Exercise 8.2: Housing Data

Justin Wisniewski

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i:

Explain any transformations or modifications you made to the dataset.

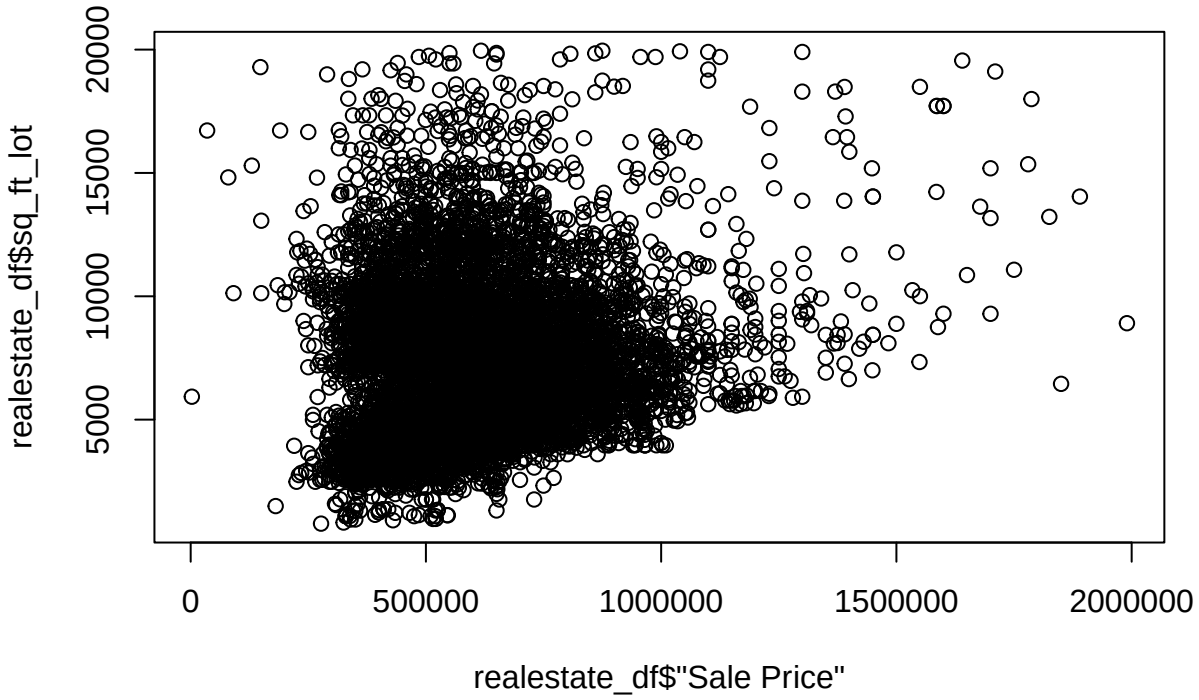
- Transformations and Modifications:
  - Added total bathroom column
  - Removed rows whose sale price is > 2 million and square foot lot > 20000 as they are outliers and would skew the data
  - Removed properties with sale warning and no bedrooms as those are empty lots
  - Removed columns Sale_date, sale_reason, sale_instrument, sale_warning, site_type as they are not relevant
  - Removed columns Address, ctyname, postalcty, lon, lat, current_zoning, prop_type and present_use

```
setwd("C:/Users/jwiz3/Desktop/Data Statistics/dsc520")
library(readxl)
## Load the `data/week-7-housing.xlsx` to
realestate_df <- read_excel("data/week-7-housing.xlsx")
## Add a calculated column total_bath which provides no of bathroom in total
realestate_df <- within(realestate_df, total_bath <- bath_full_count + (bath_half_count/2) + (bath_3qtr
## Select relevant data points, sale price < 2000000 and square foot lot < 20000
realestate_df = realestate_df[realestate_df$'Sale Price' < 2000000 & realestate_df$sq_ft_lot < 20000, ]
realestate_df <- realestate_df[(is.na(realestate_df$sale_warning)) & (realestate_df$bedrooms != 0), ]
## Selecting only relevant columns
realestate_df <- realestate_df[, c(2,8,13, 14,15,19,20, 22, 25)]
summary(realestate_df)
```

```
##    Sale Price           zip5       building_grade   square_feet_total_living
##  Min.   :   2500   Min.   :98052   Min.   : 5.000   Min.   : 530
##  1st Qu.: 474800   1st Qu.:98052   1st Qu.: 8.000   1st Qu.:1800
##  Median : 584000   Median :98052   Median : 8.000   Median :2310
##  Mean   : 610864   Mean   :98052   Mean   : 8.116   Mean   :2396
##  3rd Qu.: 719950   3rd Qu.:98053   3rd Qu.: 9.000   3rd Qu.:2930
##  Max.   :1990000   Max.   :98074   Max.   :12.000   Max.   :7980
##     bedrooms        year_built   year_renovated   sq_ft_lot
##  Min.   : 1.000   Min.   :1900   Min.   :   0   Min.   :  785
##  1st Qu.: 3.000   1st Qu.:1979   1st Qu.:   0   1st Qu.: 4998
##  Median : 3.000   Median :2003   Median :   0   Median : 6973
##  Mean   : 3.439   Mean   :1995   Mean   :  17   Mean   : 7329
##  3rd Qu.: 4.000   3rd Qu.:2008   3rd Qu.:   0   3rd Qu.: 9055
```

```
##  Max.   :11.000   Max.   :2016   Max.   :2016   Max.   :19954
##    total_bath
##  Min.   :0.3333
##  1st Qu.:1.8333
##  Median :2.5000
##  Mean   :2.2363
##  3rd Qu.:2.5000
##  Max.   :6.6667
```

```
plot(realestate_df$'Sale Price',realestate_df$sq_ft_lot)
```



ii:

Create two variables; one that will contain the variables Sale Price and Square Foot of Lot (same variables used from previous assignment on simple regression) and one that will contain Sale Price and several additional predictors of your choice. Explain the basis for your additional predictor selections.

