3qtr_count   year_built   year_renovated
##  Min.   :0.0000   Min.   :0.000   Min.   :1900   Min.   :   0.00
##  1st Qu.:0.0000   1st Qu.:0.000   1st Qu.:1979   1st Qu.:   0.00
##  Median :1.0000   Median :0.000   Median :1998   Median :   0.00
##  Mean   :0.6134   Mean   :0.494   Mean   :1993   Mean   :  26.24
##  3rd Qu.:1.0000   3rd Qu.:1.000   3rd Qu.:2007   3rd Qu.:   0.00
##  Max.   :8.0000   Max.   :8.000   Max.   :2016   Max.   :2016.00
```

```
##  current_zoning       sq_ft_lot        prop_type          present_use
##  Length:12865       Min.   :    785   Length:12865       Min.   :  0.000
##  Class :character   1st Qu.:   5355   Class :character   1st Qu.:  2.000
##  Mode  :character   Median :   7965   Mode  :character   Median :  2.000
##                     Mean   :  22229                      Mean   :  6.598
##                     3rd Qu.:  12632                      3rd Qu.:  2.000
##                     Max.   :1631322                      Max.   :300.000
```

```
#change names for consistency
colnames(housing_df)[1] <- "Sale_Date"
colnames(housing_df)[2] <- "Sale_Price"

head(housing_df$sale_warning)
```

```
## [1] ""      ""      ""      ""      "15"    "18 51"
```

```
#change "" to 0 in sale_warning
housing_df$sale_warning <- sub("^$", 0, housing_df$sale_warning)
head(housing_df$sale_warning)
```

```
## [1] "0"     "0"     "0"     "0"     "15"    "18 51"
```

```
#change "" to NA in ctyname
unique(is.na(housing_df$ctyname))
```

```
## [1] FALSE
```

```
housing_df$ctyname <- sub("^$", NA, housing_df$ctyname)
unique(is.na(housing_df$ctyname))
```

```
## [1] FALSE  TRUE
```

I completed a few changes to the data set. First, I converted it to a .csv file. I also changed the names of the first two columns for consistency sake. From there, I changed any "" in sale_warning to a 0 to represent FALSE. Finally, I couldn't find a quick way to change all the "" in ctyname and confirm that they were accurate so I changed the "" to NA.

Question 2

```
#check to make sure no ""
unique(housing_df$building_grade)
```

```
##  [1]  9  8  7 10  6 11 12  5  4 13  2  3
```

```
unique(housing_df$year_built)
```

```
##   [1] 2003 2006 1987 1968 1980 2005 1993 1988 1978 1976 1975 2011 1990 1972 1977
##  [16] 1986 2007 1998 1979 1966 1983 1970 1991 1999 1973 1964 2002 1963 1984 1989
##  [31] 2004 1992 1985 1981 1967 2000 2001 1952 1955 1995 1942 2008 2014 1974 1994
##  [46] 1900 1969 2015 1957 1918 1953 1982 1965 2016 1997 1996 1958 1971 2013 1954
##  [61] 2010 1959 1950 1961 1913 1951 1933 1930 1947 1914 1943 1946 1905 1948 2012
##  [76] 1929 1920 1960 1962 2009 1922 1903 1956 1941 1940 1938 1926 1927 1949 1939
##  [91] 1944 1923 1924 1925 1937 1945 1934 1935 1909 1932 1912 1931 1916 1906 1936
## [106] 1928 1915 1919 1910
```

```
var3 <- housing_df[housing_df$sq_ft_lot=="", ]
print(var3)
```

```
##  [1] Sale_Date               Sale_Price              sale_reason
##  [4] sale_instrument         sale_warning            sitetype
##  [7] addr_full               zip5                    ctyname
## [10] postalctyn              lon                     lat
## [13] building_grade          square_feet_total_living bedrooms
## [16] bath_full_count         bath_half_count         bath_3qtr_count
## [19] year_built              year_renovated          current_zoning
## [22] sq_ft_lot               prop_type               present_use
## <0 rows> (or 0-length row.names)
```

