

RegressionR

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```
library(plyr)
library(dplyr)

##
## Attaching package: 'dplyr'
## The following objects are masked from 'package:plyr':
##
##      arrange, count, desc, failwith, id, mutate, rename, summarise,
##      summarize
## The following objects are masked from 'package:stats':
##
##      filter, lag
## The following objects are masked from 'package:base':
##
##      intersect, setdiff, setequal, union
library(purrr)

##
## Attaching package: 'purrr'
## The following object is masked from 'package:plyr':
##
##      compact
library(readxl)
library(stringr)
library(tidyverse)

## -- Attaching packages ----- tidyverse 1.3.1 --
## v ggplot2 3.3.5      v readr   2.1.1
## v tibble  3.1.6      v forcats 0.5.1
## v tidyr   1.1.4

## -- Conflicts ----- tidyverse_conflicts() --
## x dplyr::arrange() masks plyr::arrange()
## x purrr::compact() masks plyr::compact()
## x dplyr::count()   masks plyr::count()
## x dplyr::failwith() masks plyr::failwith()
## x dplyr::filter()  masks stats::filter()
## x dplyr::id()       masks plyr::id()
## x dplyr::lag()      masks stats::lag()
## x dplyr::mutate()   masks plyr::mutate()
```

```

## x dplyr::rename()      masks plyr::rename()
## x dplyr::summarise() masks plyr::summarise()
## x dplyr::summarize() masks plyr::summarize()
library(regclass)

## Warning: package 'regclass' was built under R version 4.1.3
## Loading required package: bestglm
## Warning: package 'bestglm' was built under R version 4.1.3
## Loading required package: leaps
## Loading required package: VGAM
## Warning: package 'VGAM' was built under R version 4.1.3
## Loading required package: stats4
## Loading required package: splines
## Loading required package: rpart
## Loading required package: randomForest
## Warning: package 'randomForest' was built under R version 4.1.3
## randomForest 4.7-1.1
## Type rfNews() to see new features/changes/bug fixes.
##
## Attaching package: 'randomForest'
## The following object is masked from 'package:ggplot2':
##
##     margin
## The following object is masked from 'package:dplyr':
##
##     combine
## Important regclass change from 1.3:
## All functions that had a . in the name now have an _
## all.correlations -> all_correlations, cor.demo -> cor_demo, etc.
library(car)

```

```

## Loading required package: carData
##
## Attaching package: 'car'
## The following object is masked from 'package:VGAM':
##
##     logit
## The following object is masked from 'package:purrr':
##
##     some
## The following object is masked from 'package:dplyr':
##
##     recode

```

```
setwd('/Users/logan/Documents/GitHub/DSC520LQ')
housing_df <- read_excel('/Users/logan/Documents/GitHub/DSC520LQ/week-6-housing.xlsx')
var_names <- colnames(housing_df)
var_names
```

```
## [1] "Sale Date"           "Sale Price"
## [3] "sale_reason"         "sale_instrument"
## [5] "sale_warning"        "sitetype"
## [7] "addr_full"           "zip5"
## [9] "ctyname"              "postalctyn"
## [11] "lon"                  "lat"
## [13] "building_grade"      "square_feet_total_living"
## [15] "bedrooms"             "bath_full_count"
## [17] "bath_half_count"     "bath_3qtr_count"
## [19] "year_built"           "year_renovated"
## [21] "current_zoning"      "sq_ft_lot"
## [23] "prop_type"            "present_use"
```

I.) Explain any transformations or modifications you are making to the dataset
I will be removing some variables that are not useful in my analysis or that had missing data.
I ended up renaming Sale Price due to errors with variables in second equation as well.

```
refined_cols <- c('Sale Date', 'Sale Price', 'zip5', 'bedrooms', 'sq_ft_lot', 'square_feet_total_living')
housing_df_final <- housing_df[refined_cols]
names(housing_df_final)[names(housing_df_final) == 'Sale Price'] <- 'sale_price'
```

II.) Create two variables one that will contain the variables Sale Price and Square Foot of Lot (same as before)
and one that will contain Sale Price and several additional predictors of your choice. Explain the ba

```
price_lot_lm <- lm(sale_price ~ sq_ft_lot, housing_df_final)
multiple_pred_lm <- lm(sale_price ~ square_feet_total_living + sq_ft_lot + bedrooms + year_built, housing_df_final)
```

Chose predictors zip code, square feet total living and year built.
These are common factors that go into pricing a house such as price/sq ft total living, new construction, etc.

III.) Execute a summary() function on two variables defined in the previous step to compare the model results
summary(price_lot_lm)

```
##
## Call:
## lm(formula = sale_price ~ sq_ft_lot, data = housing_df_final)
##
## 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(multiple_pred_lm)
```

```
##
## Call:
## lm(formula = sale_price ~ square_feet_total_living + sq_ft_lot +
##     bedrooms + year_built, data = housing_df_final)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2147040  -119970   -41454    45830   3766517
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    -5.333e+06  4.046e+05 -13.181  < 2e-16 ***
## square_feet_total_living  1.717e+02  4.425e+00  38.809  < 2e-16 ***
## sq_ft_lot          2.729e-01  5.917e-02   4.612  4.02e-06 ***
## bedrooms         -9.085e+03  4.557e+03  -1.994   0.0462 *
## year_built        2.801e+03  2.031e+02  13.789  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 357100 on 12860 degrees of freedom
## Multiple R-squared:  0.2202, Adjusted R-squared:  0.22
## F-statistic: 907.9 on 4 and 12860 DF,  p-value: < 2.2e-16
```

```
## The R2 for the simple regression for Sale Price/Sq_ft_lot were
```

```
## R2 = 0.01435, Adjusted R2 = 0.01428
```

```
## The R2 for the multiple predictors were
```

```
## R2 = 0.2202, Adjusted R2 = 0.22
```

```
## As R2 is a measure of fit for the model we can see neither model is a great fit for the data.
```

```
## However, the additional predictor model performed much better (0.014 vs 0.2202)
```

```
## likely due to the predictors (sq_foot_total_living, sq_ft_lot, bedrooms and year_built) being more p
```

```
# 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(lm.beta)
lm.beta(price_lot_lm)
```

```
##
## Call:
## lm(formula = sale_price ~ sq_ft_lot, data = housing_df_final)
##
## Standardized Coefficients::
## (Intercept)    sq_ft_lot
##  0.0000000    0.1198122
```

```
lm.beta(multiple_pred_lm)
```

```
##
## Call:
## lm(formula = sale_price ~ square_feet_total_living + sq_ft_lot +
##     bedrooms + year_built, data = housing_df_final)
```

```
##
## Standardized Coefficients::
##           (Intercept) square_feet_total_living          sq_ft_lot
##           0.000000000          0.42036390          0.03842553
##           bedrooms          year_built
##           -0.01968450          0.11928935

## These standardized betas for the simple regression indicate that for every standard deviation change
## The standardized betas for the multiple predictors indicate that for every std dev change in the pred
## square_feet_total_living = 0.4203, sq_ft_lot = .038, year_built = 0.119, bedrooms = -0.19
## This indicates that square_feet_total_living drives the biggest increase in Sales Price.

