HARVARD EXTENSION SCHOOL

EXT CSCI E-106 Model Data Class Group Project Template

Will Greaves Flora Lo Matt Michel Thaylan Toth Kaylee Vo Zhenzhen Yin

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Abstract

We aimed to develop models for predicting house prices in Kings County, USA using statistical modeling and machine learning approaches. Our dataset contained historical home sales prices of 21,613 houses in Kings County, USA (May 2014-May 2015), out of which we used 70% for training and 30% for testing. We selected several significant features using feature selection methods to build the models. Seven different linear regression models were developed using R and compared against each other, with lasso regression achieving the highest adjusted R-squared (0.775). In addition, we developed alternative models using regression tree, which achieved an adjusted R-squared value of _____. Our models suggest that the most frequent and significant features contributing to home prices in Kings County were _____, _____, _____. In conclusion, we proposed a model that could predict house sales prices based on commonly measured variables. We believe such a model can serve as a helpful tool for prospective consumers and real estate service providers to estimate the value of future properties on the market, and for them to understand significant factors that may increase or decrease home values. Importantly, we expect this model to be valid only within the geographical region of King County and for a limited period of time into the future. It is subject to changes in the market and broader economic conditions, thus we also provided a detailed model monitoring plan to alert us of significant deviations from our model.

Contents

House Sales in King County, USA data to be used in the Final Project

Variable	Description
id	**Unique ID for each home sold (it is not a predictor)**
date	*Date of the home sale*
price	*Price of each home sold*
bedrooms	*Number of bedrooms*
bathrooms	*Number of bathrooms, where ".5" accounts for a bathroom with a toilet but no shower*
sqft_living	*Square footage of the apartment interior living space*
sqft_lot	*Square footage of the land space*
floors	*Number of floors*
waterfront	*A dummy variable for whether the apartment was overlooking the waterfront or not*
view	*An index from 0 to 4 of how good the view of the property was*
condition	*An index from 1 to 5 on the condition of the apartment,*
grade	*An index from 1 to 13, where 1-3 falls short of building construction and design, 7 has an average level of construction and design, and 11-13 has a high-quality level of construction and design.*
sqft_above	*The square footage of the interior housing space that is above ground level*
sqft_basement	*The square footage of the interior housing space that is below ground level*
yr_built	*The year the house was initially built*
yr_renovated	*The year of the house's last renovation*
zipcode	*What zipcode area the house is in*
lat	*Latitude*
long	*Longitude*
sqft_living15	*The square footage of interior housing living space for the nearest 15 neighbors*
sqft_lot15	*The square footage of the land lots of the nearest 15 neighbors*

Instructions:

0. Join a team with your fellow students with appropriate size (Four Students total)
1. Load and Review the dataset named "KC_House_Sales'csv
2. Create the train data set which contains 70% of the data and use set.seed (1023). The remaining 30% will be your test data set.
3. Investigate the data and combine the level of categorical variables if needed and drop variables as needed. For example, you can drop id, Latitude, Longitude, etc.
4. Build a regression model to predict price.
5. Create scatter plots and a correlation matrix for the train data set. Interpret the possible relationship between the response.
6. Build the best multiple linear models by using the stepwise selection method. Compare the performance of the best two linear models.
7. Make sure that model assumption(s) are checked for the final model. Apply remedy measures (transformation, etc.) that helps satisfy the assumptions.
8. Investigate unequal variances and multicollinearity. If necessary, apply remedial methods (WLS, Ridge, Elastic Net, Lasso, etc.).
9. Build an alternative model based on one of the following approaches to predict price: regression tree, NN, or SVM. Check the applicable model assumptions. Explore using a logistic regression.
10. Use the test data set to assess the model performances from above.
11. Based on the performances on both train and test data sets, determine your primary (champion) model and the other model which would be your benchmark model.
12. Create a model development document that describes the model following this template, input the name of the authors, Harvard IDs, the name of the Group, all of your code and calculations, etc..:

Due Date: December 18th, 2023 at 11:59 pm EST

Notes No typographical errors, grammar mistakes, or misspelled words, use English language All tables need to be numbered and describe their content in the body of the document All figures/graphs need to be numbered and describe their content All results must be accurate and clearly explained for a casual reviewer to fully understand their purpose and impact Submit both the RMD markdown file and PDF with the sections with appropriate explanations. A more formal document in Word can be used in place of the pdf file but must include all appropriate explanations.

Executive Summary

This section will describe the model usage, your conclusions and any regulatory and internal requirements. In a real world scneario, this section is for senior management who do not need to know the details. They need to know high level (the purpose of the model, limitations of the model and any issues).

In this report, we describe the development of a statistical model that can be used to predict house sales prices in Kings county, USA based on historic house sales data collected between May 2014 and May 2015. Validation in a test data set showed that the model is significant and has an adjusted R-squared value of _____. The model may be applied to estimate property value for consumers and property market agents, as well as to generate insights into the key factors contributing to home prices. It is important to note that we expect the model to work well only in geographical locations within King County and within a limited time frame into the future. As such, we have also included a model monitoring plan to detect substantial future deviations of our model.

I. Introduction (5 points)

This section needs to introduce the reader to the problem to be resolved, the purpose, and the scope of the statistical testing applied. What you are doing with your prediction? What is the purpose of the model? What methods were trained on the data, how large is the test sample, and how did you build the model?

In this project, our goal is to build a statistical model that can predict house sales prices in Kings county, USA based on house sales data collected in that area between May 2014 and May 2015. The dataset contains information on 21613 houses, including the sale price, number of rooms, square footage, year built and renovated, view, and condition of the property. The house sale price was used as the outcome variable and all other variables were considered as independent variables. 70% of the dataset was used as training set and 30% was used as testing set.

Using this framework, we built several different models using linear regression, logistic regression, regression tree, and neural network. When building each model, feature selection methods were used and the appropriate diagnostic tests were applied to verify that model assumptions were met. <TODO: Elaborate more on each model>

Finally, the performance of each models was evaluated by its accuracy in predicting house prices in the test set, specifically by examining the adjusted R-squared and MSE of predicted values. Based on that, we propose that the best predictive model is _____. This model indicated that the most important factors that influence house prices in King County, USA are _____. This model may be useful for estimating property prices for home buyers, sellers, or property market professionals. It may also contribute to research on key factors contributing to home prices. Importantly, we expect the model to be valid only in geographical locations within King County and within a limited time frame into the future. We have also detailed a model monitoring plan to detect substantial deviations of our model in the future.

II. Description of the data and quality (15 points)

Here you need to review your data, the statistical test applied to understand the predictors and the response and how are they correlated. Extensive graph analysis is recommended. Is the data continuous, or categorical, do any transformation needed? Do you need dummies?

```
library(ggplot2)
library(corrplot)
```

```
## corrplot 0.92 loaded
```

```
str(HouseSales)
```

```
## 'data.frame':    21613 obs. of  21 variables:
##  $ id           : num  7.13e+09 6.41e+09 5.63e+09 2.49e+09 1.95e+09 ...
##  $ date         : chr  "20141013T000000" "20141209T000000" "20150225T000000" "20141209T000000" ...
##  $ price        : chr  " $221,900.00 " " $538,000.00 " " $180,000.00 " " $604,000.00 " ...
##  $ bedrooms     : int  3 3 2 4 3 4 3 3 3 3 ...
##  $ bathrooms    : num  1 2.25 1 3 2 4.5 2.25 1.5 1 2.5 ...
##  $ sqft_living  : int  1180 2570 770 1960 1680 5420 1715 1060 1780 1890 ...
##  $ sqft_lot     : int  5650 7242 10000 5000 8080 101930 6819 9711 7470 6560 ...
##  $ floors       : num  1 2 1 1 1 1 2 1 1 2 ...
##  $ waterfront   : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ view         : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ condition    : int  3 3 3 5 3 3 3 3 3 3 ...
##  $ grade        : int  7 7 6 7 8 11 7 7 7 7 ...
##  $ sqft_above   : int  1180 2170 770 1050 1680 3890 1715 1060 1050 1890 ...
##  $ sqft_basement: int  0 400 0 910 0 1530 0 0 730 0 ...
##  $ yr_built     : int  1955 1951 1933 1965 1987 2001 1995 1963 1960 2003 ...
##  $ yr_renovated : int  0 1991 0 0 0 0 0 0 0 0 ...
##  $ zipcode      : int  98178 98125 98028 98136 98074 98053 98003 98198 98146 98038 ...
##  $ lat          : num  47.5 47.7 47.7 47.5 47.6 ...
##  $ long         : num  -122 -122 -122 -122 -122 ...
##  $ sqft_living15: int  1340 1690 2720 1360 1800 4760 2238 1650 1780 2390 ...
##  $ sqft_lot15   : int  5650 7639 8062 5000 7503 101930 6819 9711 8113 7570 ...
```

By looking at the structure of the data set, it is found that the variables "date" and "price" are in character format and need to be converted to numeric format. Also, we split the "date" into "year" and "month" and drop the variable "id", which is not a predictor.

```
# Data cleaning (price)
df = read.csv("KC_House_Sales.csv")
df$price = parse_number(df$price)
```

```
# Transformation (date)
df$year = as.integer(substr(df$date, 1, 4))
df$month = as.integer(substr(df$date, 5, 6))
year = df$year
month = df$month
df = subset(df, select = -c(id, date))
```

The variable "year" has only two categories, 2014 and 2015, and does not need further processing. However, "month" is a multi-categorical variable, so it is not ideal to use only one regression coefficient to explain the change in relationship between the multi-categorical variables and its influence on the dependent variable. Therefore, we convert "month" into 12 dummy variables representing different months, using "1" for "yes" and "0" for "no". In this way, the results of regression are easier to interpret and have more practical utility, for example in pointing out the months that have particularly strong influence on house pricing.

```
# dummy (month, True(1), False(0))
df$month_Jan = ifelse(df$month == 1, 1, 0)
df$month_Feb = ifelse(df$month == 2, 1, 0)
df$month_Mar = ifelse(df$month == 3, 1, 0)
df$month_Apr = ifelse(df$month == 4, 1, 0)
df$month_May = ifelse(df$month == 5, 1, 0)
df$month_Jun = ifelse(df$month == 6, 1, 0)
df$month_Jul = ifelse(df$month == 7, 1, 0)
df$month_Aug = ifelse(df$month == 8, 1, 0)
df$month_Sep = ifelse(df$month == 9, 1, 0)
df$month_Oct = ifelse(df$month == 10, 1, 0)
df$month_Nov = ifelse(df$month == 11, 1, 0)
df$month_Dec = ifelse(df$month == 12, 1, 0)

df = subset(df, select = -(month))
```