- Additional predictor selections
  - The variables building_grade, square_feet_total_living, bedrooms, year_built, and total_bath have a significant impact on the sale price of the property
  - Total bathrooms = bath_full_count + (bath_half_count/2) + (bath_3qtr_count/3) to make it a lump sum

```
cor(realestate_df)
```

```
##                           Sale Price        zip5 building_grade
## Sale Price                1.00000000  0.04946348     0.64853955
## zip5                      0.04946348  1.00000000     0.07739962
## building_grade            0.64853955  0.07739962     1.00000000
## square_feet_total_living 0.73280440  0.06064458     0.66728632
## bedrooms                  0.37791091 -0.07349727     0.29690360
## year_built                0.38819417  0.16130642     0.43988990
## year_renovated            0.05191527 -0.01782266    -0.01084515
## sq_ft_lot                 0.11916511  0.02336914     0.06007563
## total_bath                0.52925631  0.07702720     0.50144470
##                           square_feet_total_living     bedrooms   year_built
## Sale Price                             0.73280440  0.377910910  0.388194175
## zip5                                   0.06064458 -0.073497274  0.161306421
## building_grade                         0.66728632  0.296903602  0.439889897
## square_feet_total_living               1.00000000  0.628011451  0.420570192
## bedrooms                               0.62801145  1.000000000 -0.009455569
## year_built                             0.42057019 -0.009455569  1.000000000
## year_renovated                         0.03958108  0.024417942 -0.199569889
## sq_ft_lot                              0.11737705  0.217320060 -0.528780889
## total_bath                             0.67634670  0.392656869  0.533229220
##                           year_renovated   sq_ft_lot  total_bath
## Sale Price                    0.05191527  0.11916511  0.52925631
## zip5                         -0.01782266  0.02336914  0.07702720
## building_grade               -0.01084515  0.06007563  0.50144470
## square_feet_total_living      0.03958108  0.11737705  0.67634670
## bedrooms                      0.02441794  0.21732006  0.39265687
## year_built                   -0.19956989 -0.52878089  0.53322922
## year_renovated                1.00000000  0.12678523  0.02289362
## sq_ft_lot                     0.12678523  1.00000000 -0.13015370
## total_bath                    0.02289362 -0.13015370  1.00000000
```

```
## Fit a linear model using the `Square foot of Lot` variable as the predictor and `Sale Price` as the
salepricebysqft_lm <-  lm(realestate_df$'Sale Price'~realestate_df$sq_ft_lot,data = realestate_df)
## Fit a linear model using several predictors variable and `Sale Price` as the outcome
salepricebymultiplevar_lm <-  lm(realestate_df$'Sale Price'~realestate_df$square_feet_total_living+reale
                                 ,data = realestate_df)
```

iii:

Execute a summary() function on two variables defined in the previous step to compare the model results. What are the R2 and Adjusted R2 statistics? Explain what these results tell you about the overall model. Did the inclusion of the additional predictors help explain any large variations found in Sale Price?

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

```
##
## Call:
```

```
## lm(formula = realestate_df$"Sale Price" ~ realestate_df$sq_ft_lot,
##     data = realestate_df)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -645897 -136979  -24938  106739 1367351
##
## Coefficients:
##                           Estimate Std. Error t value Pr(>|t|)
## (Intercept)             5.562e+05  5.335e+03  104.26   <2e-16 ***
## realestate_df$sq_ft_lot 7.457e+00  6.708e-01   11.12   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 191900 on 8579 degrees of freedom
## Multiple R-squared:  0.0142, Adjusted R-squared:  0.01409
## F-statistic: 123.6 on 1 and 8579 DF,  p-value: < 2.2e-16
```

```
## View the summary of your new model using `summary()`
summary(salepricebymultiplevar_lm)
```

```
##
## Call:
## lm(formula = realestate_df$"Sale Price" ~ realestate_df$square_feet_total_living +
##     realestate_df$year_built + realestate_df$bedrooms + realestate_df$total_bath +
##     realestate_df$building_grade, data = realestate_df)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -881746  -75243  -12843   58597 1292098
##
## Coefficients:
##                                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)                         -4.686e+05  2.063e+05  -2.272  0.02314
## realestate_df$square_feet_total_living  1.428e+02  3.309e+00  43.173  < 2e-16
## realestate_df$year_built                1.471e+02  1.053e+02   1.397  0.16237
## realestate_df$bedrooms                 -1.650e+04  2.150e+03  -7.674 1.85e-14
## realestate_df$total_bath                9.044e+03  3.389e+03   2.669  0.00762
## realestate_df$building_grade            5.919e+04  2.161e+03  27.394  < 2e-16
##
## (Intercept)                         *
## realestate_df$square_feet_total_living ***
## realestate_df$year_built
## realestate_df$bedrooms                 ***
## realestate_df$total_bath               **
## realestate_df$building_grade           ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 124200 on 8575 degrees of freedom
## Multiple R-squared:  0.5874, Adjusted R-squared:  0.5872
## F-statistic:  2442 on 5 and 8575 DF,  p-value: < 2.2e-16
```

- The R2 value at the bottom of each summary tells us whether the model is successful in predicting

the outcome and if the difference between R2 and adjusted R2 values is small this would indicate that the sample taken is a good representation of the population.