# V.) Calculate the confidence intervals for the parameters in your model and explain what the results
confint.lm(price_lot_lm, parameter=0.95)

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

confint.lm(multiple_pred_lm, parameter=0.95)

##           2.5 %          97.5 %
## (Intercept) -6.125803e+06 -4.539774e+06
## square_feet_total_living 1.630620e+02 1.804098e+02
## sq_ft_lot               1.569387e-01 3.889127e-01
## bedrooms               -1.801844e+04 -1.525239e+02
## year_built              2.403070e+03 3.199472e+03

## The results indicate that with 95% confidence the results would be within these two bounds for the p
## These results also confirm that sq ft total living is the best predictor due to the smallest margin

# VI.) Assess the improvement of the new model compared to your original model (simple regression model,
# whether this change is significant by performing an analysis of variance.
anova(price_lot_lm,multiple_pred_lm)

## Analysis of Variance Table
##
## Model 1: sale_price ~ sq_ft_lot
## Model 2: sale_price ~ square_feet_total_living + sq_ft_lot + bedrooms +
##           year_built
##   Res.Df    RSS Df Sum of Sq    F    Pr(>F)
## 1  12863 2.0734e+15
## 2  12860 1.6404e+15   3 4.3302e+14 1131.6 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# The F score of 1131.6 and a p value under 0.05 (2.2e-16) indicate that the changes were statistically

# 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

residuals <- resid(multiple_pred_lm)
stdresiduals <- rstandard(multiple_pred_lm)
stdntresiduals <- rstudent(multiple_pred_lm)
cookscases <- cooks.distance(multiple_pred_lm)
dfbetacases <- dfbeta(multiple_pred_lm)
dffitcases <- dffits(multiple_pred_lm)
```

```

leveragecases <- hatvalues(multiple_pred_lm)
covratiocases <- covratio(multiple_pred_lm)

casewise_df <- data.frame(residuals, stdresiduals, stdntresiduals, cookscases, dfbetacases, dffitcases,

# VIII.) Calculate the standardized residuals using the appropriate command, specifying those that are
# storing the results of large residuals in a variable you create.

casewise_df$largeres <- casewise_df$stdresiduals > 2 | casewise_df$stdresiduals < -2

# IX.) Use the appropriate function to show the sum of large residuals
sum(casewise_df$largeres_df)

## [1] 0

# X.) Which specific variables have large residuals (only cases that evaluate as TRUE)
colnames(casewise_df)

## [1] "residuals"          "stdresiduals"
## [3] "stdntresiduals"     "cookscases"
## [5] "X.Intercept."       "square_foot_total_living"
## [7] "sq_ft_lot"          "bedrooms"
## [9] "year_built"         "dffitcases"
## [11] "leveragecases"      "covratiocases"
## [13] "largeres"

large_residuals_var <- casewise_df$largeres
sum(large_residuals_var)

## [1] 335

## There are 335 variables that have large residuals.

# XI.) Investigate further by calculating the leverage, cooks distance, and covariance ratios.
# Comment on all cases that are problematics.

problematics <- casewise_df[casewise_df$largeres, c("cookscases", "leveragecases", 'covratiocases')]
problematics