For the same reason, the variable "zipcode", as a multi-categorical variable with 199 categories, also needs to be converted into a dummy variable. Considering that zip codes can be used for positioning, we divided the variable "zipcode" into two categories, one format "980xx" and the other format "981xx", so that it can represent two different regions. "981xx" largely corresponds to areas within Seattle, WA and "980xx" specifies the neighboring suburban areas.

```
# dummy (zipcode, Divided into two groups, 980xx and 981xx)
df$zipcode_start = as.integer(substr(df$zipcode, 1, 3))
df = subset(df, select = -(zipcode))

knitr::kable(table(df$zipcode_start), col.names=c("zipcode","frequency"))
```

zipcode	frequency
980	12636
981	8977

```
# Split into train/ test set:
set.seed(1023)
sample = sample(c(TRUE, FALSE), nrow(df), replace = TRUE, prob = c(0.7, 0.3))
train = df[sample, ]
test = df[!sample, ]

summary(train)
```

```
##      price            bedrooms        bathrooms      sqft_living
##  Min.   :  75000   Min.   : 0.000   Min.   :0.000   Min.   :  380
##  1st Qu.: 320000   1st Qu.: 3.000   1st Qu.:1.750   1st Qu.: 1430
##  Median : 450000   Median : 3.000   Median :2.250   Median : 1910
##  Mean   : 539801   Mean   : 3.374   Mean   :2.116   Mean   : 2081
##  3rd Qu.: 644362   3rd Qu.: 4.000   3rd Qu.:2.500   3rd Qu.: 2550
##  Max.   :7700000   Max.   :33.000   Max.   :8.000   Max.   :13540
##     sqft_lot          floors        waterfront           view
##  Min.   :    572   Min.   :1.000   Min.   :0.000000   Min.   :0.0000
##  1st Qu.:   5029   1st Qu.:1.000   1st Qu.:0.000000   1st Qu.:0.0000
##  Median :   7576   Median :1.500   Median :0.000000   Median :0.0000
##  Mean   :  14962   Mean   :1.497   Mean   :0.007651   Mean   :0.2336
##  3rd Qu.:  10650   3rd Qu.:2.000   3rd Qu.:0.000000   3rd Qu.:0.0000
##  Max.   :1651359   Max.   :3.500   Max.   :1.000000   Max.   :4.0000
##    condition         grade          sqft_above   sqft_basement
##  Min.   :1.000   Min.   : 3.000   Min.   : 380   Min.   :   0.0
##  1st Qu.:3.000   1st Qu.: 7.000   1st Qu.:1200   1st Qu.:   0.0
```

```
##  Median :3.000   Median : 7.000   Median :1560   Median :   0.0
##  Mean   :3.412   Mean   : 7.655   Mean   :1791   Mean   : 290.4
##  3rd Qu.:4.000   3rd Qu.: 8.000   3rd Qu.:2220   3rd Qu.: 560.0
##  Max.   :5.000   Max.   :13.000   Max.   :9410   Max.   :4820.0
##     yr_built     yr_renovated          lat             long
##  Min.   :1900   Min.   :   0.00   Min.   :47.16   Min.   :-122.5
##  1st Qu.:1951   1st Qu.:   0.00   1st Qu.:47.47   1st Qu.:-122.3
##  Median :1975   Median :   0.00   Median :47.57   Median :-122.2
##  Mean   :1971   Mean   :  81.86   Mean   :47.56   Mean   :-122.2
##  3rd Qu.:1997   3rd Qu.:   0.00   3rd Qu.:47.68   3rd Qu.:-122.1
##  Max.   :2015   Max.   :2015.00   Max.   :47.78   Max.   :-121.3
##  sqft_living15    sqft_lot15          year        month_Jan
##  Min.   : 399   Min.   :   651   Min.   :2014   Min.   :0.00000
##  1st Qu.:1480   1st Qu.:  5100   1st Qu.:2014   1st Qu.:0.00000
##  Median :1840   Median :  7620   Median :2014   Median :0.00000
##  Mean   :1986   Mean   : 12786   Mean   :2014   Mean   :0.04564
##  3rd Qu.:2360   3rd Qu.: 10095   3rd Qu.:2015   3rd Qu.:0.00000
##  Max.   :6210   Max.   :871200   Max.   :2015   Max.   :1.00000
##    month_Feb        month_Mar         month_Apr        month_May
##  Min.   :0.0000   Min.   :0.00000   Min.   :0.0000   Min.   :0.0000
##  1st Qu.:0.0000   1st Qu.:0.00000   1st Qu.:0.0000   1st Qu.:0.0000
##  Median :0.0000   Median :0.00000   Median :0.0000   Median :0.0000
##  Mean   :0.0583   Mean   :0.08257   Mean   :0.1054   Mean   :0.1135
##  3rd Qu.:0.0000   3rd Qu.:0.00000   3rd Qu.:0.0000   3rd Qu.:0.0000
##  Max.   :1.0000   Max.   :1.00000   Max.   :1.0000   Max.   :1.0000
##    month_Jun        month_Jul        month_Aug        month_Sep
##  Min.   :0.0000   Min.   :0.0000   Min.   :0.0000   Min.   :0.00000
##  1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:0.00000
##  Median :0.0000   Median :0.0000   Median :0.0000   Median :0.00000
##  Mean   :0.1003   Mean   :0.1022   Mean   :0.0899   Mean   :0.08502
##  3rd Qu.:0.0000   3rd Qu.:0.0000   3rd Qu.:0.0000   3rd Qu.:0.00000
##  Max.   :1.0000   Max.   :1.0000   Max.   :1.0000   Max.   :1.00000
##    month_Oct         month_Nov         month_Dec       zipcode_start
##  Min.   :0.00000   Min.   :0.00000   Min.   :0.00000   Min.   :980.0
##  1st Qu.:0.00000   1st Qu.:0.00000   1st Qu.:0.00000   1st Qu.:980.0
##  Median :0.00000   Median :0.00000   Median :0.00000   Median :980.0
##  Mean   :0.08508   Mean   :0.06523   Mean   :0.06681   Mean   :980.4
##  3rd Qu.:0.00000   3rd Qu.:0.00000   3rd Qu.:0.00000   3rd Qu.:981.0
##  Max.   :1.00000   Max.   :1.00000   Max.   :1.00000   Max.   :981.0
```

Through the correlation matrix and graph, it can be found that variables "sqft_living", "grade", "sqft_above" and "sqft_living15" have a relatively high correlation with the response variable "price", around 0.6. However, the variables "sqft_lot", "condition", "yr_built", "long", "sqft_lot15", "year", "zipcode_start" and 12 different months have a very low correlation with "price", all below 0.1.

```
cor_matrix = round(cor(train), 3)
cor_matrix
```

```
##                price bedrooms bathrooms sqft_living sqft_lot floors waterfront
## price          1.000    0.306     0.522       0.707    0.092  0.263      0.291
## bedrooms       0.306    1.000     0.509       0.573    0.041  0.177      0.005
## bathrooms      0.522    0.509     1.000       0.752    0.088  0.506      0.076
## sqft_living    0.707    0.573     0.752       1.000    0.176  0.359      0.121
## sqft_lot       0.092    0.041     0.088       0.176    1.000  0.000      0.025
## floors         0.263    0.177     0.506       0.359    0.000  1.000      0.025
## waterfront     0.291    0.005     0.076       0.121    0.025  0.025      1.000
## view           0.393    0.080     0.184       0.283    0.073  0.032      0.406
## condition      0.050    0.035    -0.116      -0.047   -0.009 -0.254      0.016
## grade          0.669    0.356     0.665       0.761    0.119  0.459      0.091
```