```
#Question 2
sq_ft_lot_lm <- lm(Sale_Price ~ sq_ft_lot, data=housing_df, na.action = na.omit)
mult_pred_lm <- lm(Sale_Price ~ sq_ft_lot + building_grade + year_built, data = housing_df, na.action =
```

I chose my additional predictors based off the theoretical importance they have in regard to buying or selling a house.I felt that the quality of the build (building_grade) was important to the sale price because a cheaply made house should go for less money. I felt when the house was built was important to the sale price because an older house made need more repairs than a new house.

Question 3

```
summary(sq_ft_lot_lm)
```

```
##
## Call:
## lm(formula = Sale_Price ~ sq_ft_lot, data = housing_df, na.action = na.omit)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2016064  -194842   -63293    91565  3735109
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 6.418e+05  3.800e+03  168.90   <2e-16 ***
## sq_ft_lot   8.510e-01  6.217e-02   13.69   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
## Residual standard error: 401500 on 12863 degrees of freedom
## Multiple R-squared:  0.01435,    Adjusted R-squared:  0.01428
## F-statistic: 187.3 on 1 and 12863 DF,  p-value: < 2.2e-16
```

```
summary(mult_pred_lm)
```

```
##
## Call:
## lm(formula = Sale_Price ~ sq_ft_lot + building_grade + year_built,
##     data = housing_df, na.action = na.omit)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2172605  -137008   -44312    54092  3706547
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)    -6.724e+06  4.016e+05  -16.74   <2e-16 ***
## sq_ft_lot       6.577e-01  5.870e-02   11.20   <2e-16 ***
## building_grade  1.218e+05  3.251e+03   37.47   <2e-16 ***
## year_built      3.194e+03  2.062e+02   15.49   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 367800 on 12861 degrees of freedom
## Multiple R-squared:  0.1729, Adjusted R-squared:  0.1727
## F-statistic: 896.1 on 3 and 12861 DF,  p-value: < 2.2e-16
```

The R^2 and Adjusted R^2 for the simple regression are .01435 and .01428 respectfully. The R^2 value tells us that the sq_ft_lot accounts for 1.44% of the variation in sale price. The Adjusted R^2 tells us how well our model generalizes. We want the value to be close to the value of R^2. It tells us that there is a .007% in shrinkage which means it would generalize well.

The R^2 and Adjusted R^2 for the multiple regression are .1729 and .1727 respectfully. The R^2 value tells us that the multple predictors account for 17.29% of variance in sale price which means it covers more compared to just sq_ft_lot. The Adjusted R^2 tells us there is a .02% in shrinkage which means it would generalize well.

Question 4

For the simple regression, the b_0 = 6.418e+05 and b_1 = 8.510e-01. This tells me that when X = 0, the sale price is going to be $641,800 and for every sq_ft_lot added, the price will go up by .851.

For the multiple regression, b_0 = -6.724e+06, b_1 = 6.577e-01, b_2 = 1.218e+05, and b_3 = 3.194e+03. The negative intercept is a cause for concern. It means that there there might be an issue with the assumption of linearity. The other coefficients show how much the sale price would go up if one sq_ft_lot or the build grade went up or there was a change in year the house was built.

Question 5

```
confint(sq_ft_lot_lm)
```

```
##                    2.5 %       97.5 %
## (Intercept) 6.343730e+05 6.492698e+05
## sq_ft_lot   7.291208e-01 9.728641e-01
```

```
confint(mult_pred_lm)
```

```
##                         2.5 %        97.5 %
## (Intercept)    -7.511117e+06 -5.936765e+06
## sq_ft_lot       5.426072e-01  7.727464e-01
## building_grade  1.154567e+05  1.282031e+05
## year_built      2.790059e+03  3.598422e+03
```

The confidence intervals are stating that in 95% of these samples it will contain the b that represents the population. The confidence intervals look good because they don't cross zero and the two ends are close to each other for each interval.

Question 6

```
anova(sq_ft_lot_lm, mult_pred_lm)
```

```
## Analysis of Variance Table
##
## Model 1: Sale_Price ~ sq_ft_lot
## Model 2: Sale_Price ~ sq_ft_lot + building_grade + year_built
##   Res.Df        RSS Df  Sum of Sq      F    Pr(>F)
## 1  12863 2.0734e+15
## 2  12861 1.7399e+15  2 3.3349e+14 1232.5 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

We can say it has significantly improved.