##          cookscases leveragecases covratiocases
## 6      0.0003240312 0.0003401775    0.9988782
## 25     0.0007865132 0.0006715173    0.9987854
## 115    0.0047459701 0.0026231740    0.9995064
## 160    0.0034078340 0.0034820171    1.0019825
## 178    0.0011037879 0.0009282485    0.9990080
## 239    0.0006287502 0.0007246524    0.9994281
## 246    0.0047813247 0.0018843263    0.9973525
## 287    0.0007293987 0.0005447957    0.9983332
## 295    0.0009048370 0.0007087467    0.9986180
## 300    0.0072561886 0.0026945880    0.9978657
## 341    0.0003590686 0.0004155890    0.9991257
## 344    0.0082677601 0.0084873716    1.0070592
## 359    0.0020833468 0.0013002693    0.9985792
## 385    0.0035339447 0.0016722548    0.9979615
## 396    0.0016338162 0.0010402006    0.9983797
## 475    0.0005856695 0.0005399580    0.9988217

```

## 482	0.0013294210	0.0013910718	0.9999252
## 508	0.0030437630	0.0023072743	1.0001395
## 528	0.0011173074	0.0010257866	0.9992996
## 576	0.0010115371	0.0012215718	1.0000031
## 661	0.0044081787	0.0035938710	1.0016140
## 670	0.0025062163	0.0006567978	0.9936475
## 679	0.0088317665	0.0029877643	0.9976512
## 784	0.0018092943	0.0014351925	0.9993774
## 802	0.0010063379	0.0012063064	0.9999758
## 811	0.0049123216	0.0009099768	0.9908456
## 853	0.0007058860	0.0008016599	0.9994803
## 877	0.0017697971	0.0012324103	0.9988336
## 916	0.0050484746	0.0024418810	0.9988234
## 1009	0.0002540462	0.0002690618	0.9988232
## 1119	0.0030017253	0.0016510226	0.9985125
## 1142	0.0021206587	0.0013066399	0.9985454
## 1155	0.0172726958	0.0079820273	1.0042369
## 1305	0.0014548006	0.0014532345	0.9998995
## 1368	0.0009025077	0.0010966004	0.9998876
## 1380	0.0003882723	0.0003702544	0.9987217
## 1442	0.0021360702	0.0017628304	0.9998012
## 1492	0.0005239153	0.0005363802	0.9990276
## 1504	0.0072045866	0.0031566648	0.9991260
## 1550	0.0012051683	0.0008878024	0.9986406
## 1633	0.0005019761	0.0005026186	0.9989512
## 1650	0.0217550455	0.0058688344	0.9991063
## 1716	0.0010248719	0.0005472079	0.9972995
## 1745	0.0015079748	0.0008682439	0.9978851
## 1870	0.0083979026	0.0069304211	1.0050160
## 1962	0.0029142766	0.0011253299	0.9964897
## 1963	0.0004509376	0.0003680614	0.9983768
## 1964	0.0019868661	0.0007499854	0.9959982
## 1976	0.0017528192	0.0003797357	0.9918242
## 1977	0.0009112237	0.0001808120	0.9908072
## 1978	0.0009130558	0.0001860725	0.9910685
## 1979	0.0008901442	0.0001774381	0.9908482
## 1980	0.0008930300	0.0001772415	0.9908058
## 1981	0.0035347964	0.0007933420	0.9925481
## 1982	0.0018086844	0.0003807502	0.9915657
## 2022	0.0031718390	0.0015713136	0.9980437
## 2099	0.0007531715	0.0006608847	0.9988361
## 2137	0.0007537450	0.0003737193	0.9968467
## 2157	0.0006808854	0.0004326814	0.9977653
## 2257	0.0002310956	0.0002447384	0.9987988
## 2264	0.0024661868	0.0009148376	0.9960733
## 2302	0.0051196103	0.0045035507	1.0027057
## 2360	0.0008071574	0.0005916226	0.9983306
## 2361	0.0048820278	0.0015557052	0.9958595
## 2469	0.0004786945	0.0003011629	0.9976029
## 2604	0.0001916116	0.0002106094	0.9988315
## 2684	0.0018763871	0.0003877680	0.9914017
## 2685	0.0010264948	0.0002268459	0.9918466
## 2686	0.0018114657	0.0004688356	0.9933666
## 2687	0.0009522420	0.0002029393	0.9914998

## 2688	0.0008510969	0.0001743425	0.9911054
## 2689	0.0017370598	0.0004342537	0.9930684
## 2690	0.0017636648	0.0004473110	0.9931922
## 2699	0.0483078230	0.0252934719	1.0226399
## 2708	0.0014904737	0.0006646073	0.9967004
## 2709	0.0016364919	0.0008455465	0.9974772
## 2710	0.0017156144	0.0008386260	0.9972564
## 2717	0.0037008622	0.0012609738	0.9959572
## 2742	0.0004904024	0.0003397552	0.9979250
## 2852	0.0374216977	0.0079162189	0.9992115
## 2867	0.0007019562	0.0008701039	0.9996921
## 2934	0.0010239339	0.0005472079	0.9973029
## 2937	0.0009895288	0.0005472079	0.9974248
## 3097	0.0031620235	0.0011311475	0.9960971
## 3102	0.0009529929	0.0006077096	0.9979512
## 3110	0.0007077977	0.0005809253	0.9986031
## 3111	0.0007423807	0.0007385918	0.9991751
## 3168	0.0045449066	0.0004036234	0.9790851
## 3169	0.0045449066	0.0004036234	0.9790851
## 3170	0.0031231487	0.0002876399	0.9797382
## 3171	0.0025586529	0.0002393943	0.9800147
## 3172	0.0026449398	0.0002465421	0.9799451
## 3173	0.0025633861	0.0002398885	0.9800196
## 3174	0.0026442202	0.0002464680	0.9799445
## 3175	0.0034628999	0.0003123700	0.9793270
## 3176	0.0024807347	0.0002351148	0.9802722
## 3177	0.0023159581	0.0002196155	0.9802675
## 3178	0.0023174486	0.0002197765	0.9802695
## 3179	0.0029795741	0.0002737858	0.9796765
## 3180	0.0023195389	0.0002200004	0.9802721
## 3181	0.0029780878	0.0002736378	0.9796755
## 3182	0.0045453479	0.0004036773	0.9790859
## 3183	0.0045445612	0.0004035808	0.9790844
## 3184	0.0045445612	0.0004035808	0.9790844
## 3185	0.0045454010	0.0004036837	0.9790860
## 3186	0.0045449066	0.0004036234	0.9790851
## 3187	0.0045449066	0.0004036234	0.9790851
## 3188	0.0045486003	0.0004040591	0.9790912
## 3189	0.0034606561	0.0003121513	0.9793257
## 3190	0.0026408383	0.0002461186	0.9799413
## 3191	0.0034597595	0.0003120638	0.9793251
## 3192	0.0025591031	0.0002394416	0.9800152
## 3193	0.0026400875	0.0002460407	0.9799405
## 3194	0.0026395949	0.0002459894	0.9799400
## 3195	0.0023166867	0.0002196944	0.9802685
## 3196	0.0023182373	0.0002198612	0.9802705
## 3197	0.0024917909	0.0002362780	0.9802832
## 3198	0.0045463037	0.0004037919	0.9790876
## 3199	0.0045462216	0.0004037822	0.9790875
## 3200	0.0045445612	0.0004035808	0.9790844
## 3201	0.0045445612	0.0004035808	0.9790844
## 3202	0.0045445612	0.0004035808	0.9790844
## 3260	0.0003796139	0.0004697513	0.9992884
## 3424	0.0005659668	0.0003791051	0.9978683

## 3464	0.0033943936	0.0003120044	0.9797216
## 3465	0.0030458913	0.0002857896	0.9801189
## 3466	0.0022708341	0.0002195401	0.9806538
## 3467	0.0022741613	0.0002199068	0.9806582
## 3468	0.0033967377	0.0003122376	0.9797230
## 3469	0.0029143966	0.0002728801	0.9800633
## 3470	0.0022700349	0.0002194508	0.9806526
## 3471	0.0030475671	0.0002859613	0.9801201
## 3472	0.0025102228	0.0002394315	0.9804048
## 3473	0.0025924575	0.0002463157	0.9803336
## 3474	0.0034022566	0.0003127856	0.9797262
## 3475	0.0025149283	0.0002399324	0.9804097
## 3476	0.0022938659	0.0002214771	0.9806298
## 3477	0.0025133073	0.0002397606	0.9804081
## 3478	0.0044601322	0.0004035808	0.9794842
## 3479	0.0044601322	0.0004035808	0.9794842
## 3480	0.0044601322	0.0004035808	0.9794842
## 3481	0.0044601322	