- First regression model, R2 is 0.0142 so this indicated that sq_ft_lot accounted for only 1.42% of the variation in sale price
- Multiple regression model, R2 is 0.5874, so this multiple predictor model accounted for 58.74% of the variation in sale price.
- The inclusion of the new predictors has explained a large amount of the variation in sale price, from 1.42% to 58.74%

iv:

Considering the parameters of the multiple regression model you have created. What are the standardized betas for each parameter and what do the values indicate?

```
library('QuantPsyc')
```

```
## Loading required package: boot
```

```
## Loading required package: MASS
```

```
##
## Attaching package: 'QuantPsyc'
```

```
## The following object is masked from 'package:base':
##
##     norm
```

```
##standardized betas for each parameter
lm.beta(salepricebymultiplevar_lm)
```

```
## realestate_df$square_feet_total_living              realestate_df$year_built
##                             0.57954215                            0.01267996
##                 realestate_df$bedrooms              realestate_df$total_bath
##                            -0.07528203                            0.02723217
##           realestate_df$building_grade
##                             0.26493730
```

Standardized beta estimates tell us the number of standard deviations by which the outcome will change as a result of one standard deviation change in the predictor. Looking at the outcome, we can figure out that square_feet_total_living and building_grade have more degree of importance in prediction than the others.

v:

Calculate the confidence intervals for the parameters in your model and explain what the results indicate.

```
confint(salepricebymultiplevar_lm)
```

```
##                                             2.5 %      97.5 %
## (Intercept)                           -872966.50303 -64223.3607
## realestate_df$square_feet_total_living     136.36233    149.3343
## realestate_df$year_built                   -59.25909    353.4163
## realestate_df$bedrooms                  -20717.95186 -12287.1934
## realestate_df$total_bath                  2402.06681  15686.7220
## realestate_df$building_grade             54953.31011  63423.9444
```

- square_feet_total_living 136.36 - 149.33, very tight confidence interval, indicates that the estimates for the current model are likely to be representative of the true population values
- building_grade 54953.31011 - 63423.9444, this is a good predictor, but has more gap
- bedrooms -20717.95186 - 12287.1934, this is a good predictor, but has more gap
- total_bath 2402.06681 - 15686.7220, this is a good predictor, but has more gap
- year_built -59.25909 - 353.4163, confidence intervals that cross zero, indicates that some samples the predictor has a negative relationship to the outcome whereas in others it has a positive relationship

vi:

Assess the improvement of the new model compared to your original model (simple regression model) by testing whether this change is significant by performing an analysis of variance.

```
anova(salepricebysqft_lm, salepricebymultiplevar_lm)
```

```
## Analysis of Variance Table
##
## Model 1: realestate_df$"Sale Price" ~ realestate_df$sq_ft_lot
## Model 2: realestate_df$"Sale Price" ~ realestate_df$square_feet_total_living +
##     realestate_df$year_built + realestate_df$bedrooms + realestate_df$total_bath +
##     realestate_df$building_grade
##   Res.Df        RSS Df  Sum of Sq      F    Pr(>F)
## 1   8579 3.1584e+14
## 2   8575 1.3219e+14  4 1.8365e+14 2978.2 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The variance table analysis shows: $F(4, 8575) = 2978.2$ with $p < 0.001$ hence the multiple regression model significantly improved the fit of the model to the data compared to salepricebysqft_lm.

vii:

Perform casewise diagnostics to identify outliers and/or influential cases, storing each function's output in a dataframe assigned to a unique variable name.

```
## Outliers
realestate_df$residuals <- resid(salepricebymultiplevar_lm)
realestate_df$studentized.residuals <- rstudent(salepricebymultiplevar_lm)
realestate_df$standardized.residuals <- rstandard(salepricebymultiplevar_lm)
## Influential Cases
realestate_df$dffit <- dffits(salepricebymultiplevar_lm)
realestate_df$leverage <- hatvalues(salepricebymultiplevar_lm)
realestate_df$covariance.ratios <- covratio(salepricebymultiplevar_lm)
```

```
realestate_df$cooks.distance <- cooks.distance(salepricebymultiplevar_lm)
realestate_df$dfbeta <- dfbeta(salepricebymultiplevar_lm)
summary(realestate_df)
```