Question 7

```
housing_df$residuals <- resid(mult_pred_lm)
housing_df$standardized.residuals <- rstandard(mult_pred_lm)
housing_df$studentized.residuals <- rstudent(mult_pred_lm)
housing_df$cooks.distance <- cooks.distance(mult_pred_lm)
housing_df$dfbeta <- dfbeta(mult_pred_lm)
housing_df$dffit <- dffits(mult_pred_lm)
housing_df$leverage <- hatvalues(mult_pred_lm)
housing_df$covariance.ratios <- covratio(mult_pred_lm)
```

Question 8

```
head(housing_df$standardized.residuals > 2 | housing_df$standardized.residuals < -2)
```

```
## [1] FALSE FALSE FALSE FALSE FALSE FALSE
```

```
housing_df$large.residuals <- housing_df$standardized.residuals > 2 | housing_df$standardized.residuals
head(housing_df$large.residuals)
```

```
## [1] FALSE FALSE FALSE FALSE FALSE FALSE
```

Question 9

```
sum(housing_df$large.residuals)
```

```
## [1] 327
```

```
percent.large <- (sum(housing_df$large.residuals)/nrow(housing_df)) * 100
print(head(percent.large))
```

```
## [1] 2.54178
```

Question 10

```
first.results <- housing_df[housing_df$large.residuals, c("Sale_Price", "sq_ft_lot", "building_grade",
head(first.results)
```

```
##     Sale_Price sq_ft_lot building_grade year_built standardized.residuals
## 14      165000    278891             9       2011              -2.216749
## 72     1900000     37017            11       1990               2.455721
## 108    1520000     19173             9       1952               2.447062
## 115    1390000    225640             6       1955               2.693326
## 160     229000    236966            10       2008              -2.272395
## 239    1588359      8752             9       2005               2.190472
```