0.0004035808	0.9794842
## 3482	0.0044601322	0.0004035808	0.9794842
## 3483	0.0044601344	0.0004035810	0.9794842
## 3484	0.0044601254	0.0004035799	0.9794842
## 3485	0.0025065718	0.0002433760	0.9807626
## 3486	0.0029136086	0.0002727994	0.9800627
## 3487	0.0023855584	0.0002311270	0.9807078
## 3488	0.0025894149	0.0002459939	0.9803306
## 3489	0.0025084085	0.0002392364	0.9804028
## 3490	0.0025925672	0.0002463272	0.9803337
## 3491	0.0041923786	0.0004022819	0.9806876
## 3492	0.0030461648	0.0002858177	0.9801191
## 3493	0.0022715157	0.0002196158	0.9806547
## 3494	0.0033973201	0.0003122956	0.9797233
## 3495	0.0044601344	0.0004035810	0.9794842
## 3496	0.0044601344	0.0004035810	0.9794842
## 3497	0.0044601344	0.0004035810	0.9794842
## 3523	0.0023044383	0.0010135181	0.9969898
## 3837	0.0007340967	0.0005286531	0.9982204
## 3918	0.0018950937	0.0016510226	0.9998130
## 3919	0.0013819232	0.0013066399	0.9996426
## 4055	0.0006873189	0.0003741231	0.9971956
## 4056	0.0081831731	0.0016843061	0.9926636
## 4248	0.0009505931	0.0011731651	0.9999891
## 4285	0.0003868698	0.0003872595	0.9988351
## 4391	0.0019064458	0.0019959097	1.0005334
## 4435	0.0004215942	0.0003974469	0.9987254
## 4571	0.0008125303	0.0009614349	0.9997091
## 4648	0.1455620065	0.0101978847	0.9832400
## 4649	0.9623861409	0.0441602393	1.0049059
## 4671	0.0039230534	0.0032684268	1.0013372
## 4695	0.0017358361	0.0003452645	0.9909951
## 4696	0.0018647562	0.0009250220	0.9974008
## 4740	0.0003508655	0.0003711812	0.9989234
## 4821	0.0011608990	0.0007145214	0.9979485
## 4834	0.0027139781	0.0015713136	0.9986088
## 4840	0.0180519961	0.0079820273	1.0040477

## 4934	0.0014439853	0.0010529200	0.9987791
## 5083	0.1050613500	0.0298030096	1.0242819
## 5491	0.0001849418	0.0001961399	0.9987528
## 5494	0.0001788007	0.0001937871	0.9987897
## 5495	0.0001853408	0.0001963767	0.9987513
## 5496	0.0001849829	0.0001961621	0.9987526
## 5497	0.0004875578	0.0005019856	0.9990039
## 5549	0.0005858141	0.0006201300	0.9991738
## 5935	0.0029306766	0.0015412890	0.9982407
## 6055	0.0013451798	0.0013310266	0.9997583
## 6230	0.0013486804	0.0002053038	0.9878838
## 6231	0.0015053454	0.0002387630	0.9884264
## 6232	0.0015600205	0.0002550420	0.9888049
## 6233	0.0014235139	0.0002112187	0.9875619
## 6234	0.0028982573	0.0004385596	0.9880415
## 6235	0.0029265643	0.0004413770	0.9880021
## 6236	0.0028981590	0.0004385549	0.9880418
## 6237	0.0030017656	0.0004539386	0.9880489
## 6238	0.0014586582	0.0002132371	0.9873695
## 6239	0.0015058028	0.0002388307	0.9884263
## 6429	0.0040024484	0.0002028496	0.9628035
## 6430	0.0053953774	0.0002516256	0.9596301
## 6431	0.0047126921	0.0002267872	0.9608507
## 6432	0.0041295604	0.0002037975	0.9618018
## 6433	0.0087623610	0.0004362891	0.9623721
## 6434	0.0092268516	0.0004608433	0.9625139
## 6435	0.0078830222	0.0004104969	0.9640065
## 6436	0.0045683525	0.0002213424	0.9611106
## 6437	0.0049408204	0.0002325778	0.9599842
## 6438	0.0040366167	0.0001893061	0.9597914
## 6439	0.0038327293	0.0001915016	0.9622587
## 6440	0.0040782409	0.0002089087	0.9632047
## 6441	0.0042250210	0.0002073743	0.9615965
## 6442	0.0040454525	0.0002014587	0.9621429
## 6443	0.0094988841	0.0005287937	0.9664680
## 6444	0.0079486689	0.0004572522	0.9674932
## 6445	0.0051811656	0.0002794175	0.9651233
## 6446	0.0038564032	0.0002178753	0.9666548
## 6447	0.0071652884	0.0004231482	0.9683117
## 6448	0.0044312471	0.0002399223	0.9652221
## 6449	0.0069083692	0.0004132157	0.9687085
## 6450	0.0066209979	0.0004087786	0.9696926
## 6451	0.0048883076	0.0002634415	0.9650830
## 6452	0.0038282873	0.0002167251	0.9667214
## 6453	0.0070268516	0.0004223445	0.9688708
## 6454	0.0076594123	0.0004443280	0.9677555
## 6455	0.0099471776	0.0005499928	0.9662572
## 6456	0.0043199242	0.0002366950	0.9656318
## 6457	0.0075608879	0.0004399774	0.9678524
## 6512	0.0028243110	0.0008863531	0.9950948
## 6527	0.0007215151	0.0006294394	0.9987917
## 6739	0.0005688433	0.0004404078	0.9983203
## 6766	0.0061833846	0.0075696246	1.0064316
## 6796	0.0002650325	0.0003116946	0.9990483

## 6821	0.0010587897	0.0010426478	0.9994597
## 6931	0.0002776294	0.0002878847	0.9988029
## 6938	0.0008703473	0.0003058932	0.9951738
## 6939	0.0012570281	0.0005235826	0.9962526
## 6940	0.0007121605	0.0002155038	0.9941943
## 6941	0.0007078658	0.0002148666	0.9942133
## 6942	0.0012064574	0.0004666648	0.9958383
## 6943	0.0012066695	0.0004654257	0.9958228
## 6944	0.0013030507	0.0005624303	0.9964543
## 6945	0.0008703473	0.0003058932	0.9951738
## 6946	0.0007117867	0.0002159188	0.9942103
## 6947	0.0007150003	0.0002113652	0.9940390
## 6948	0.0007189595	0.0002101517	0.9939635
## 7021	0.0019426974	0.0024164405	1.0012496
## 7039	0.0012872978	0.0012829585	0.9997242
## 7147	0.0010650809	0.0007758639	0.9984988
## 7167	0.0062523105	0.0007759340	0.9855930
## 7210	0.0038159679	0.0010692859	0.9945386
## 7211	0.0031335963	0.0007253833	0.9927420
## 7446	0.0029786093	0.0002536820	0.9780157
## 7447	0.0033096087	0.0002773280	0.9776720
## 7448	0.0029681348	0.0002529710	0.9780310
## 7449	0.0024706536	0.0002084076	0.9777539
## 7450	0.0024726859	0.0002084484	0.9777397
## 7451	0.0024747368	0.0002084914	0.9777257
## 7452	0.0033106530	0.0002774294	0.9776733
## 7453	0.0028772831	0.0002439620	0.9779058
## 7454	0.0028549057	0.0002423727	0.9779328
## 7455	0.0031256836	0.0002617309	0.9776403
## 7456	0.0033094595	0.0002773135	0.9776718
## 7457	0.0030012138	0.0002552784	0.9779884
## 7458	0.0024714611	0.0002082496	0.9777291
## 7459	0.0035306182	0.0002930662	0.9774716
## 7460	0.0024726859	0.0002084484	0.9777397
## 7461	0.0034385220	0.0002864896	0.9775507
## 7462	0.0034840917	0.0002897447	0.9775112
## 7463	0.0034385934	0.0002864964	0.9775508
## 7507	0.0022149927	0.0014351925	0.9988289
## 7649	0.0003629867	0.0004202732	0.9991310
## 7650	0.0003633113	0.0004207235	0.9991317
## 7791	0.0018965629	0.0019607378	1.0004745
## 7871	0.0066823702	0.0031602211	0.9994548
## 8119	0.0008585507	0.0010426478	0.9998327
## 8154	0.0002867721	0.0003039746	0.9988597
## 8232	0.0022315101	0.0014351925	0.9988065
## 8262	0.0321921228	0.0116398653	1.0068032
## 8320	0.0095544493	0.0049550613	1.0016262
## 8377	0.5278303936	0.0639808918	1.0528218
## 8457	0.0004367617	0.0003680614	0.9984516
## 8458	0.0019442656	0.0007499854	0.9961083
## 8535	0.0004539890	0.0004750345	0.9990071
## 8541	0.0005051274	0.0005026186	0.9989390
## 8698	0.0002475346	0.0002223235	0.9984479
## 8710	0.0027974029	0.0006291977	0.9924021