```
##    Sale Price           zip5       building_grade   square_feet_total_living
##  Min.   :   2500   Min.   :98052   Min.   : 5.000   Min.   : 530
##  1st Qu.: 474800   1st Qu.:98052   1st Qu.: 8.000   1st Qu.:1800
##  Median : 584000   Median :98052   Median : 8.000   Median :2310
##  Mean   : 610864   Mean   :98052   Mean   : 8.116   Mean   :2396
##  3rd Qu.: 719950   3rd Qu.:98053   3rd Qu.: 9.000   3rd Qu.:2930
##  Max.   :1990000   Max.   :98074   Max.   :12.000   Max.   :7980
##     bedrooms        year_built   year_renovated   sq_ft_lot
##  Min.   : 1.000   Min.   :1900   Min.   :   0   Min.   :  785
##  1st Qu.: 3.000   1st Qu.:1979   1st Qu.:   0   1st Qu.: 4998
##  Median : 3.000   Median :2003   Median :   0   Median : 6973
##  Mean   : 3.439   Mean   :1995   Mean   :  17   Mean   : 7329
##  3rd Qu.: 4.000   3rd Qu.:2008   3rd Qu.:   0   3rd Qu.: 9055
##  Max.   :11.000   Max.   :2016   Max.   :2016   Max.   :19954
##    total_bath       residuals       studentized.residuals
##  Min.   :0.3333   Min.   :-881746   Min.   :-7.129288
##  1st Qu.:1.8333   1st Qu.: -75243   1st Qu.:-0.606191
##  Median :2.5000   Median : -12843   Median :-0.103465
##  Mean   :2.2363   Mean   :      0   Mean   : 0.000084
##  3rd Qu.:2.5000   3rd Qu.:  58598   3rd Qu.: 0.472080
##  Max.   :6.6667   Max.   :1292098   Max.   :10.478545
##  standardized.residuals     dffit               leverage
##  Min.   :-7.108665      Min.   :-0.6485180   Min.   :0.0001761
##  1st Qu.:-0.606213      1st Qu.:-0.0140526   1st Qu.:0.0004280
##  Median :-0.103471      Median :-0.0025020   Median :0.0006049
##  Mean   : 0.000006      Mean   : 0.0002524   Mean   :0.0006992
##  3rd Qu.: 0.472101      3rd Qu.: 0.0112635   3rd Qu.:0.0008253
##  Max.   :10.412695      Max.   : 0.5580787   Max.   :0.0121037
##  covariance.ratios cooks.distance
##  Min.   :0.9282    Min.   :0.000e+00
##  1st Qu.:1.0007    1st Qu.:6.310e-06
##  Median :1.0010    Median :2.845e-05
##  Mean   :1.0007    Mean   :1.883e-04
##  3rd Qu.:1.0013    3rd Qu.:8.825e-05
##  Max.   :1.0096    Max.   :6.971e-02
##   dfbeta.(Intercept)   dfbeta.realestate_df$square_feet_total_living  dfbeta.realestate_df$year_buil
##  Min.   :-63277.76     Min.   :-0.9072594    Min.   :-48.61350     Min.   :-621.2461     Min.   :-16
##  1st Qu.:  -692.11     1st Qu.:-0.0098428    1st Qu.: -0.34156     1st Qu.:  -6.2076     1st Qu.:  -
##  Median :     6.47     Median :-0.0000643    Median : -0.00241     Median :   0.3097     Median :
##  Mean   :     0.08     Mean   :-0.0000013    Mean   : -0.00005     Mean   :  -0.0003     Mean   :
##  3rd Qu.:   686.12     3rd Qu.: 0.0104603    3rd Qu.:  0.36343     3rd Qu.:   7.5582     3rd Qu.:
##  Max.   : 98912.34     Max.   : 0.9312512    Max.   : 34.30849     Max.   : 292.5238     Max.   : 10
```

viii:

Calculate the standardized residuals using the appropriate command, specifying those that are +-2, storing the results of large residuals in a variable you create.

```
realestate_df$large.residual <- realestate_df$standardized.residuals > 2 | realestate_df$standardized.r
summary(realestate_df)
```

```
##    Sale Price           zip5       building_grade   square_feet_total_living
##  Min.   :   2500   Min.   :98052   Min.   : 5.000   Min.   : 530
##  1st Qu.: 474800   1st Qu.:98052   1st Qu.: 8.000   1st Qu.:1800
##  Median : 584000   Median :98052   Median : 8.000   Median :2310
##  Mean   : 610864   Mean   :98052   Mean   : 8.116   Mean   :2396
##  3rd Qu.: 719950   3rd Qu.:98053   3rd Qu.: 9.000   3rd Qu.:2930
##  Max.   :1990000   Max.   :98074   Max.   :12.000   Max.   :7980
##     bedrooms        year_built   year_renovated   sq_ft_lot
##  Min.   : 1.000   Min.   :1900   Min.   :   0   Min.   :  785
##  1st Qu.: 3.000   1st Qu.:1979   1st Qu.:   0   1st Qu.: 4998
##  Median : 3.000   Median :2003   Median :   0   Median : 6973
##  Mean   : 3.439   Mean   :1995   Mean   :  17   Mean   : 7329
##  3rd Qu.: 4.000   3rd Qu.:2008   3rd Qu.:   0   3rd Qu.: 9055
##  Max.   :11.000   Max.   :2016   Max.   :2016   Max.   :19954
##    total_bath       residuals       studentized.residuals
##  Min.   :0.3333   Min.   :-881746   Min.   :-7.129288
##  1st Qu.:1.8333   1st Qu.: -75243   1st Qu.:-0.606191
##  Median :2.5000   Median : -12843   Median :-0.103465
##  Mean   :2.2363   Mean   :      0   Mean   : 0.000084
##  3rd Qu.:2.5000   3rd Qu.:  58598   3rd Qu.: 0.472080
##  Max.   :6.6667   Max.   :1292098   Max.   :10.478545
##  standardized.residuals     dffit               leverage
##  Min.   :-7.108665      Min.   :-0.6485180   Min.   :0.0001761
##  1st Qu.:-0.606213      1st Qu.:-0.0140526   1st Qu.:0.0004280
##  Median :-0.103471      Median :-0.0025020   Median :0.0006049
##  Mean   : 0.000006      Mean   : 0.0002524   Mean   :0.0006992
##  3rd Qu.: 0.472101      3rd Qu.: 0.0112635   3rd Qu.:0.0008253
##  Max.   :10.412695      Max.   : 0.5580787   Max.   :0.0121037
##  covariance.ratios cooks.distance
##  Min.   :0.9282    Min.   :0.000e+00
##  1st Qu.:1.0007    1st Qu.:6.310e-06
##  Median :1.0010    Median :2.845e-05
##  Mean   :1.0007    Mean   :1.883e-04
##  3rd Qu.:1.0013    3rd Qu.:8.825e-05
##  Max.   :1.0096    Max.   :6.971e-02
##   dfbeta.(Intercept)   dfbeta.realestate_df$square_feet_total_living  dfbeta.realestate_df$year_buil
##  Min.   :-63277.76     Min.   :-0.9072594    Min.   :-48.61350     Min.   :-621.2461     Min.   :-16
##  1st Qu.:  -692.11     1st Qu.:-0.0098428    1st Qu.: -0.34156     1st Qu.:  -6.2076     1st Qu.:  -
##  Median :     6.47     Median :-0.0000643    Median : -0.00241     Median :   0.3097     Median :
##  Mean   :     0.08     Mean   :-0.0000013    Mean   : -0.00005     Mean   :  -0.0003     Mean   :
##  3rd Qu.:   686.12     3rd Qu.: 0.0104603    3rd Qu.:  0.36343     3rd Qu.:   7.5582     3rd Qu.:
##  Max.   : 98912.34     Max.   : 0.9312512    Max.   : 34.30849     Max.   : 292.5238     Max.   : 10
##  large.residual
##  Mode :logical
##  FALSE:8297
##  TRUE :284
##
##
##
```

ix:

Use the appropriate function to show the sum of large residuals.