Question 11

```
second.results <- housing_df[housing_df$large.residuals, c("cooks.distance", "leverage", "covariance.ra
head(second.results)
```

```
##     cooks.distance     leverage covariance.ratios
## 14     0.002343891 0.0019043048         1.0006888
## 72     0.001038161 0.0006881257         0.9991237
## 108    0.001164074 0.0007769857         0.9992258
## 115    0.002968210 0.0016340540         0.9996897
## 160    0.001761850 0.0013629149         1.0000685
## 239    0.000165206 0.0001377053         0.9989567
```

```
#cooks distance greater than 1 = concern
housing_df[housing_df$cooks.distance > 1, ]
```

```
##  [1] Sale_Date                Sale_Price               sale_reason
##  [4] sale_instrument          sale_warning             sitetype
##  [7] addr_full                zip5                     ctyname
## [10] postalctyn               lon                      lat
## [13] building_grade           square_feet_total_living bedrooms
## [16] bath_full_count          bath_half_count          bath_3qtr_count
## [19] year_built               year_renovated           current_zoning
## [22] sq_ft_lot                prop_type                present_use
## [25] residuals                standardized.residuals   studentized.residuals
## [28] cooks.distance           dfbeta                   dffit
## [31] leverage                 covariance.ratios        large.residuals
## <0 rows> (or 0-length row.names)
```

```
twice.leverage = 2 * ((3+1) / 12864)
three.leverage = 3 * ((3+1) / 12864)

third.results <- housing_df[housing_df$leverage > three.leverage, ]
head(third.results)
```

```
##     Sale_Date Sale_Price sale_reason sale_instrument sale_warning sitetype
## 14   1/4/2006     165000           1               3            0       R1
## 65  1/26/2006     446400           8               3           12       R1
## 115 2/15/2006    1390000           1               3            0       R1
## 116 2/15/2006    1390000           1               3            0       R1
## 131 2/21/2006     650000           1               3            0       R1
## 160 2/27/2006     229000          18               3           13       R1
##               addr_full  zip5 ctyname postalctyn       lon      lat
## 14    2921 288TH AVE NE 98053    <NA>    REDMOND -121.9577 47.63382
## 65     28616 NE 47TH PL 98053    <NA>    REDMOND -121.9569 47.65066
## 115 19656 NE REDMOND RD 98053    <NA>    REDMOND -122.0772 47.69595
## 116 19656 NE REDMOND RD 98053    <NA>    REDMOND -122.0772 47.69595
## 131    26608 NE 15TH ST 98053    <NA>    REDMOND -121.9831 47.62150
## 160    28527 NE 47TH PL 98053    <NA>    REDMOND -121.9580 47.64833
##     building_grade square_feet_total_living bedrooms bath_full_count
## 14               9                     1850        3               2
## 65               7                     1770        3               3
## 115              6                      660        0               1
## 116             10                     3280        3               2
## 131              9                     3960        4               2
## 160             10                     3840        0               0
##     bath_half_count bath_3qtr_count year_built year_renovated current_zoning
## 14                0               0       2011              0           RA5
## 65                0               0       1984              0           RA5
## 115               0               0       1955              0           RA5
## 116               0               1       2000              0           RA5
## 131               1               2       1995              0           RA5
## 160               0               0       2008              0           RA5
##     sq_ft_lot prop_type present_use residuals standardized.residuals
## 14     278891         R           2 -814566.1             -2.2167494
## 65     220654         R           2 -164960.7             -0.4487772
```

```
## 115    225640         R           2  989822.9              2.6933263
## 116    225640         R           2  358762.6              0.9759815
## 131    217800         R           2 -238280.2             -0.6481659
## 160    236966         R         300 -835240.2             -2.2723953
##     studentized.residuals cooks.distance dfbeta.(Intercept) dfbeta.sq_ft_lot
## 14             -2.2170868   2.343891e-03       1.404118e+04    -5.422020e-03
## 65             -0.4487632   6.353258e-05       8.454823e+02    -8.668139e-04
## 115             2.6939814   2.968210e-03       9.156804e+03     5.097091e-03
## 116             0.9759797   2.832488e-04      -1.969672e+03     1.725497e-03
## 131            -0.6481513   1.074077e-04       1.277533e+03    -1.145039e-03
## 160            -2.2727633   1.761850e-03       8.995790e+03    -4.379147e-03
##     dfbeta.building_grade dfbeta.year_built       dffit    leverage
## 14           3.970472e+01     -7.180759e+00 -0.09684224 0.001904305
## 65           2.252595e+01     -5.141369e-01 -0.01594097 0.001260223
## 115         -1.588384e+02     -3.955913e+00  0.10898906 0.001634054
## 116          2.365842e+01      8.852379e-01  0.03365993 0.001188033
## 131          1.009564e-01     -6.379585e-01 -0.02072707 0.001021596
## 160         -3.951887e+01     -4.334068e+00 -0.08396238 0.001362915
##     covariance.ratios large.residuals
## 14          1.0006888            TRUE
## 65          1.0015105           FALSE
## 115         0.9996897            TRUE
## 116         1.0012042           FALSE
## 131         1.0012032           FALSE
## 160         1.0000685            TRUE
```

```
CVR.upper <- 1 + (3 * (3+1)/12864)
CVR.lower <- 1 - (3 * (3+1)/12864)

sum(housing_df$covariance.ratios > CVR.upper | housing_df$covariance.ratios < CVR.lower)
```

```
## [1] 755
```

There are no issues with Cook's Distance. However, there are well over 430 cases that the average leverage is above three times the average leverage. Additionally, there are 755 cases where the covariance ratios are outside of the upper and lower limits. This is cause for major concern.

Question 12

```
durbinWatsonTest(mult_pred_lm)
```

```
##  lag Autocorrelation D-W Statistic p-value
##    1       0.6982173     0.6035601       0
##  Alternative hypothesis: rho != 0
```

The assumption of independence has not been met after running the durbinWatsonTest() function. Anything less than 1 or greater than three is a cause for concern. The ideal scenario is to be as close to 2 as possible. The function returns 0.6035601 which is below 1.