```
## 8763 0.0006119122 0.0004740102 0.9983553
## 8887 0.0108275135 0.0017443407 0.9901234
## 8911 0.0013434042 0.0012523507 0.9995589
## 8946 0.0013434042 0.0012523507 0.9995589
## 9215 0.0038411161 0.0028340795 1.0005991
## 9293 0.0011443070 0.0010257866 0.9992485
## 9369 0.0018890072 0.0020387833 1.0006320
## 9420 0.0068031389 0.0052250914 1.0031139
## 9453 0.0005412740 0.0005472079 0.9990144
## 9528 0.0094198048 0.0025857453 0.9959176
## 9546 0.0007032097 0.0005286531 0.9983338
## 9722 0.0006156877 0.0003711812 0.9975387
## 10125 0.0019940892 0.0020851676 1.0006208
## 10318 0.0216423861 0.0223926837 1.0214252
## 10371 0.0008177928 0.0007100602 0.9988619
## 10418 0.0019509311 0.0018592855 1.0002134
## 10623 0.0005587155 0.0005960403 0.9991639
## 10707 0.0001205613 0.0001228020 0.9986039
## 10723 0.0005685941 0.0006111940 0.9991928
## 10741 0.0002882247 0.0003543058 0.9991624
## 10787 0.0036447505 0.0013549077 0.9965256
## 10844 0.0019345571 0.0016035455 0.9996516
## 10958 0.0006936713 0.0005236912 0.9983397
## 10995 0.0037596234 0.0038339254 1.0023334
## 11165 0.0005092099 0.0003552569 0.9979600
## 11289 0.0008315614 0.0002218824 0.9933436
## 11413 0.0039266679 0.0012259344 0.9954032
## 11558 0.0042413983 0.0007451496 0.9901141
## 11586 0.0022977140 0.0010848807 0.9973632
## 11728 0.0095531185 0.0047264310 1.0012150
## 11758 0.0008760885 0.0007100602 0.9987025
## 11772 0.0177302690 0.0020066766 0.9853345
## 11822 0.0034721766 0.0006384908 0.9904968
## 11898 0.0570217579 0.0350849815 1.0336069
## 11899 0.1187767849 0.0370160658 1.0326174
## 11982 0.0095990661 0.0024418810 0.9952161
## 11992 0.1023364898 0.0045587795 0.9620658
## 12212 0.0023446837 0.0016436109 0.9992646
## 12255 0.0031498730 0.0014169344 0.9974926
## 12256 0.0015214308 0.0011177163 0.9988639
## 12392 0.0009154026 0.0008564528 0.9991695
## 12472 0.0038898867 0.0008731282 0.9926289
## 12487 0.0036167660 0.0015660616 0.9974747
## 12577 0.0060419341 0.0016677942 0.9950346
## 12582 0.0287602671 0.0027484092 0.9829597
## 12643 0.0098430722 0.0008252960 0.9782344
## 12686 0.0003446506 0.0003850846 0.9990349
## 12759 0.0003729966 0.0004465431 0.9992124
## 12764 0.0077344820 0.0022281006 0.9958901
```

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