```
sum(realestate_df$large.residual)
```

```
## [1] 284
```

x:

Which specific variables have large residuals (only cases that evaluate as TRUE)?

```
realestate_df[realestate_df$large.residual, c("Sale Price", "building_grade", "square_feet_total_living
```

```
## # A tibble: 284 x 8
##    `Sale Price` building_grade square_feet_total~ bedrooms total_bath year_built
##           <dbl>          <dbl>               <dbl>    <dbl>      <dbl>      <dbl>
##  1      1392000              9                3740        4       4.33       1998
##  2      1053649              9                2680        2       2.5        2005
##  3      1080135              9                2700        3       2.33       2006
##  4       732500              9                5710        5       4.33       1977
##  5       370000              9                4000        4       3.5        2014
##  6      1588359              9                3360        2       2.5        2005
##  7      1450000              8                3480        3       2.5        1972
##  8      1450000              6                 900        2       1          1918
##  9      1369900             11                4630        5       2.67       2005
## 10      1174477              9                2800        3       2.5        2006
## # ... with 274 more rows, and 2 more variables: sq_ft_lot <dbl>,
## #   standardized.residuals <dbl>
```

xi:

Investigate further by calculating the leverage, cooks distance, and covariance rations. Comment on all cases that are problematic.

```
realestate_df[realestate_df$large.residual, c("cooks.distance", "leverage", "covariance.ratios")]
```

```
## # A tibble: 284 x 3
##    cooks.distance leverage covariance.ratios
##             <dbl>    <dbl>             <dbl>
##  1       0.00717  0.00238              0.990
##  2       0.000993 0.000883             0.997
##  3       0.000478 0.000334             0.995
##  4       0.00926  0.00544              0.999
##  5       0.00266  0.000883             0.989
##  6       0.00990  0.00158              0.976
##  7       0.0103   0.00203              0.982
##  8       0.0514   0.00341              0.942
##  9       0.00173  0.00190              0.999
## 10       0.000710 0.000335             0.992
## # ... with 274 more rows
```

Out of 284 total rows, no distance is greater than 1, meaning there is no problematic row.

xii:

Perform the necessary calculations to assess the assumption of independence and state if the condition is met or not.

install.packages("car")

```
library("car")
```

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

```
##
## Attaching package: 'car'
```

```
## The following object is masked from 'package:boot':
##
##     logit
```

```
dwt(salepricebymultiplevar_lm)
```

```
##  lag Autocorrelation D-W Statistic p-value
##    1       0.4054537      1.189018       0
##  Alternative hypothesis: rho != 0
```

> Using the Durbin–Watson test, we can obtain this statistic along with a measure of autocorrelation and a p-value in R. The statistic should be between 1 and 3 and should be closer to 2, in our case, it is 1.18. The p-value of 0 confirms this conclusion.

xiii:

Perform the necessary calculations to assess the assumption of no multicollinearity and state if the condition is met or not.

```
## vif
vif(salepricebymultiplevar_lm)
```

```
## realestate_df$square_feet_total_living              realestate_df$year_built
##                                3.745030                                 1.711507
##                 realestate_df$bedrooms              realestate_df$total_bath
##                                2.000033                                 2.163369
##           realestate_df$building_grade
##                                1.943865
```

```
## 1/vif
1/vif(salepricebymultiplevar_lm)
```

```
## realestate_df$square_feet_total_living              realestate_df$year_built
##                                0.2670206                                0.5842806
##                 realestate_df$bedrooms              realestate_df$total_bath
##                                0.4999917                                0.4622420
##           realestate_df$building_grade
##                                0.5144390
```