Question 13

```
vif(mult_pred_lm)
```

```
##      sq_ft_lot building_grade     year_built
##       1.062196       1.200062       1.198887
```

```
1/vif(mult_pred_lm)
```

```
##      sq_ft_lot building_grade     year_built
##      0.9414461      0.8332905      0.8341072
```

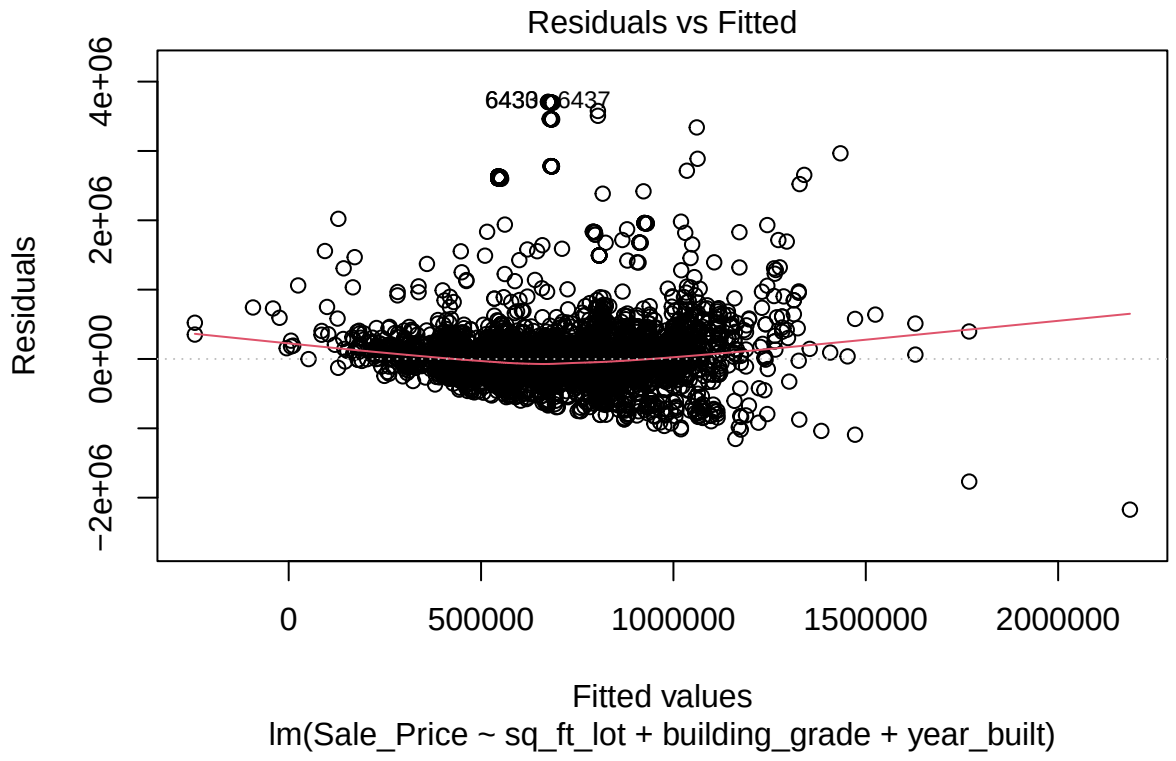