```
dwt(multiple_pred_lm)
```

```
## lag Autocorrelation D-W Statistic p-value
## 1 0.7209323 0.5581258 0
## Alternative hypothesis: rho != 0
## The statistic is less than 1 which means the assumption has not been met.

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

VIF(multiple_pred_lm)

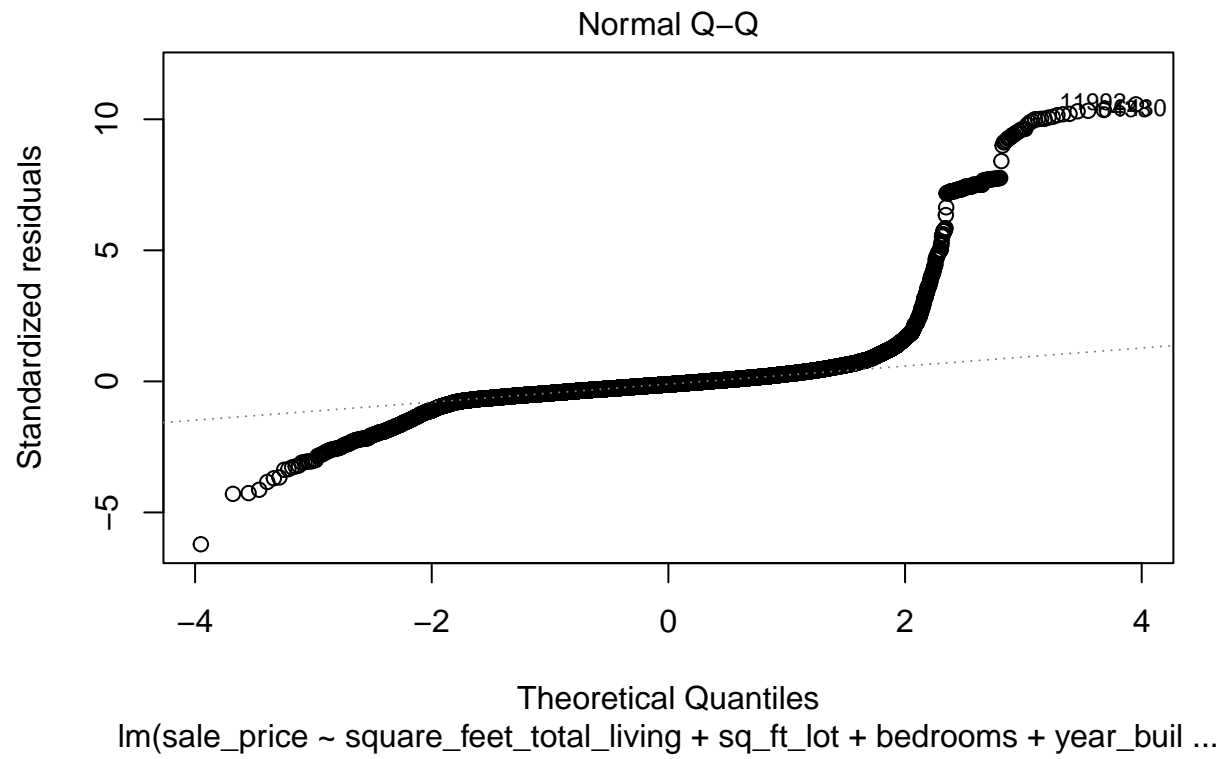
## square_feet_total_living sq_ft_lot bedrooms
## 1.934814 1.144597 1.607780
## year_built
## 1.234185
1/vif(multiple_pred_lm)

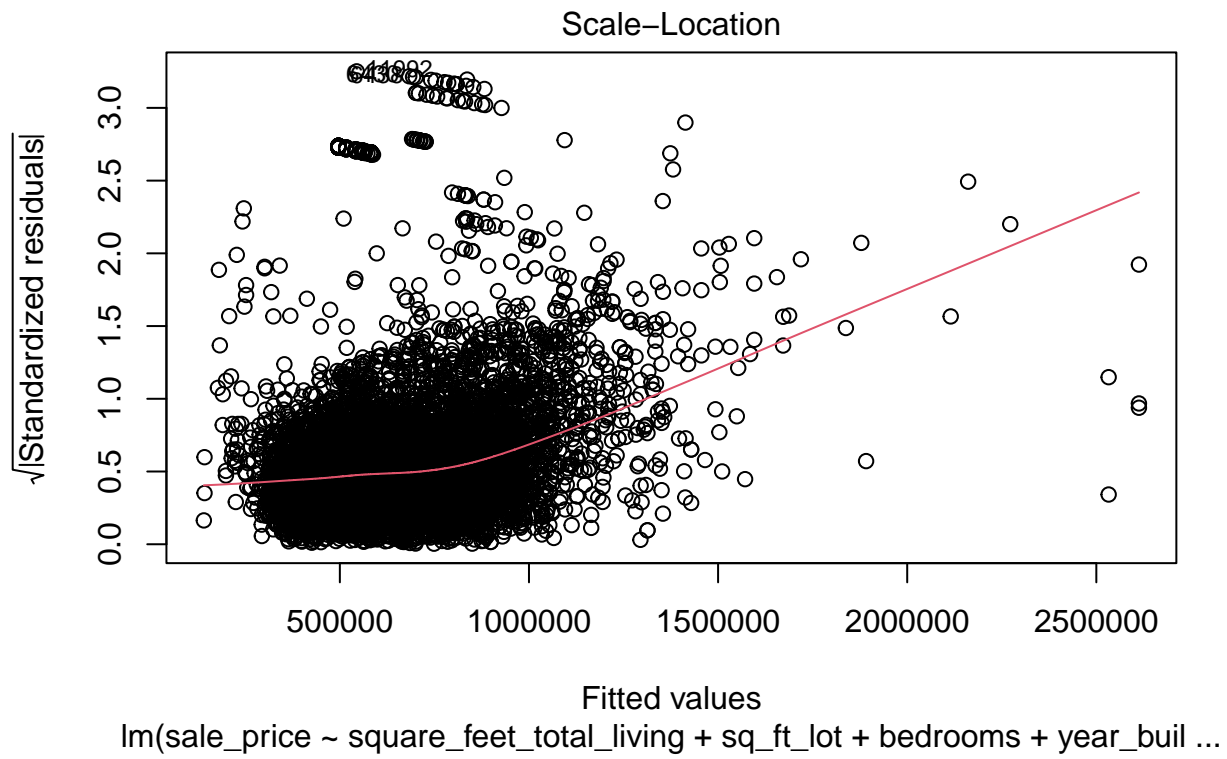
## square_feet_total_living sq_ft_lot bedrooms
## 0.5168455 0.8736699 0.6219757
## year_built
## 0.8102512
mean(vif(multiple_pred_lm))