```
## mean
mean(vif(salepricebymultiplevar_lm))
```

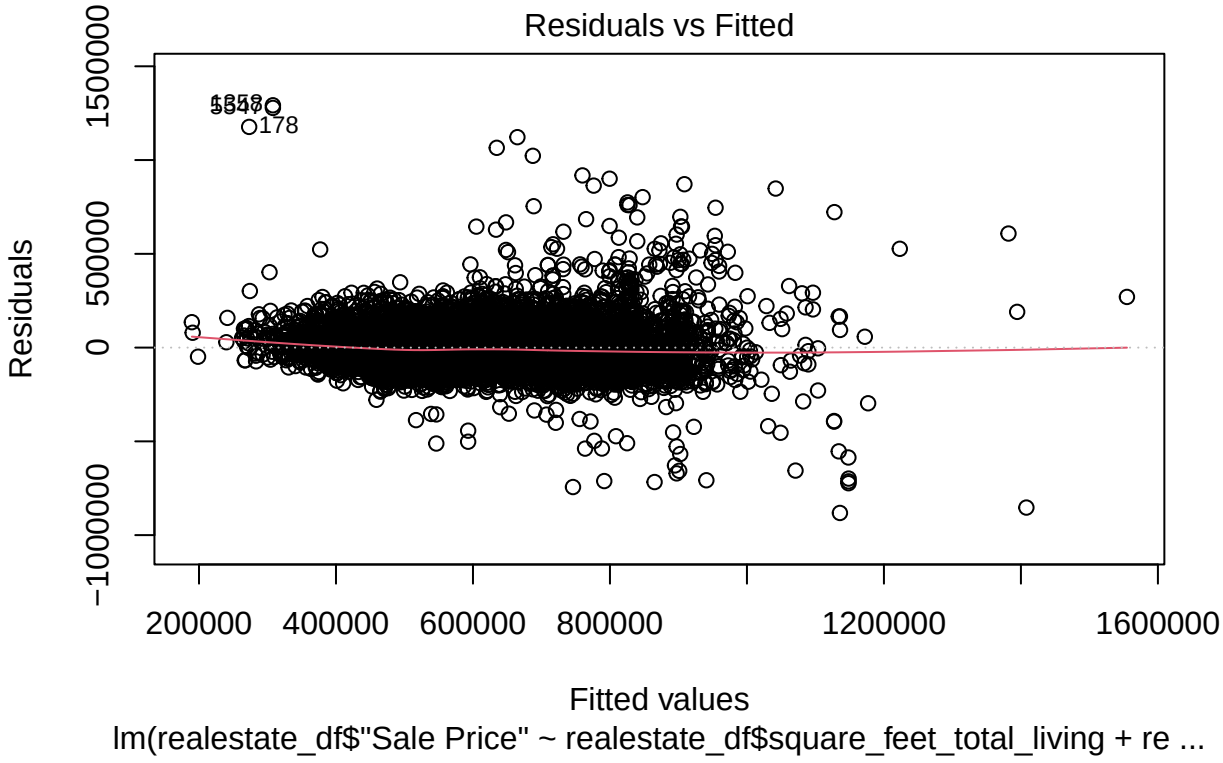
```
## [1] 2.312761
```

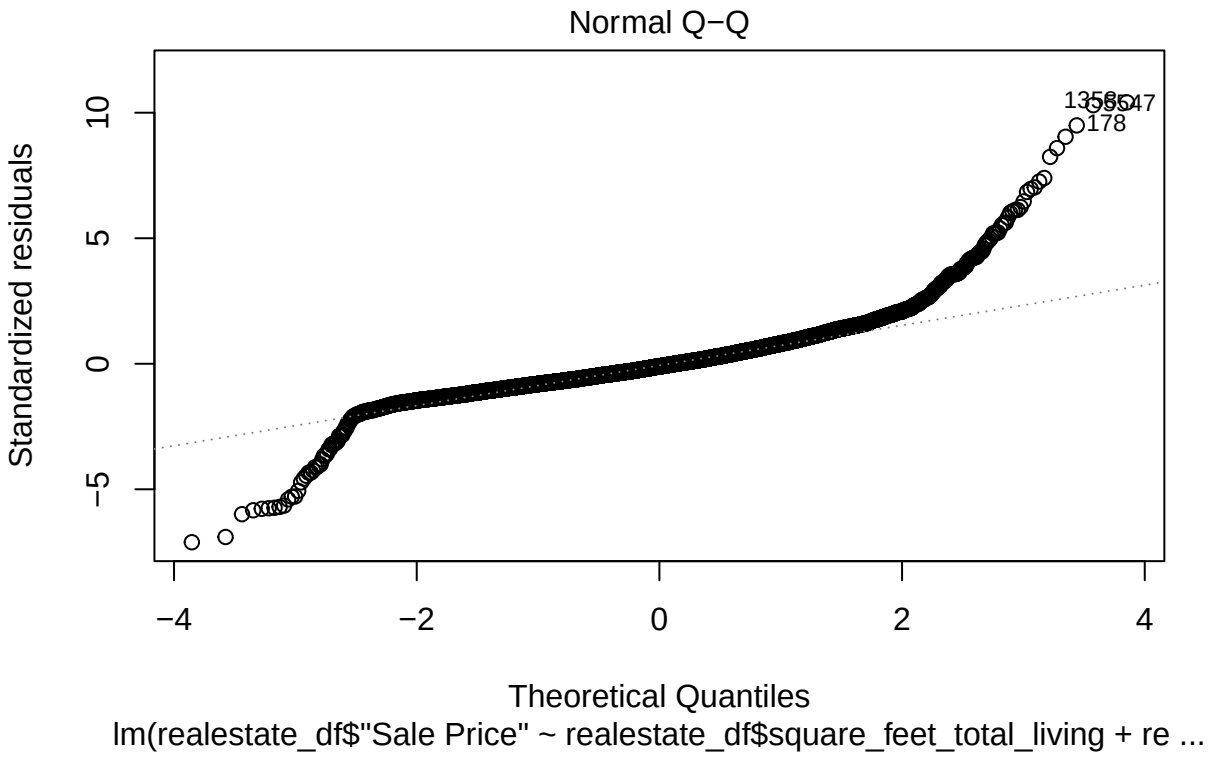
The VIF values are all well below 10 and the tolerance statistics all well above 0.2. Also, the average VIF is very close to 1. Based on these measures there is no collinearity within our data.