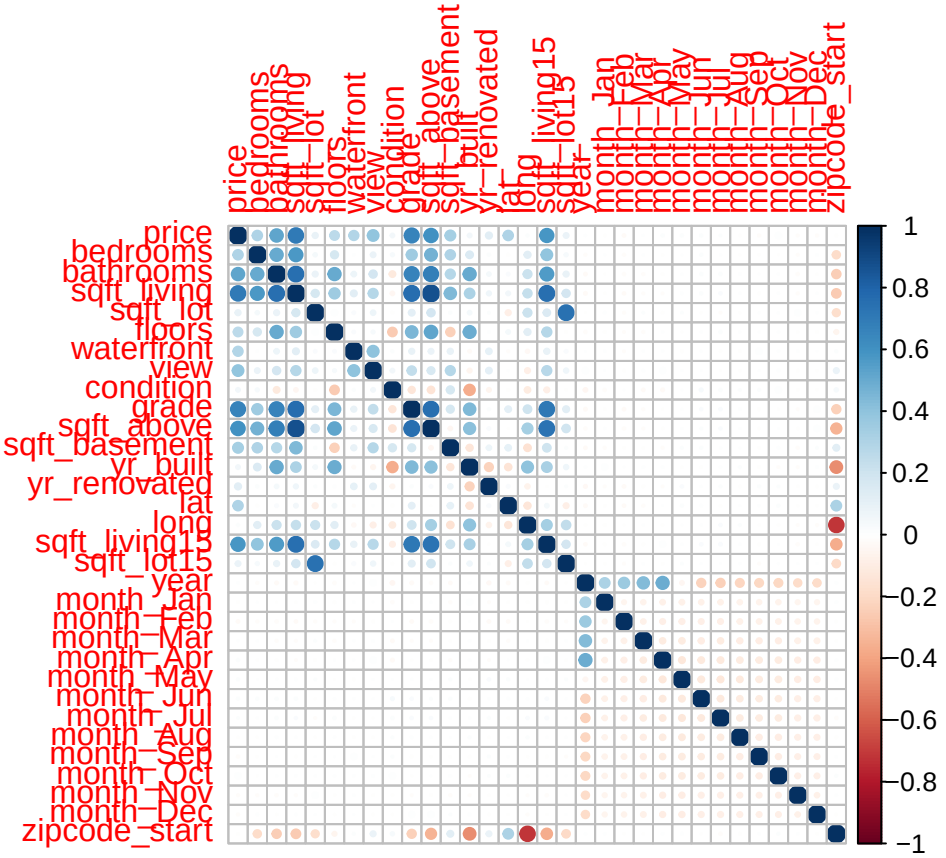
```
## sqft_above     0.607    0.476     0.684       0.876    0.186  0.528      0.084
## sqft_basement  0.335    0.301     0.285       0.441    0.019 -0.239      0.094
## yr_built       0.051    0.156     0.506       0.312    0.048  0.490     -0.026
## yr_renovated   0.129    0.018     0.045       0.060    0.012  0.009      0.107
## lat            0.306   -0.010     0.028       0.052   -0.089  0.048     -0.013
## long           0.017    0.130     0.219       0.231    0.215  0.126     -0.040
## sqft_living15  0.589    0.390     0.568       0.756    0.151  0.284      0.095
## sqft_lot15     0.081    0.036     0.090       0.182    0.744 -0.006      0.029
## year           0.005   -0.014    -0.027      -0.028   -0.001 -0.020      0.001
## month_Jan     -0.007    0.002    -0.001      -0.004    0.009 -0.010      0.006
## month_Feb     -0.025   -0.016    -0.020      -0.021   -0.014 -0.013     -0.012
## month_Mar      0.004    0.004    -0.015      -0.013    0.010 -0.015      0.004
## month_Apr      0.019   -0.005    -0.007      -0.011   -0.008  0.003      0.004
## month_May      0.016    0.001     0.004       0.009    0.010 -0.002     -0.008
## month_Jun      0.017    0.018     0.019       0.018   -0.003  0.005      0.003
## month_Jul      0.010    0.004     0.019       0.020   -0.011  0.019     -0.005
## month_Aug     -0.005   -0.003     0.007       0.003   -0.002  0.005     -0.006
## month_Sep     -0.017   -0.004     0.002      -0.007    0.002  0.003      0.000
## month_Oct      0.000   -0.001     0.004       0.005    0.004  0.006      0.006
## month_Nov     -0.013   -0.013    -0.018      -0.014    0.000 -0.004      0.007
## month_Dec     -0.015    0.007    -0.004       0.005    0.002 -0.005      0.001
## zipcode_start -0.007   -0.186    -0.241      -0.255   -0.175 -0.056      0.015
##                  view condition  grade sqft_above sqft_basement yr_built
## price           0.393     0.050  0.669      0.607         0.335    0.051
## bedrooms        0.080     0.035  0.356      0.476         0.301    0.156
## bathrooms       0.184    -0.116  0.665      0.684         0.285    0.506
## sqft_living     0.283    -0.047  0.761      0.876         0.441    0.312
## sqft_lot        0.073    -0.009  0.119      0.186         0.019    0.048
## floors          0.032    -0.254  0.459      0.528        -0.239    0.490
## waterfront      0.406     0.016  0.091      0.084         0.094   -0.026
## view            1.000     0.050  0.249      0.165         0.280   -0.056
## condition       0.050     1.000 -0.132     -0.148         0.179   -0.363
## grade           0.249    -0.132  1.000      0.755         0.172    0.446
## sqft_above      0.165    -0.148  0.755      1.000        -0.046    0.419
## sqft_basement   0.280     0.179  0.172     -0.046         1.000   -0.134
## yr_built       -0.056    -0.363  0.446      0.419        -0.134    1.000
## yr_renovated    0.113    -0.053  0.017      0.027         0.074   -0.222
## lat             0.003    -0.010  0.114     -0.001         0.109   -0.144
## long           -0.086    -0.108  0.201      0.339        -0.151    0.409
## sqft_living15   0.278    -0.086  0.716      0.733         0.202    0.324
## sqft_lot15      0.066    -0.006  0.122      0.194         0.015    0.066
## year            0.000    -0.047 -0.028     -0.019        -0.023    0.008
## month_Jan       0.001    -0.019 -0.006      0.004        -0.015    0.000
## month_Feb      -0.009     0.002 -0.023     -0.020        -0.006    0.001
## month_Mar       0.008    -0.025 -0.012     -0.012        -0.004    0.007
## month_Apr       0.000    -0.030 -0.002     -0.005        -0.014    0.008
## month_May       0.002     0.001  0.003      0.002         0.014   -0.004
## month_Jun       0.001     0.032  0.021      0.012         0.015   -0.007
## month_Jul      -0.001     0.019  0.022      0.020         0.004    0.005
## month_Aug      -0.003     0.011  0.009      0.003         0.001    0.013
## month_Sep       0.001     0.014 -0.010     -0.005        -0.005   -0.008
## month_Oct       0.009     0.000 -0.002      0.001         0.009   -0.011
## month_Nov      -0.007    -0.007 -0.011     -0.007        -0.016   -0.012
## month_Dec      -0.005    -0.004  0.000      0.000         0.010    0.009
## zipcode_start   0.087     0.039 -0.231     -0.349         0.120   -0.461
##                yr_renovated    lat   long sqft_living15 sqft_lot15   year
## price                 0.129  0.306  0.017         0.589      0.081  0.005
## bedrooms              0.018 -0.010  0.130         0.390      0.036 -0.014
## bathrooms             0.045  0.028  0.219         0.568      0.090 -0.027
## sqft_living           0.060  0.052  0.231         0.756      0.182 -0.028
```

```
## sqft_lot            0.012 -0.089  0.215         0.151      0.744 -0.001
## floors              0.009  0.048  0.126         0.284     -0.006 -0.020
## waterfront          0.107 -0.013 -0.040         0.095      0.029  0.001
## view                0.113  0.003 -0.086         0.278      0.066  0.000
## condition          -0.053 -0.010 -0.108        -0.086     -0.006 -0.047
## grade               0.017  0.114  0.201         0.716      0.122 -0.028
## sqft_above          0.027 -0.001  0.339         0.733      0.194 -0.019
## sqft_basement       0.074  0.109 -0.151         0.202      0.015 -0.023
## yr_built           -0.222 -0.144  0.409         0.324      0.066  0.008
## yr_renovated        1.000  0.029 -0.066        -0.002      0.010 -0.032
## lat                 0.029  1.000 -0.134         0.048     -0.084 -0.026
## long               -0.066 -0.134  1.000         0.332      0.245 -0.009
## sqft_living15      -0.002  0.048  0.332         1.000      0.181 -0.021
## sqft_lot15          0.010 -0.084  0.245         0.181      1.000 -0.003
## year               -0.032 -0.026 -0.009        -0.021     -0.003  1.000
## month_Jan          -0.012 -0.006 -0.009        -0.010     -0.005  0.318
## month_Feb          -0.025 -0.023 -0.003        -0.019     -0.012  0.362
## month_Mar          -0.008 -0.015  0.003        -0.010      0.005  0.436
## month_Apr          -0.011  0.001 -0.007         0.000     -0.005  0.499
## month_May           0.022  0.016  0.001         0.006      0.011 -0.050
## month_Jun           0.003  0.009  0.006         0.022      0.002 -0.230
## month_Jul           0.014 -0.006  0.021         0.026      0.001 -0.232
## month_Aug          -0.006  0.001  0.014         0.003      0.003 -0.216
## month_Sep           0.013  0.004 -0.004        -0.009     -0.011 -0.210
## month_Oct           0.010  0.016 -0.006         0.001      0.003 -0.210
## month_Nov          -0.005 -0.002 -0.011        -0.019      0.002 -0.182
## month_Dec          -0.006 -0.003 -0.014        -0.003      0.002 -0.184
## zipcode_start       0.085  0.319 -0.712        -0.369     -0.197  0.007
##               month_Jan month_Feb month_Mar month_Apr month_May month_Jun
## price            -0.007    -0.025     0.004     0.019     0.016     0.017
## bedrooms          0.002    -0.016     0.004    -0.005     0.001     0.018
## bathrooms        -0.001    -0.020    -0.015    -0.007     0.004     0.019
## sqft_living      -0.004    -0.021    -0.013    -0.011     0.009     0.018
## sqft_lot          0.009    -0.014     0.010    -0.008     0.010    -0.003
## floors           -0.010    -0.013    -0.015     0.003    -0.002     0.005
## waterfront        0.006    -0.012     0.004     0.004    -0.008     0.003
## view              0.001    -0.009     0.008     0.000     0.002     0.001
## condition        -0.019     0.002    -0.025    -0.030     0.001     0.032
## grade            -0.006    -0.023    -0.012    -0.002     0.003     0.021
## sqft_above        0.004    -0.020    -0.012    -0.005     0.002     0.012
## sqft_basement    -0.015    -0.006    -0.004    -0.014     0.014     0.015
## yr_built          0.000     0.001     0.007     0.008    -0.004    -0.007
## yr_renovated     -0.012    -0.025    -0.008    -0.011     0.022     0.003
## lat              -0.006    -0.023    -0.015     0.001     0.016     0.009
## long             -0.009    -0.003     0.003    -0.007     0.001     0.006
## sqft_living15    -0.010    -0.019    -0.010     0.000     0.006     0.022
## sqft_lot15       -0.005    -0.012     0.005    -0.005     0.011     0.002
## year              0.318     0.362     0.436     0.499    -0.050    -0.230
## month_Jan         1.000    -0.054    -0.066    -0.075    -0.078    -0.073
## month_Feb        -0.054     1.000    -0.075    -0.085    -0.089    -0.083
## month_Mar        -0.066    -0.075     1.000    -0.103    -0.107    -0.100
## month_Apr        -0.075    -0.085    -0.103     1.000    -0.123    -0.115
## month_May        -0.078    -0.089    -0.107    -0.123     1.000    -0.119
## month_Jun        -0.073    -0.083    -0.100    -0.115    -0.119     1.000
## month_Jul        -0.074    -0.084    -0.101    -0.116    -0.121    -0.113
## month_Aug        -0.069    -0.078    -0.094    -0.108    -0.112    -0.105
## month_Sep        -0.067    -0.076    -0.091    -0.105    -0.109    -0.102
## month_Oct        -0.067    -0.076    -0.091    -0.105    -0.109    -0.102
## month_Nov        -0.058    -0.066    -0.079    -0.091    -0.095    -0.088
## month_Dec        -0.059    -0.067    -0.080    -0.092    -0.096    -0.089
```

```
## zipcode_start     0.008    -0.005    -0.005     0.008     0.009    -0.003
##               month_Jul month_Aug month_Sep month_Oct month_Nov month_Dec
## price             0.010    -0.005    -0.017     0.000    -0.013    -0.015
## bedrooms          0.004    -0.003    -0.004    -0.001    -0.013     0.007
## bathrooms         0.019     0.007     0.002     0.004    -0.018    -0.004
## sqft_living       0.020     0.003    -0.007     0.005    -0.014     0.005
## sqft_lot         -0.011    -0.002     0.002     0.004     0.000     0.002
## floors            0.019     0.005     0.003     0.006    -0.004    -0.005
## waterfront       -0.005    -0.006     0.000     0.006     0.007     0.001
## view             -0.001    -0.003     0.001     0.009    -0.007    -0.005
## condition         0.019     0.011     0.014     0.000    -0.007    -0.004
## grade             0.022     0.009    -0.010    -0.002    -0.011     0.000
## sqft_above        0.020     0.003    -0.005     0.001    -0.007     0.000
## sqft_basement     0.004     0.001    -0.005     0.009    -0.016     0.010
## yr_built          0.005     0.013    -0.008    -0.011    -0.012     0.009
## yr_renovated      0.014    -0.006     0.013     0.010    -0.005    -0.006
## lat              -0.006     0.001     0.004     0.016    -0.002    -0.003
## long              0.021     0.014    -0.004    -0.006    -0.011    -0.014
## sqft_living15     0.026     0.003    -0.009     0.001    -0.019    -0.003
## sqft_lot15        0.001     0.003    -0.011     0.003     0.002     0.002
## year             -0.232    -0.216    -0.210    -0.210    -0.182    -0.184
## month_Jan        -0.074    -0.069    -0.067    -0.067    -0.058    -0.059
## month_Feb        -0.084    -0.078    -0.076    -0.076    -0.066    -0.067
## month_Mar        -0.101    -0.094    -0.091    -0.091    -0.079    -0.080
## month_Apr        -0.116    -0.108    -0.105    -0.105    -0.091    -0.092
## month_May        -0.121    -0.112    -0.109    -0.109    -0.095    -0.096
## month_Jun        -0.113    -0.105    -0.102    -0.102    -0.088    -0.089
## month_Jul         1.000    -0.106    -0.103    -0.103    -0.089    -0.090
## month_Aug        -0.106     1.000    -0.096    -0.096    -0.083    -0.084
## month_Sep        -0.103    -0.096     1.000    -0.093    -0.081    -0.082
## month_Oct        -0.103    -0.096    -0.093     1.000    -0.081    -0.082
## month_Nov        -0.089    -0.083    -0.081    -0.081     1.000    -0.071
## month_Dec        -0.090    -0.084    -0.082    -0.082    -0.071     1.000
## zipcode_start    -0.020    -0.009     0.005     0.014     0.006    -0.006
##               zipcode_start
## price                -0.007
## bedrooms             -0.186
## bathrooms            -0.241
## sqft_living          -0.255
## sqft_lot             -0.175
## floors               -0.056
## waterfront            0.015
## view                  0.087
## condition             0.039
## grade                -0.231
## sqft_above           -0.349
## sqft_basement         0.120
## yr_built             -0.461
## yr_renovated          0.085
## lat                   0.319
## long                 -0.712
## sqft_living15        -0.369
## sqft_lot15           -0.197
## year                  0.007
## month_Jan             0.008
## month_Feb            -0.005
## month_Mar            -0.005
## month_Apr             0.008
## month_May             0.009
## month_Jun            -0.003
```