```
mean(vif(mult_pred_lm))
```

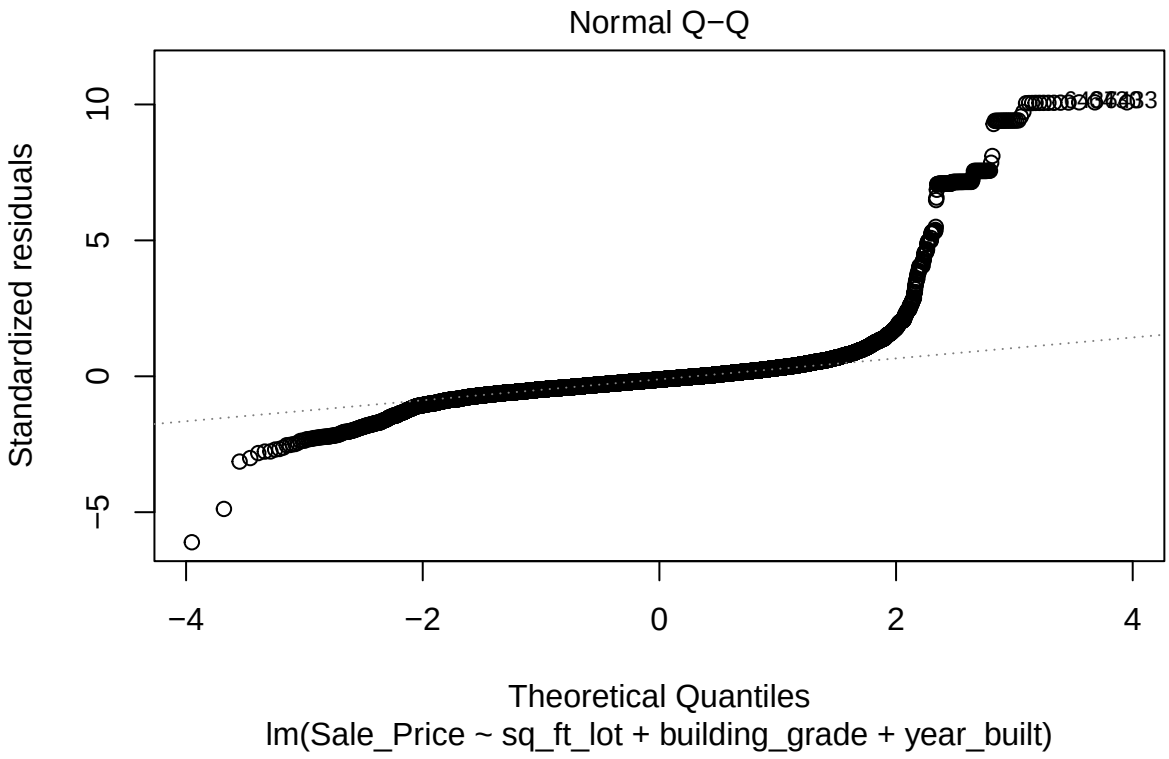
```
## [1] 1.153715
```

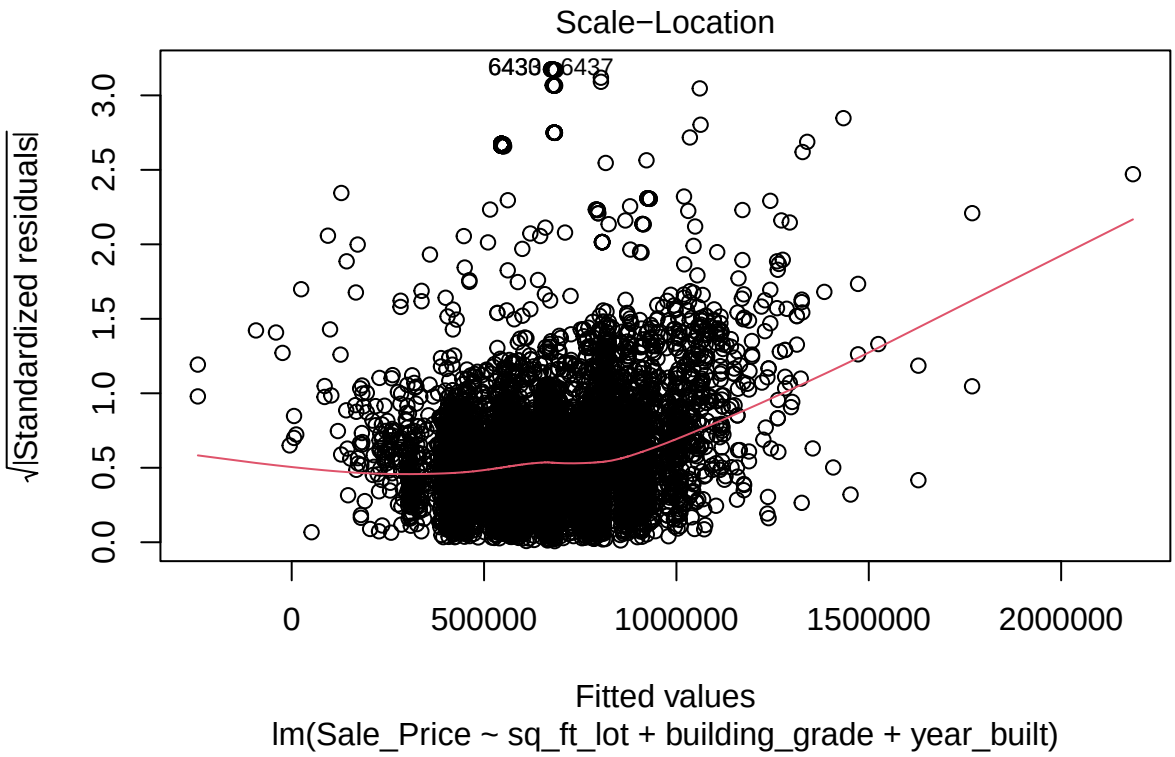
The assumption of no multicollinearity has been met because the largest VIF is less than 10, the average VIF is not substantially greater than 1, and the tolerance is above .2.