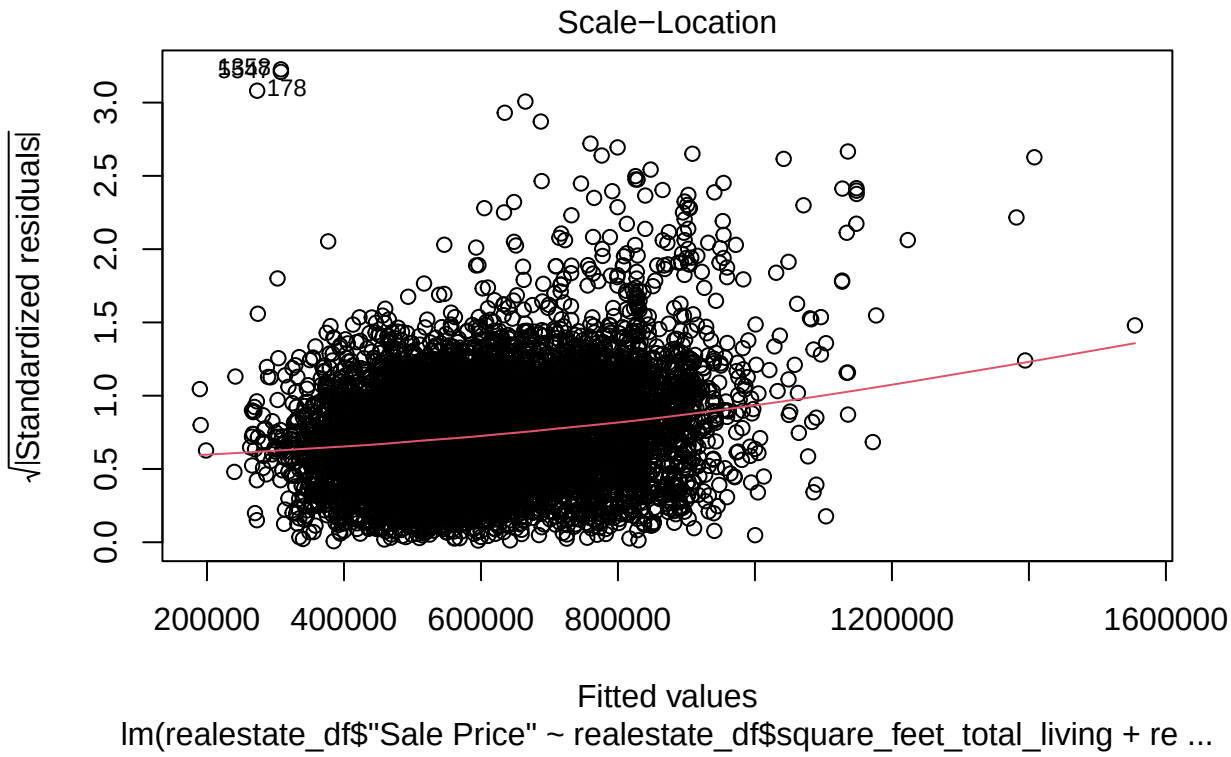
xiv:

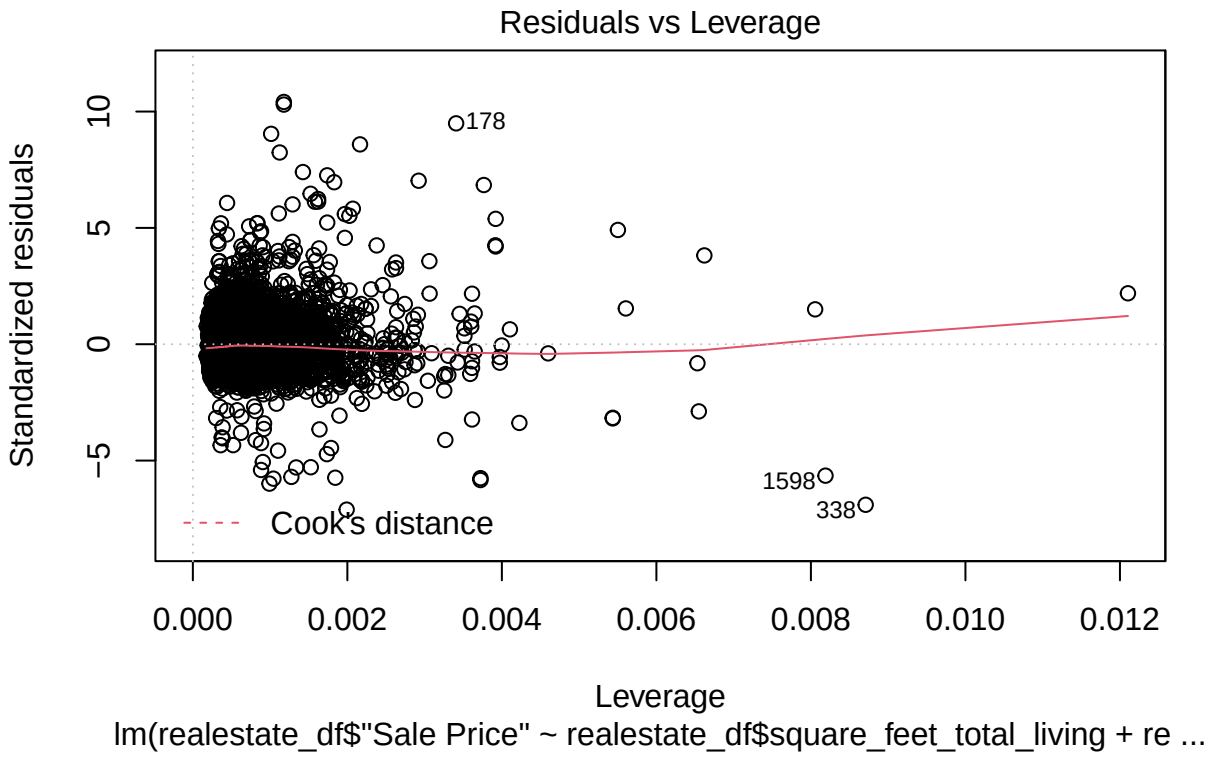
Visually check the assumptions related to the residuals using the plot() and hist() functions. Summarize what each graph is informing you of and if any anomalies are present.