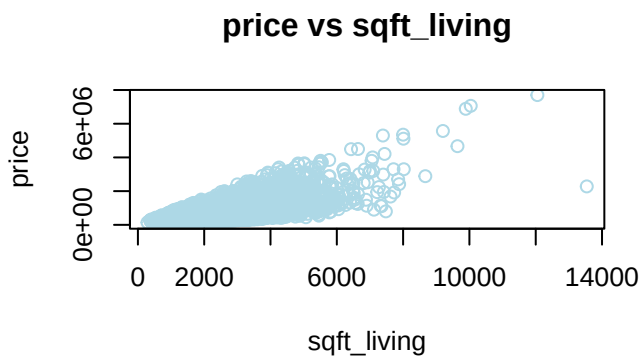
```
## month_Jul            -0.020
## month_Aug            -0.009
## month_Sep             0.005
## month_Oct             0.014
## month_Nov             0.006
## month_Dec            -0.006
## zipcode_start         1.000
```

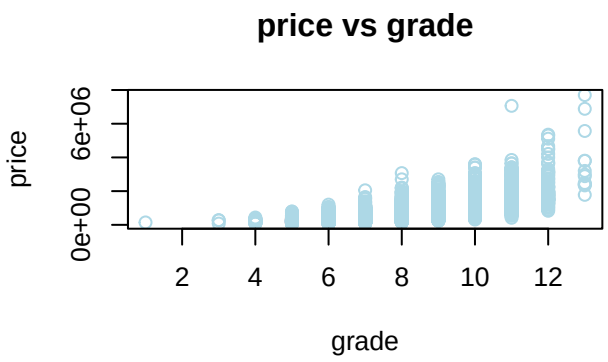
```
corrplot(cor_matrix, method = "circle")
```

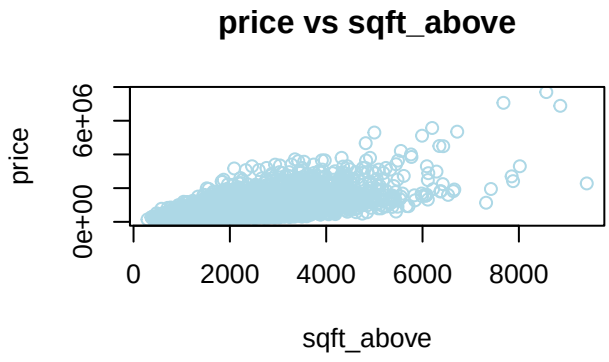


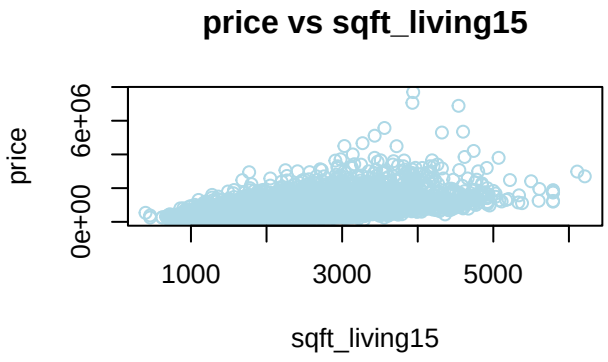
To further examine the top variables correlating with "price", we plot several scatter plots below. This initial analysis shows that price is indeed positively correlated with "sqft_living", "grade", "sqft_above" and "sqft_living15". It also appears that the prices of homes show a large range from 75,000 to 7,700,000, with most data points concentrated on the lower half of this scale. We will perform further testing during model development to understand if a transformation of the price variable would be beneficial.

```
par(mfrow=c(2,2))

top.corr<-c("sqft_living", "grade", "sqft_above", "sqft_living15")
for (i in top.corr){
  plot(x=df[,i],y=df[,"price"], main = paste("price vs",i), col= "lightblue",
       xlab=i,ylab="price")
}
```