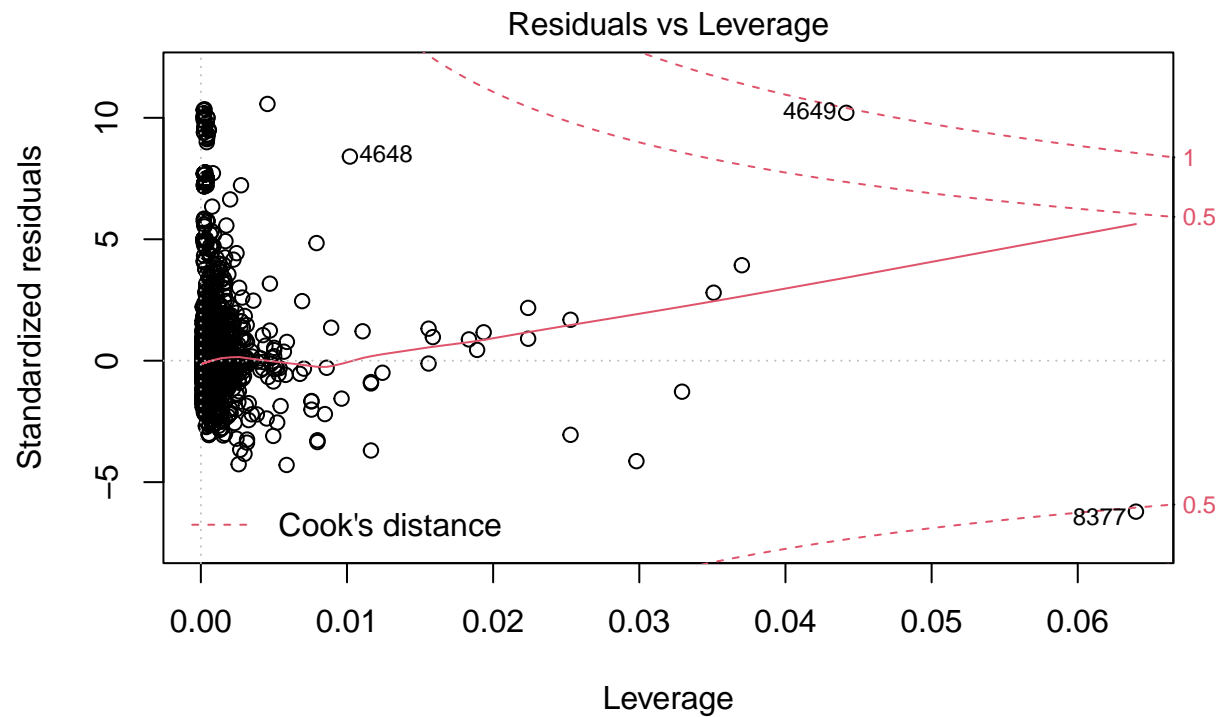
## [1] 1.480344
## The VIFs are all below 10 and the tolerance statistics are all above 0.2 and the average is only slightly above 1.