```
library(ggplot2)
plot(salepricebymultiplevar_lm)
```

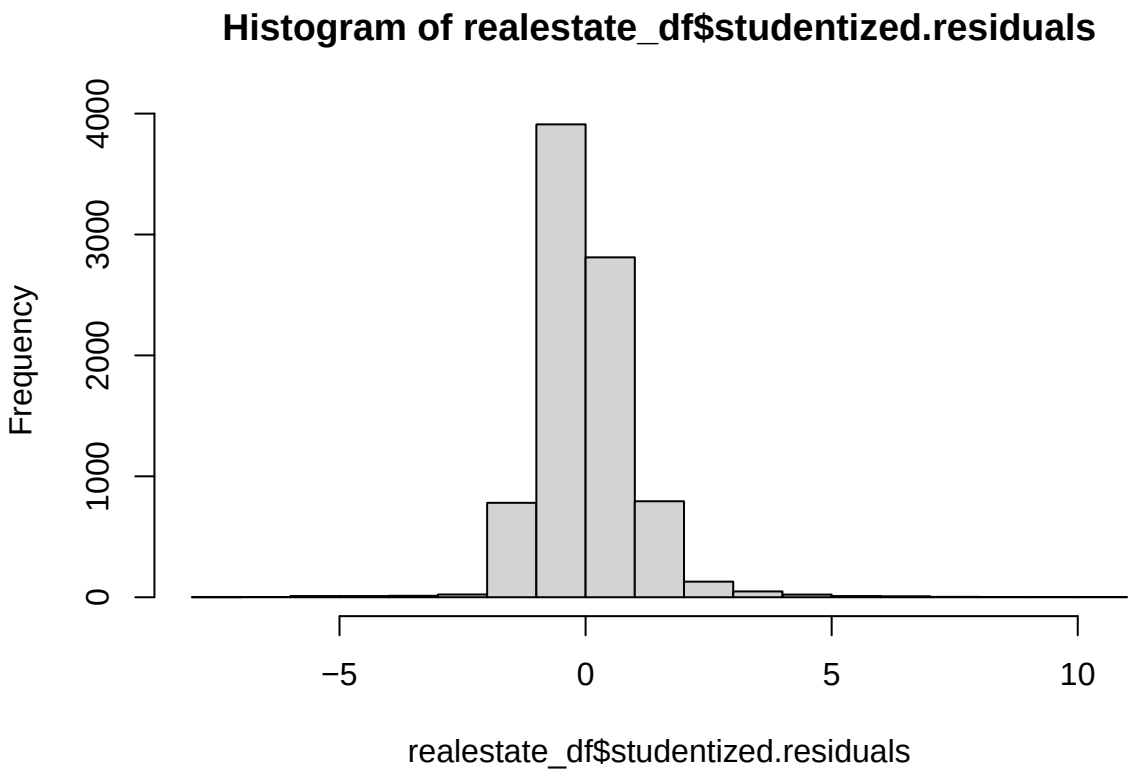



Normal Q−Q
Standardized residuals
10
5
0
−5
1358
1547
178
−4
−2
0
2
4
Theoretical Quantiles
lm(realestate_df$"Sale Price" ~ realestate_df$square_feet_total_living + re ...


Scale−Location
178
√|Standardized residuals|
0.0
0.5
1.0
1.5
2.0
2.5
3.0
200000
400000
600000
800000
1200000
1600000
Fitted values
lm(realestate_df$"Sale Price" ~ realestate_df$square_feet_total_living + re ...




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




```
scatter <- ggplot(realestate_df, aes(fitted, studentized.residuals)) + geom_point() + geom_smooth(metho
```

- The first graph shows the plot of fitted values against residuals. Graph is not funneling out, so there are no chances that there is heteroscedasticity in the data. There is no curve in the graph, so it is not violating any assumptions of linearity.
- The Normal Q-Q plot should show deviations from normality. In the plot above, it deviates from both the ends of the line, which indicates deviation of normality at the extreme values.

xv:

Overall, is this regression model unbiased? If an unbiased regression model, what does this tell us about the sample vs. the entire population model?

Looking at all the ouputs and calculations performed on the data model after removing the outliers, we can safely conclude that the regression model is unbiased. The sample is a good representation of the entire population model.