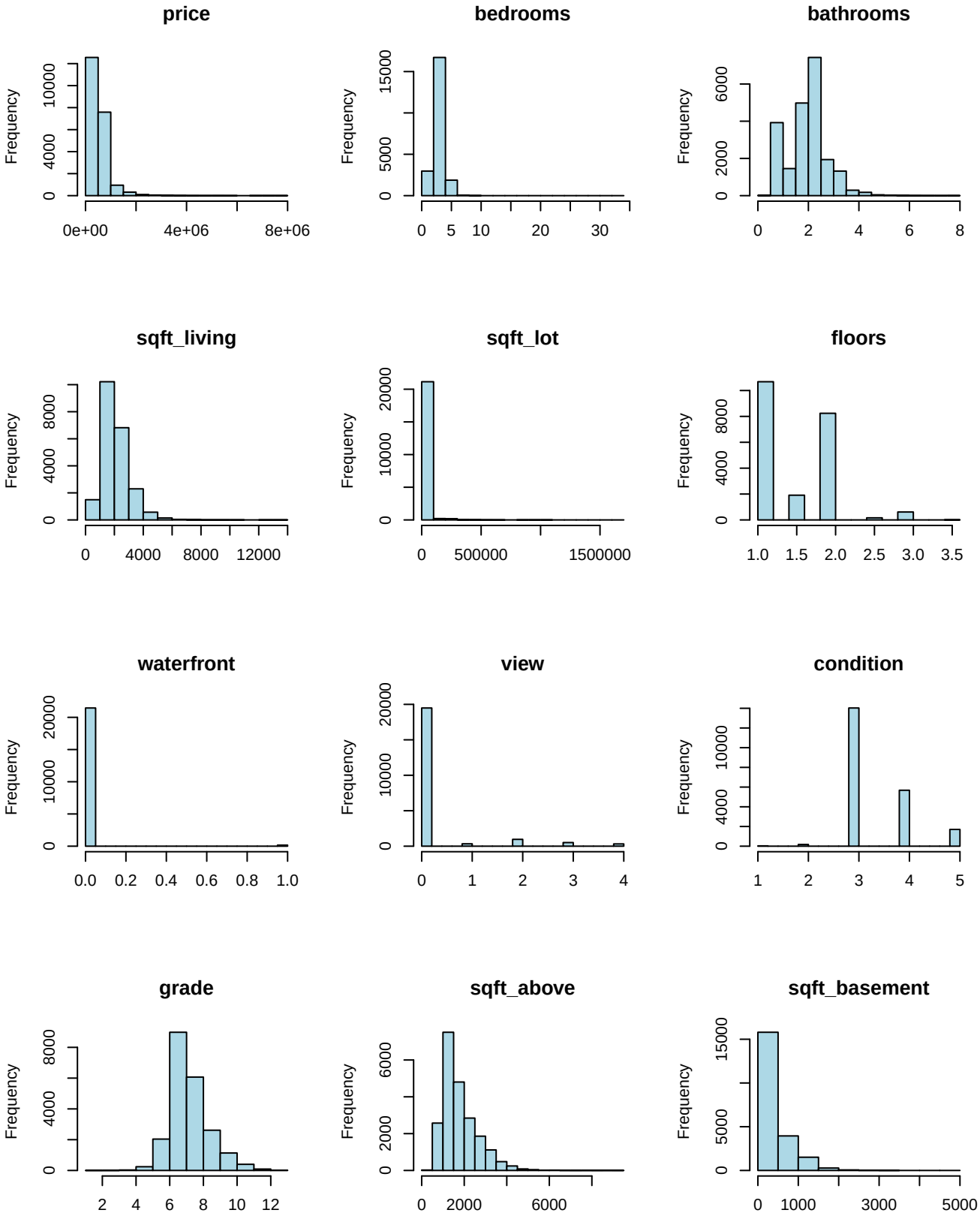


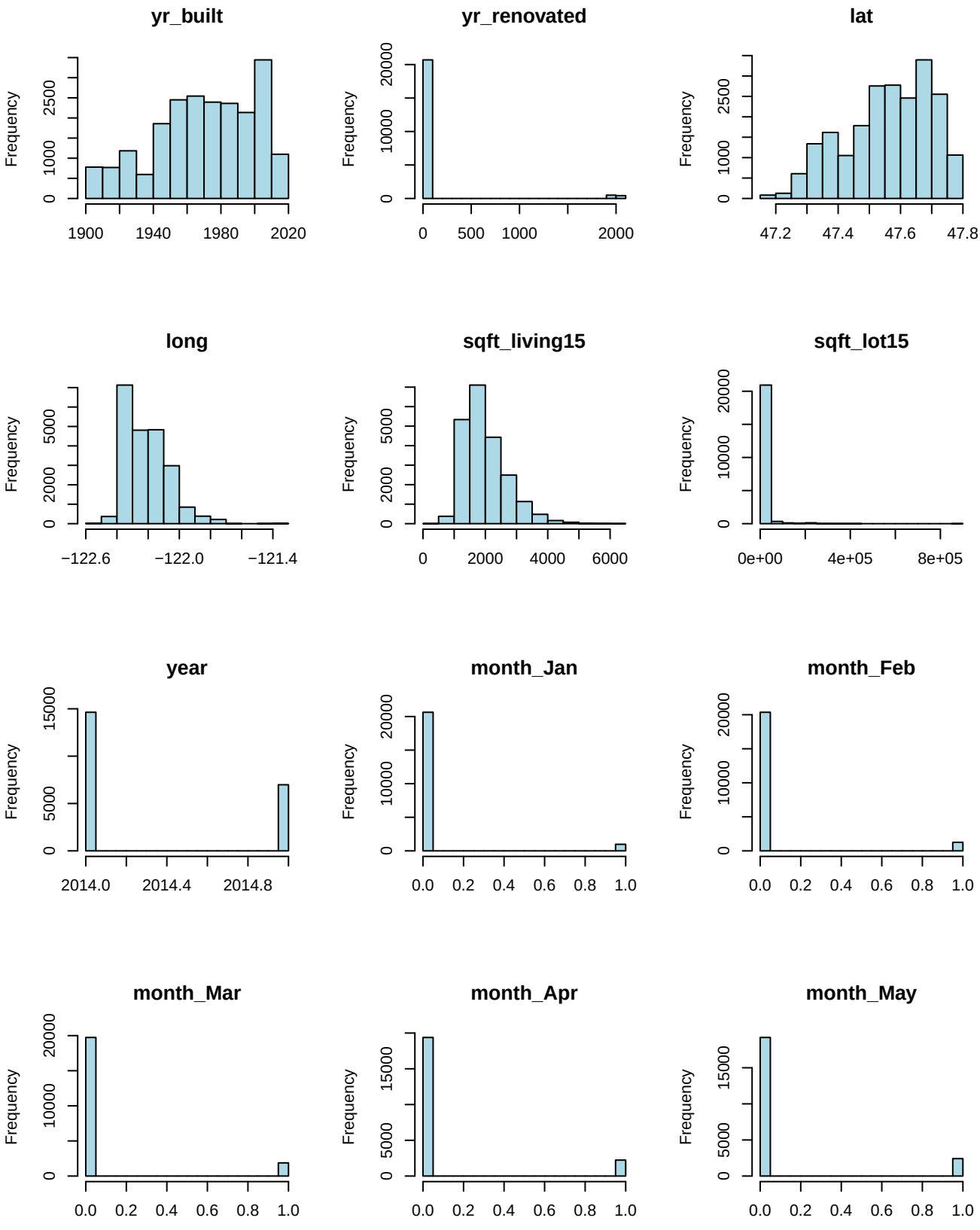


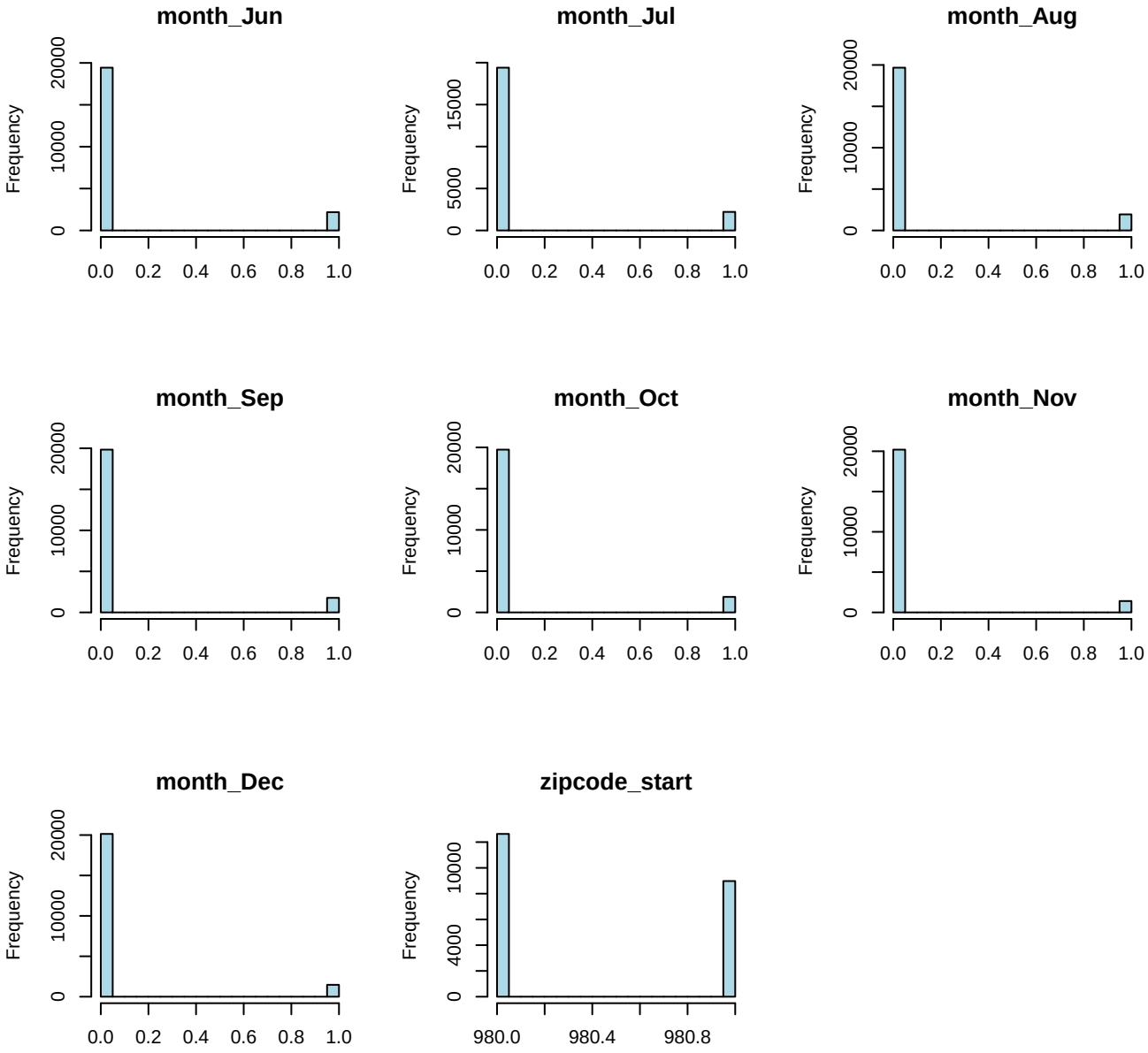


Using bar charts and boxplots, we can observe the types and distribution of all variables. The results are summarized in the table below.

```
# Bar charts
par(mfrow=c(2,3))

for (i in 1:ncol(df)){
  hist(df[,i], main = names(df[i]), xlab = NULL, col = "lightblue")
}
```

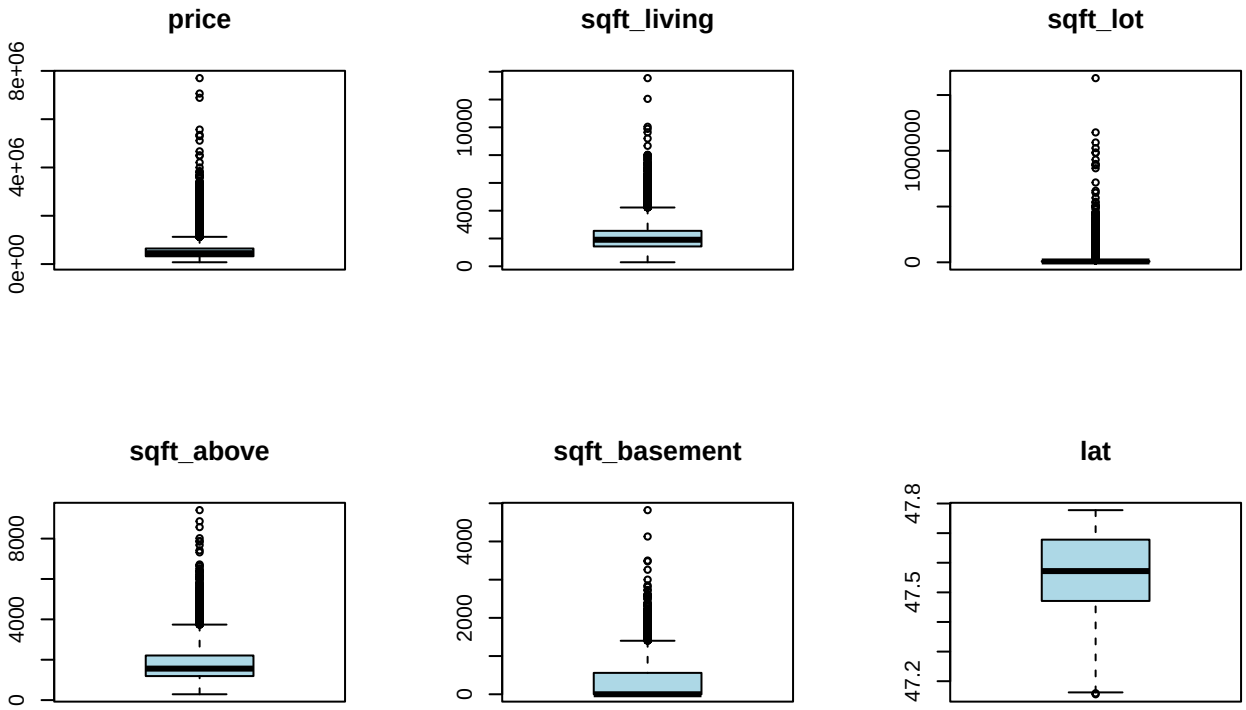

price
Frequency
0
4000
10000
0e+00
4e+06
8e+06
bedrooms
Frequency
0
5000
15000
0
5
10
20
30
bathrooms
Frequency
0
2000
6000
0
2
4
6
8
sqft_living
Frequency
0
4000
8000
0
4000
8000
12000
sqft_lot
Frequency
0
10000
20000
0
500000
1500000
floors
Frequency
0
4000
8000
1.0
1.5
2.0
2.5
3.0
3.5
waterfront
Frequency
0
10000
20000
0.0
0.2
0.4
0.6
0.8
1.0
view
Frequency
0
10000
20000
0
1
2
3
4
condition
Frequency
0
4000
10000
1
2
3
4
5
grade
Frequency
0
4000
8000
2
4
6
8
10
12
sqft_above
Frequency
0
2000
6000
0
2000
6000
sqft_basement
Frequency
0
5000
15000
0
1000
3000
5000