# 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.
plot(multiple_pred_lm)
```



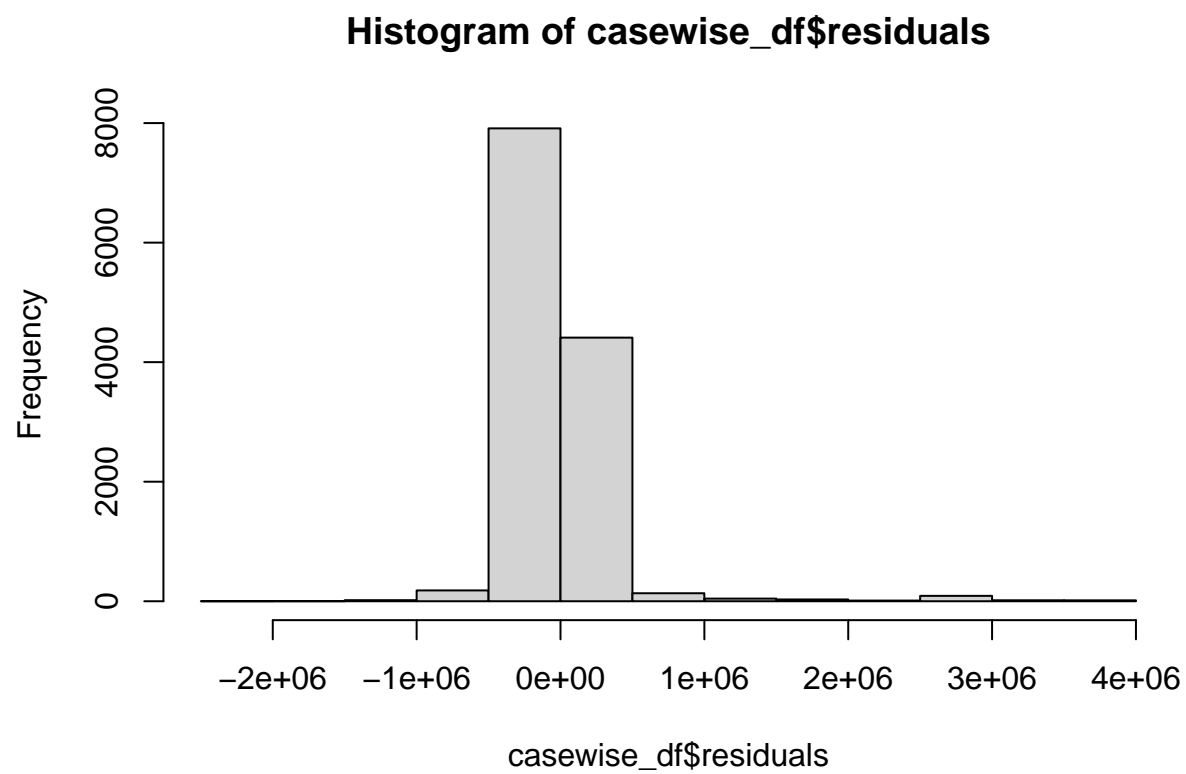




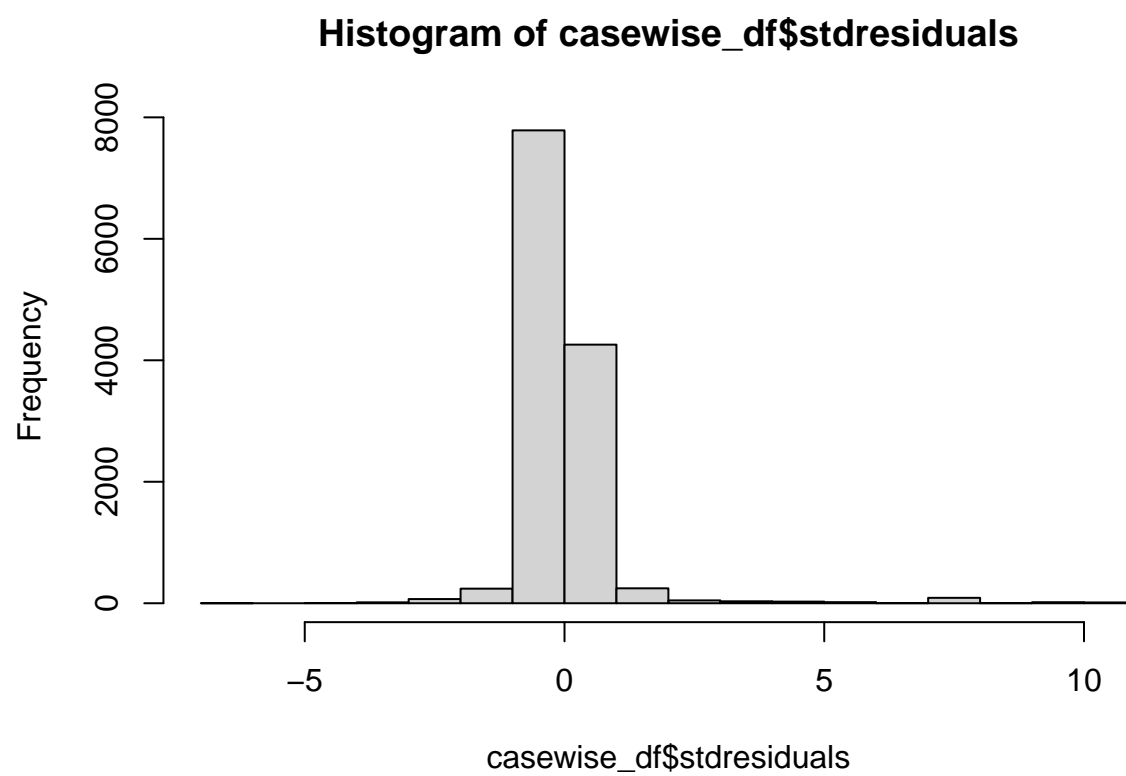


lm(sale_price ~ square_feet_total_living + sq_ft_lot + bedrooms + year_buil ...

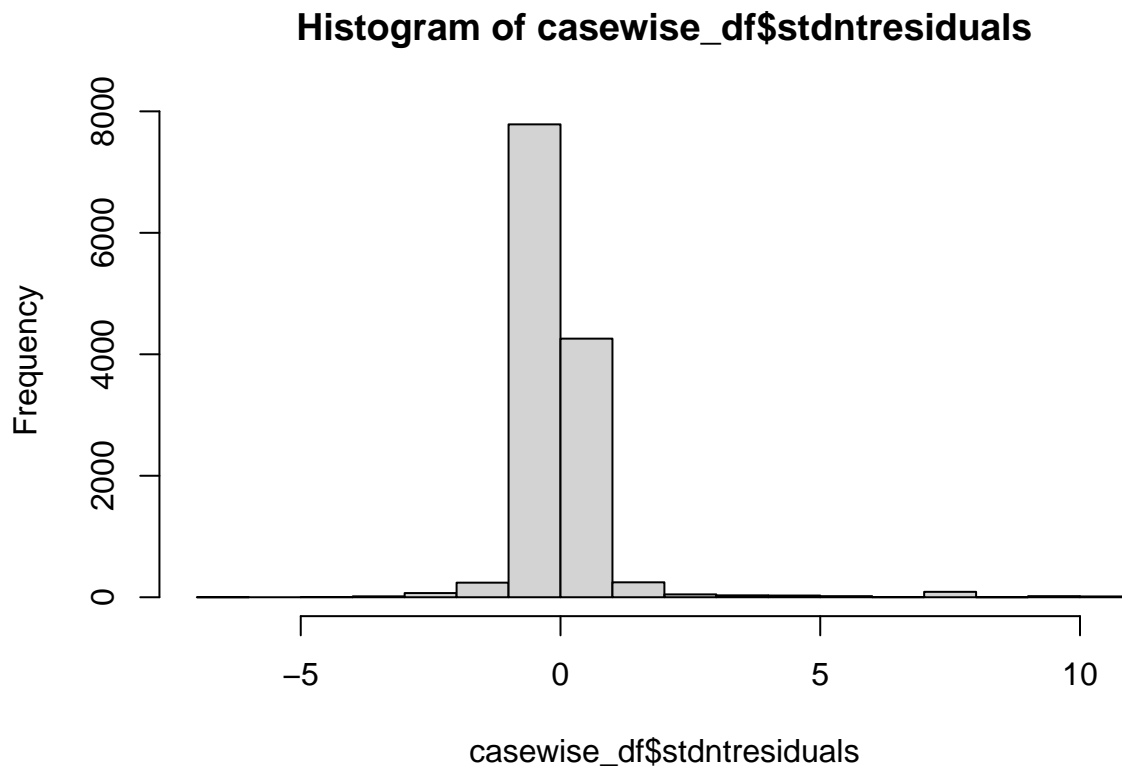
```
hist(casewise_df$residuals)
```



```
hist(casewise_df$stdresiduals)
```



```
hist(casewise_df$stdntresiduals)
```



```
# XV.) Overall, is this regression model unbiased?  
# If an unbiased regression model, what does this tell us about the sample vs. the entire population mo  
## Overall I would say the regression model is biased as there are 335 outliers and although not by muc
```