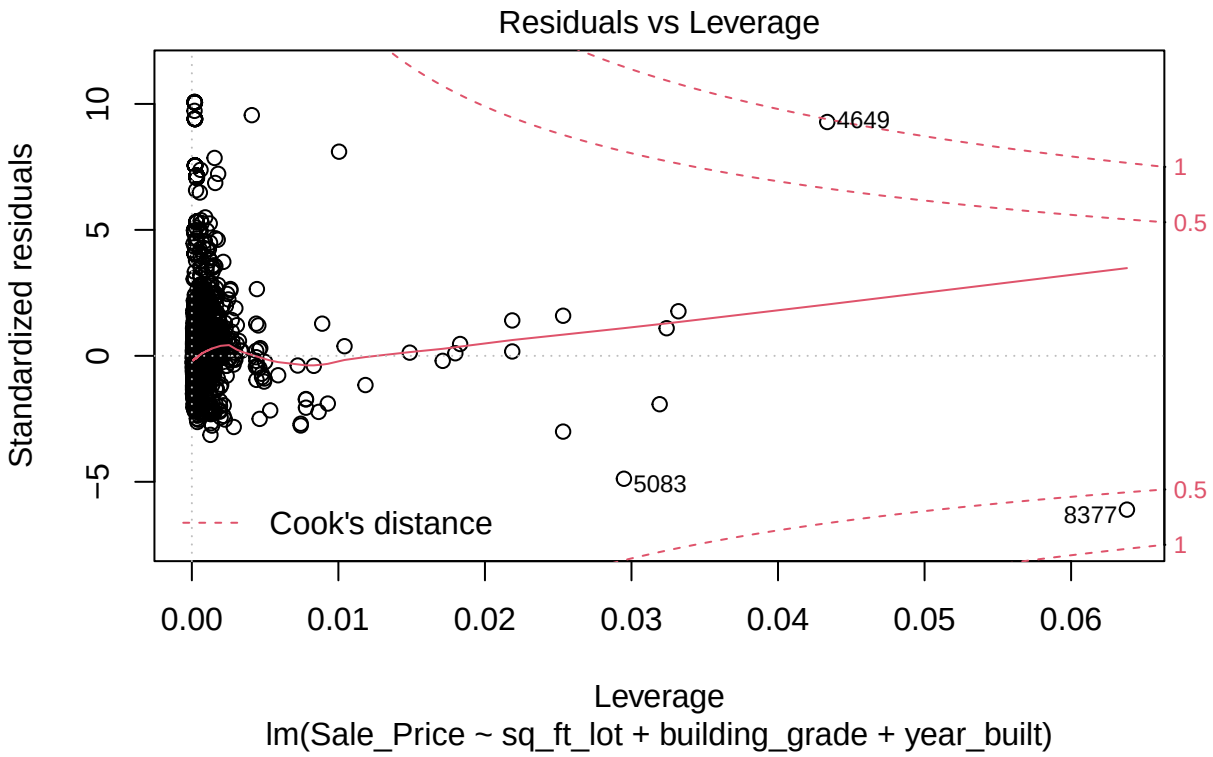
Question 14

```
plot(mult_pred_lm)
```

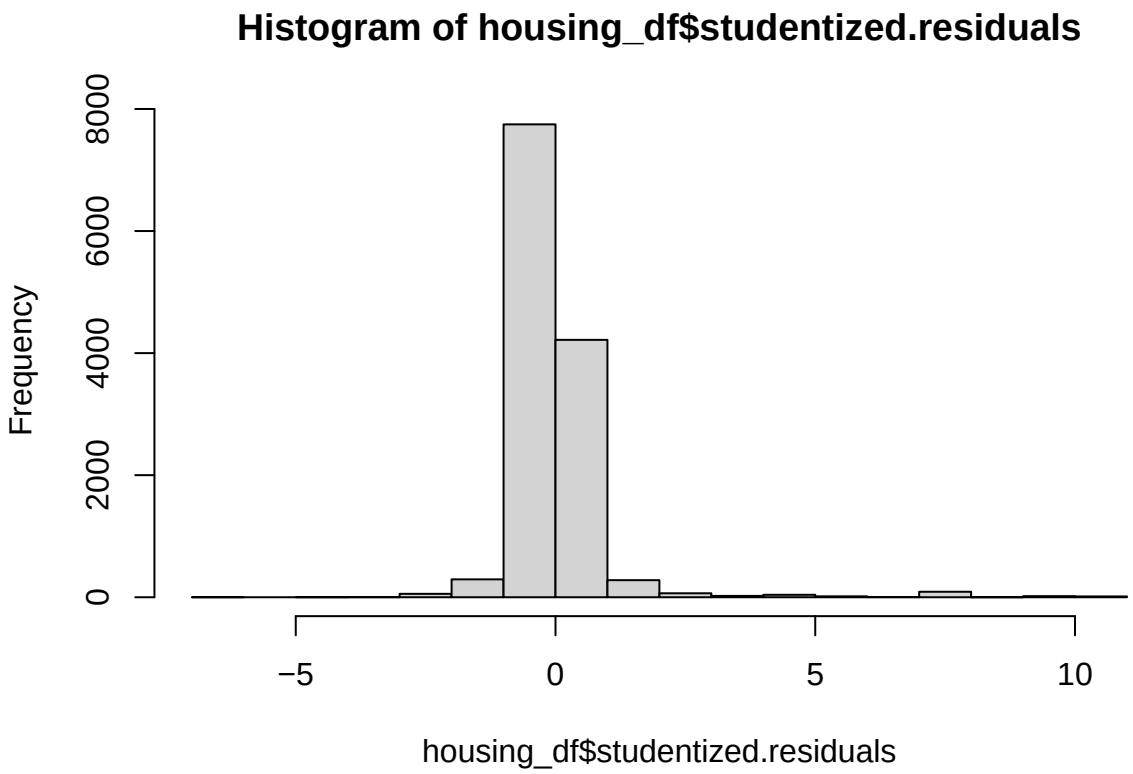



Normal Q−Q
Standardized residuals
10
5
0
−5
−4
−2
0
2
4
Theoretical Quantiles
lm(Sale_Price ~ sq_ft_lot + building_grade + year_built)


Scale−Location
6438
6437
√|Standardized residuals|
0.0
0.5
1.0
1.5
2.0
2.5
3.0
0
500000
1000000
1500000
2000000
Fitted values
lm(Sale_Price ~ sq_ft_lot + building_grade + year_built)




```
hist(housing_df$studentized.residuals)
```



The Residuals vs Fitted chart shows that the dots are all clustered and then fan out which means that there is heteroscedasticity in the data.The Q-Q plot shows deviations in the line at the extremes which means the data is not normalized and has a skew.

Question 15

The issues with leverage, covariance ratios, and the assumption of independence not being met means that the regression model is biased and not good for generalizing the population.