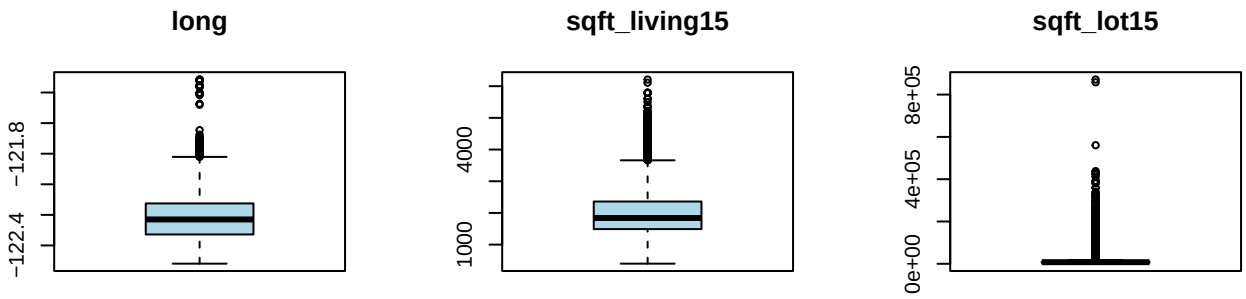

yr_built
Frequency
0
1000
2500
1900
1940
1980
2020
yr_renovated
Frequency
0
10000
20000
0
500
1000
2000
lat
Frequency
0
1000
2500
47.2
47.4
47.6
47.8
long
Frequency
0
2000
5000
−122.6
−122.0
−121.4
sqft_living15
Frequency
0
2000
5000
0
2000
4000
6000
sqft_lot15
Frequency
0
10000
20000
0e+00
4e+05
8e+05
year
Frequency
0
5000
15000
2014.0
2014.4
2014.8
month_Jan
Frequency
0
10000
20000
0.0
0.2
0.4
0.6
0.8
1.0
month_Feb
Frequency
0
10000
20000
0.0
0.2
0.4
0.6
0.8
1.0
month_Mar
Frequency
0
10000
20000
0.0
0.2
0.4
0.6
0.8
1.0
month_Apr
Frequency
0
5000
15000
0.0
0.2
0.4
0.6
0.8
1.0
month_May
Frequency
0
5000
15000
0.0
0.2
0.4
0.6
0.8
1.0




```
# Boxplots on continuous variables only
par(mfrow=c(2,3))

categorical.var<-c("bedrooms","bathrooms","floors","waterfront","view","condition","grade","yr_built","yr_reno
```

```r
df.boxplot<-dplyr::select(df,-all_of(categorical.var))

for (i in 1:ncol(df.boxplot)){
  boxplot(df.boxplot[,i], main = names(df.boxplot[i]), xlab = NULL, col = "lightblue")
}
```





Summary table of data description

Variable	Description	Type	Correlation with "price"
price	**Price of each home sold (Response variable)**	continuous	1
bedrooms	*Number of bedrooms*	categorical	0.306
bathrooms	*Number of bathrooms, where ".5" accounts for a bathroom with a toilet but no shower*	categorical	0.522
sqft_living	*Square footage of the apartment interior living space*	continuous	0.707
sqft_lot	*Square footage of the land space*	continuous	0.092
floors	*Number of floors*	categorical	0.363
waterfront	*A dummy variable for whether the apartment was overlooking the waterfront or not*	categorical	0.291
view	*An index from 0 to 4 of how good the view of the property was*	categorical	0.393
condition	*An index from 1 to 5 on the condition of the apartment,*	categorical	0.050

Variable	Description	Type	Correlation with "price"
grade	*An index from 1 to 13, where 1-3 falls short of building construction and design, 7 has an average level of construction and design, and 11-13 has a high-quality level of construction and design.*	categorical	0.669
sqft_above	*The square footage of the interior housing space that is above ground level*	continuous	0.607
sqft_basement	*The square footage of the interior housing space that is below ground level*	continuous	0.335
yr_built	*The year the house was initially built*	categorical	0.051
yr_renovated	*The year of the house's last renovation*	categorical	0.129
lat	*Latitude*	continuous	0.306
long	*Longitude*	continuous	0.017
sqft_living15	*The square footage of interior housing living space for the nearest 15 neighbors*	continuous	0.589
sqft_lot15	*The square footage of the land lots of the nearest 15 neighbors*	continuous	0.081
year	*Year of the home sale*	categorical	0.005
month_Jan	*A dummy variable for whether it is January or not*	categorical	-0.007
month_Feb	*A dummy variable for whether it is February or not*	categorical	-0.025
month_Mar	*A dummy variable for whether it is March or not*	categorical	0.004
month_Apr	*A dummy variable for whether it is April or not*	categorical	0.019
month_May	*A dummy variable for whether it is May or not*	categorical	0.016
month_Jun	*A dummy variable for whether it is June or not*	categorical	0.017
month_Jul	*A dummy variable for whether it is July or not*	categorical	0.010
month_Aug	*A dummy variable for whether it is August or not*	categorical	-0.005
month_Sep	*A dummy variable for whether it is September or not*	categorical	-0.017
month_Oct	*A dummy variable for whether it is October or not*	categorical	-0.0001
month_Nov	*A dummy variable for whether it is November or not*	categorical	-0.013
month_Dec	*A dummy variable for whether it is December or not*	categorical	-0.015
zipcode_start	*A dummy variable that indicates whether zipcode starts with 980 or 981*	categorical	-0.007

The barplots and boxplots further indicate that distribution of price is skewed towards the right, with a median of 450,000 and a small subset of houses that are over 2,000,000. Several other factors also show a similar right-skewed distribution, for example “sqft_living” and “sqft_lot”. We also notice some data points that may be outliers, for example a house that has 33 bedrooms or some houses that are recorded as having 0 bedroom 0 bathrooms. Further testing will be performed below to evaluate whether variable transformation is needed for model building.

III. Model Development Process (15 points)

Build a regression model to predict price. And of course, create the train data set which contains 70% of the data and use set.seed (1023). The remaining 30% will be your test data set. Investigate the data and combine the level of categorical variables if needed and drop variables. For example, you can drop id, Latitude, Longitude, etc.

```
set.seed(1023)

response <- "price"

#Renaming to conform to unified convention
kc.house.df <- df %>% rename("year_built" = "yr_built")
```

```
#Feature Ideas
#Quality Adjusted Features
transform_sqft_adj_grade <- function(kc.house.df){

  sqft_adj_grade <- kc.house.df[, "sqft_living"] / kc.house.df[, "grade"]

  return (sqft_adj_grade)
}

transform_sqft_adj_condition <- function(kc.house.df){

  sqft_adj_condition <- kc.house.df[, "sqft_living"] / kc.house.df[, "condition"]

  return (sqft_adj_condition)
}

transform_sqft_adj_waterfront <- function(kc.house.df){

  sqft_adj_waterfront <- kc.house.df[, "sqft_living"] * kc.house.df[, "waterfront"]

  return (sqft_adj_waterfront)
}

transform_poly_sqft_living <- function(kc.house.df){
  #Center variables for polynomial terms
  sqft_living <- (kc.house.df$sqft_living - mean(kc.house.df$sqft_living))
  sqft_living_squared <- sqft_living^2

  return (list(center = sqft_living, squared = sqft_living_squared))
}

transform_poly_floor <- function(kc.house.df){
  floors <- (kc.house.df$floors - mean(kc.house.df$floors))
  floors_squared <- floors^2

  return(list(center = floors, squared = floors_squared))
}
```

Centering the variables do not change the interpretation of the coefficients. However they do change the interpretation of the intercept. Instead of the intercept being read as the value of price when all variables are zero. It is not read as price when all variables are zero, `floors` is equal to its average and `sqft_living` is equal to its average.

```
# Drop December dummy variable due to collinearity with other months
kc.house.df2<-dplyr::select(kc.house.df,-(month_Dec))

#Apply transformations
```

```r
kc.house.df$sqft_adj_grade <- transform_sqft_adj_grade(kc.house.df)
kc.house.df$sqft_adj_condition <- transform_sqft_adj_condition(kc.house.df)
kc.house.df$sqft_adj_waterfront <- transform_sqft_adj_waterfront(kc.house.df)

res <- transform_poly_sqft_living(kc.house.df)
kc.house.df$sqft_living <- res$center
kc.house.df$sqft_living_squared <- res$squared

res <- transform_poly_floor(kc.house.df)
kc.house.df$floors <- res$center
kc.house.df$floors_squared <- res$squared

#Remove collinear variables
# sqft_basement + sqft_above = sqft_living
kc.house.df$sqft_basement <- NULL
```

```r
set.seed(1023)

#use 70% of dataset as training set and 30% as test set
train_prop <- 0.7

index <- sample(1:nrow(HouseSales), size = round(train_prop * nrow(kc.house.df)))
kc.house.train.X <- kc.house.df[index, -which(names(kc.house.df) %in% c(response))] # modified slightly
kc.house.train.y <- kc.house.df [index, response]

kc.house.test.X <- kc.house.df [-index, -which(names(kc.house.df) %in% c(response))]
kc.house.test.y <- kc.house.df [-index, response]
```

```r
#baseline model
baseline.model <- lm(price ~ ., data = cbind(price = kc.house.train.y, kc.house.train.X))
summary(baseline.model)
```

```
##
## Call:
## lm(formula = price ~ ., data = cbind(price = kc.house.train.y,
##     kc.house.train.X))
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1749255   -88719    -9542    69497  2414076
##
## Coefficients: (1 not defined because of singularities)
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)         -1.663e+08  2.057e+07  -8.084 6.76e-16 ***
## bedrooms            -8.027e+03  2.079e+03  -3.861 0.000113 ***
## bathrooms            4.573e+04  3.500e+03  13.065  < 2e-16 ***
## sqft_living          4.844e+02  2.872e+01  16.866  < 2e-16 ***
## sqft_lot             1.267e-01  5.473e-02   2.315 0.020645 *
## floors               2.392e+04  4.611e+03   5.188 2.16e-07 ***
## waterfront          -2.303e+05  4.303e+04  -5.352 8.85e-08 ***
## view                 4.629e+04  2.346e+03  19.732  < 2e-16 ***
## condition           -1.265e+04  5.298e+03  -2.388 0.016959 *
## grade                1.498e+04  7.257e+03   2.064 0.039009 *
## sqft_above           1.425e+00  4.975e+00   0.287 0.774454
## year_built          -2.135e+03  8.271e+01 -25.818  < 2e-16 ***
## yr_renovated         3.923e+01  3.952e+00   9.927  < 2e-16 ***
## lat                  5.680e+05  1.201e+04  47.296  < 2e-16 ***
## long                -1.021e+05  1.590e+04  -6.420 1.40e-10 ***
```

```
## sqft_living15        5.585e+01  3.868e+00  14.439  < 2e-16 ***
## sqft_lot15          -2.955e-01  7.903e-02  -3.739 0.000186 ***
## year                 7.015e+04  1.002e+04   6.998 2.71e-12 ***
## month_Jan           -5.837e+04  1.342e+04  -4.348 1.38e-05 ***
## month_Feb           -5.763e+04  1.306e+04  -4.411 1.03e-05 ***
## month_Mar           -2.685e+04  1.254e+04  -2.140 0.032360 *
## month_Apr           -2.669e+04  1.240e+04  -2.152 0.031421 *
## month_May            1.130e+02  7.684e+03   0.015 0.988267
## month_Jun            2.738e+03  7.314e+03   0.374 0.708130
## month_Jul            3.667e+03  7.299e+03   0.502 0.615373
## month_Aug            3.723e+03  7.507e+03   0.496 0.619915
## month_Sep            2.051e+03  7.681e+03   0.267 0.789444
## month_Oct            1.903e+03  7.584e+03   0.251 0.801870
## month_Nov            7.633e+01  8.131e+03   0.009 0.992510
## month_Dec                   NA         NA      NA       NA
## zipcode_start       -9.362e+03  5.051e+03  -1.853 0.063847 .
## sqft_adj_grade      -2.307e+03  1.912e+02 -12.070  < 2e-16 ***
## sqft_adj_condition  -3.486e+02  3.057e+01 -11.402  < 2e-16 ***
## sqft_adj_waterfront  2.403e+02  1.223e+01  19.652  < 2e-16 ***
## sqft_living_squared  2.278e-02  1.762e-03  12.928  < 2e-16 ***
## floors_squared       1.282e+04  5.231e+03   2.450 0.014279 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 182200 on 15094 degrees of freedom
## Multiple R-squared:  0.7469, Adjusted R-squared:  0.7463
## F-statistic:  1310 on 34 and 15094 DF,  p-value: < 2.2e-16
```

IV. Model Performance Testing (15 points)

Use the test data set to assess the model performances. Here, build the best multiple linear models by using the stepwise both ways selection method. Compare the performance of the best two linear models. Make sure that model assumption(s) are checked for the final linear model. Apply remedy measures (transformation, etc.) that helps satisfy the assumptions. In particular you must deeply investigate unequal variances and multicollinearity. If necessary, apply remedial methods (WLS, Ridge, Elastic Net, Lasso, etc.).

#TODO 1. Stepwise feature selection 2. Add plots (e.g. scale location, residual vs fitted) 3. Normality plots

TODO: The following code needs to be updated once we have the updated models from stepwise feature selection.

```
#Function to generate model performance
CalcTestMetrics <- function(pred, act, n, p) {
  SST <- var(act)*(length(act)-1)
  SSE <- sum((act-pred)^2)
  SSR <- sum(pred - mean(act))^2
  rsquared <- 1- SSE/SST

  adj.rsquared <- 1 - (((1 - rsquared)*(n-1)) / (n-p-1))
  mse <- sum((act - pred)^2) / (n-p)
  mae <- (sum(abs(act-pred))) / n

  c(adj.rsquared = adj.rsquared,
    rsquared = rsquared,
    mse = mse,
    mae = mae)
}

# Coefficients
coeff.lm.df <- data.frame(Baseline = baseline.model$coefficients)
coeff.lm.df$Coefficients <- rownames(coeff.lm.df)
rownames(coeff.lm.df) <- NULL
coeff.lm.df <- dplyr::select(coeff.lm.df, Coefficients, Baseline)
coeff.q1.df <-
  coeff.lm.df %>%
  dplyr::mutate(Baseline = ifelse(Baseline == 0, "--", scales::comma(Baseline, accuracy = 1e-4)))
knitr::kable(coeff.q1.df, caption = "Model Coefficients")
```

Table 4: Model Coefficients

Coefficients	Baseline
(Intercept)	-166,310,707.6499
bedrooms	-8,027.4927
bathrooms	45,731.9969
sqft_living	484.3936
sqft_lot	0.1267
floors	23,921.4460
waterfront	-230,270.4560
view	46,291.8461
condition	-12,652.0079
grade	14,980.8525
sqft_above	1.4255
year_built	-2,135.2811
yr_renovated	39.2291
lat	567,973.0859
long	-102,082.8267
sqft_living15	55.8477
sqft_lot15	-0.2955
year	70,145.6686

Coefficients	Baseline
month_Jan	-58,367.4012
month_Feb	-57,628.3533
month_Mar	-26,845.5248
month_Apr	-26,687.3253
month_May	112.9928
month_Jun	2,738.1788
month_Jul	3,667.0506
month_Aug	3,723.3331
month_Sep	2,051.0150
month_Oct	1,903.1699
month_Nov	76.3270
month_Dec	NA
zipcode_start	-9,361.8650
sqft_adj_grade	-2,307.2998
sqft_adj_condition	-348.5952
sqft_adj_waterfront	240.3149
sqft_living_squared	0.0228
floors_squared	12,819.2042

```
# Using the function to calculate performance of the baseline model on the test set
pred <- predict(baseline.model, kc.house.test.X)
```

```
## Warning in predict.lm(baseline.model, kc.house.test.X): prediction from a
## rank-deficient fit may be misleading
```

```
act <- kc.house.test.y
n <- dim(model.matrix(baseline.model)[, -1])[1]
p <- dim(model.matrix(baseline.model)[, -1])[2]

performance_baseline = CalcTestMetrics(pred, act, n, p)
performance_baseline
```

```
## adj.rsquared     rsquared          mse          mae
## 7.373025e-01 7.379102e-01 1.621635e+10 5.065398e+04
```

```
library(olsrr)
```

```
##
## Attaching package: 'olsrr'

## The following object is masked from 'package:datasets':
##
##     rivers
```

```
stepwise_model = ols_step_both_p(baseline.model, pent=0.35, prem=0.05)
stepwise_final = stepwise_model$model
summary(stepwise_final)
```

```
##
## Call:
## lm(formula = paste(response, "~", paste(preds, collapse = " + ")),
##     data = l)
##
## Residuals:
```

```
##      Min       1Q   Median       3Q      Max
## -1750887   -88574    -9843    68477  2418297
##
## Coefficients:
##                         Estimate Std. Error t value Pr(>|t|)
## (Intercept)         -1.224e+08  7.531e+06 -16.248  < 2e-16 ***
## bathrooms            4.543e+04  3.460e+03  13.128  < 2e-16 ***
## sqft_living          4.856e+02  2.818e+01  17.230  < 2e-16 ***
## view                 4.565e+04  2.302e+03  19.826  < 2e-16 ***
## grade                1.482e+04  7.227e+03   2.051 0.040270 *
## lat                  5.602e+05  1.137e+04  49.265  < 2e-16 ***
## sqft_living15        5.746e+01  3.782e+00  15.194  < 2e-16 ***
## sqft_adj_grade      -2.313e+03  1.891e+02 -12.234  < 2e-16 ***
## sqft_adj_condition  -3.472e+02  3.034e+01 -11.442  < 2e-16 ***
## sqft_adj_waterfront  2.396e+02  1.221e+01  19.620  < 2e-16 ***
## sqft_living_squared  2.274e-02  1.758e-03  12.935  < 2e-16 ***
## year_built          -2.093e+03  7.939e+01 -26.358  < 2e-16 ***
## year                 4.500e+04  3.643e+03  12.351  < 2e-16 ***
## yr_renovated         3.956e+01  3.943e+00  10.034  < 2e-16 ***
## floors               2.332e+04  3.925e+03   5.942 2.88e-09 ***
## long                -8.406e+04  1.283e+04  -6.553 5.81e-11 ***
## waterfront          -2.263e+05  4.292e+04  -5.273 1.36e-07 ***
## month_Feb           -3.437e+04  6.950e+03  -4.945 7.71e-07 ***
## month_Jan           -3.512e+04  7.601e+03  -4.620 3.87e-06 ***
## bedrooms            -7.901e+03  2.074e+03  -3.809 0.000140 ***
## sqft_lot15          -2.903e-01  7.899e-02  -3.675 0.000239 ***
## floors_squared       1.226e+04  5.127e+03   2.392 0.016771 *
## sqft_lot             1.268e-01  5.469e-02   2.319 0.020399 *
## condition           -1.169e+04  5.268e+03  -2.219 0.026527 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 182200 on 15105 degrees of freedom
## Multiple R-squared:  0.7467, Adjusted R-squared:  0.7463
## F-statistic:  1936 on 23 and 15105 DF,  p-value: < 2.2e-16
```

Stepwise didn't give us anything more in terms of prediction, but reduced the varibles as intended. Following, I'll identify which variables were selected (and create a new dataframe to which we will use in our next interactions) and identify the ones dropped.

```
#Generating new dataframes with only the selected variables
selected_variables = names(coef(stepwise_final))
selected_variables = setdiff(selected_variables, "(Intercept)")
selected_train_df = kc.house.train.X[, selected_variables]
selected_test_df = kc.house.test.X[, selected_variables]

#Finding out which ones were dropped
original_predictors = names(kc.house.train.X)
dropped_variables = setdiff(original_predictors, selected_variables)

dropped_variables
```

```
##  [1] "sqft_above"    "month_Mar"     "month_Apr"     "month_May"
##  [5] "month_Jun"     "month_Jul"     "month_Aug"     "month_Sep"
##  [9] "month_Oct"     "month_Nov"     "month_Dec"     "zipcode_start"
```

Seems like we dropped 12 variables from our original 31. Of those 12, 10 were dummy month variables we generated, and sqft_lot and sqft_above.

```r
#Fitting a new linear model with selected variables
selected_linear_model = lm(price ~ . , data = cbind(price = kc.house.train.y, selected_train_df))

# Coefficients
coeff.sw.df <- data.frame(Stepwise = selected_linear_model$coefficients)
coeff.sw.df$Coefficients <- rownames(coeff.sw.df)
coeff.q1.df <-
  coeff.q1.df %>%
  dplyr::left_join(coeff.sw.df, by = "Coefficients") %>%
  dplyr::mutate(Stepwise = ifelse(dplyr::coalesce(Stepwise, 0) == 0, "--",
                                  scales::comma(Stepwise, accuracy = 1e-4)))
knitr::kable(coeff.q1.df, caption = "Model Coefficients")
```

Table 5: Model Coefficients

Coefficients	Baseline	Stepwise
(Intercept)	-166,310,707.6499	-122,358,944.4651
bedrooms	-8,027.4927	-7,901.2247
bathrooms	45,731.9969	45,428.4038
sqft_living	484.3936	485.5559
sqft_lot	0.1267	0.1268
floors	23,921.4460	23,324.8806
waterfront	-230,270.4560	-226,317.0611
view	46,291.8461	45,648.1857
condition	-12,652.0079	-11,688.0616
grade	14,980.8525	14,824.3893
sqft_above	1.4255	–
year_built	-2,135.2811	-2,092.6731
yr_renovated	39.2291	39.5648
lat	567,973.0859	560,171.4178
long	-102,082.8267	-84,063.5717
sqft_living15	55.8477	57.4640
sqft_lot15	-0.2955	-0.2903
year	70,145.6686	45,001.3459
month_Jan	-58,367.4012	-35,117.1640
month_Feb	-57,628.3533	-34,367.8073
month_Mar	-26,845.5248	–
month_Apr	-26,687.3253	–
month_May	112.9928	–
month_Jun	2,738.1788	–
month_Jul	3,667.0506	–
month_Aug	3,723.3331	–
month_Sep	2,051.0150	–
month_Oct	1,903.1699	–
month_Nov	76.3270	–
month_Dec	NA	–
zipcode_start	-9,361.8650	–
sqft_adj_grade	-2,307.2998	-2,313.2728
sqft_adj_condition	-348.5952	-347.1665
sqft_adj_waterfront	240.3149	239.5841
sqft_living_squared	0.0228	0.0227
floors_squared	12,819.2042	12,263.9547

```r
pred_selected <- predict(selected_linear_model, selected_test_df)
act_selected <- kc.house.test.y
n_selected <- dim(model.matrix(selected_linear_model)[, -1])[1]
p_selected <- dim(model.matrix(selected_linear_model)[, -1])[2]
```

```
performance_selected = CalcTestMetrics(pred_selected, act_selected, n_selected, p_selected)
print(performance_selected)
```

```
## adj.rsquared     rsquared          mse          mae
## 7.374118e-01 7.378110e-01 1.620961e+10 5.057684e+04
```

```
#Checking performance on the test set
library(car)
```

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

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

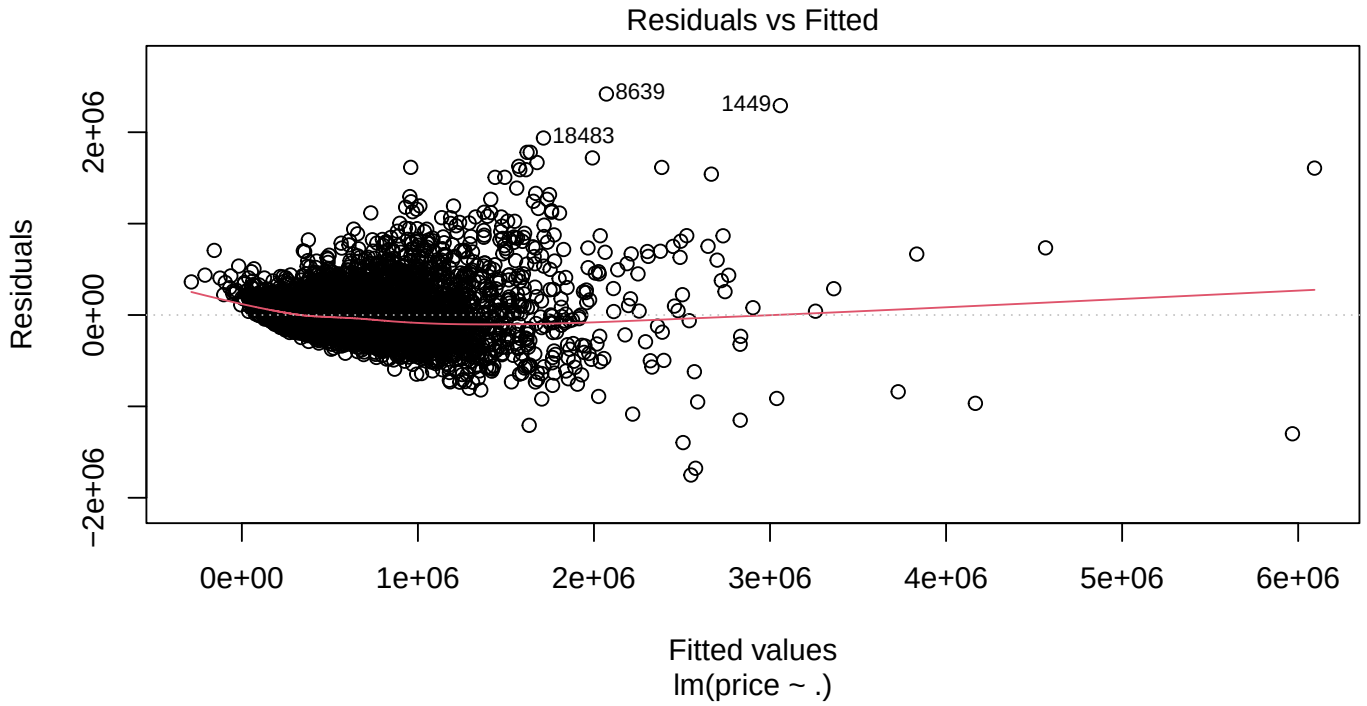
```
## The following object is masked from 'package:dplyr':
##
##     recode
```

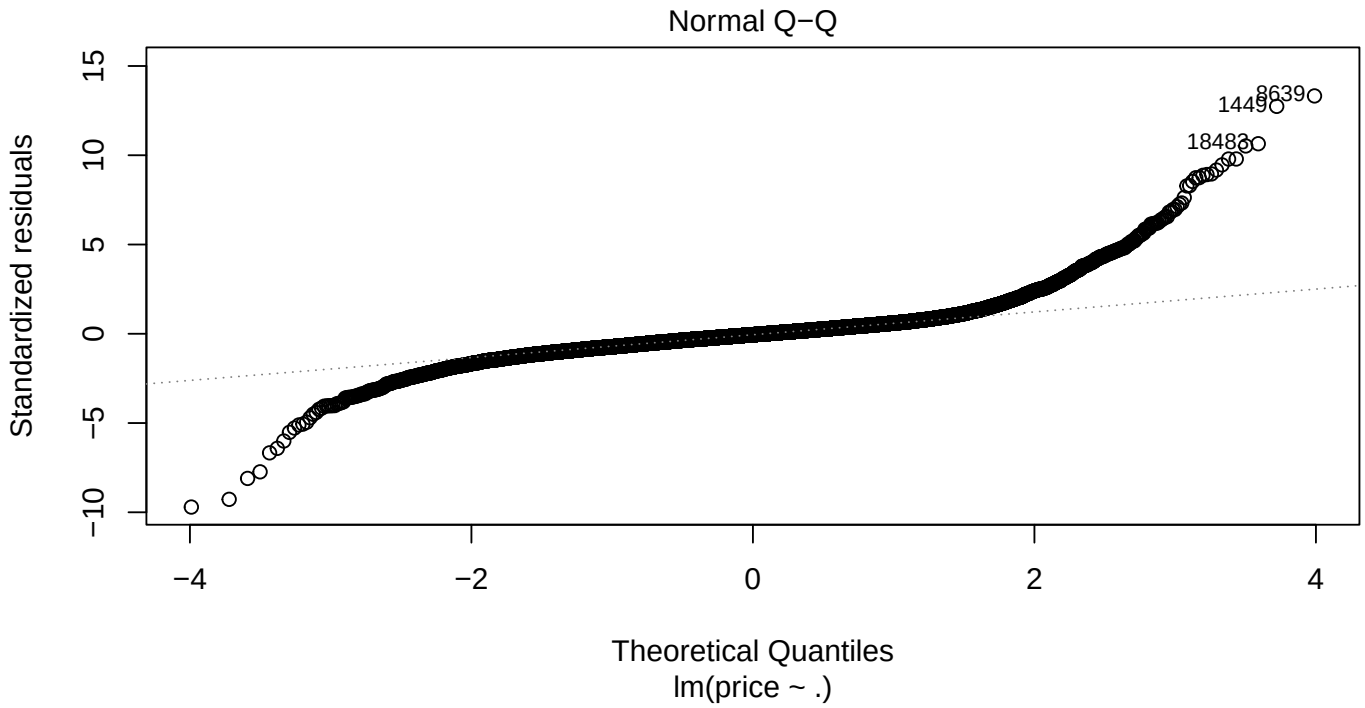
```
vif_values = vif(selected_linear_model)
variable_names <- names(vif_values)
vif_values <- as.numeric(vif_values)

# Create a data frame with variable names and VIF values
vif_results <- data.frame(Variable = variable_names, VIF = vif_values)

# Print the VIF results
print(vif_results)
```

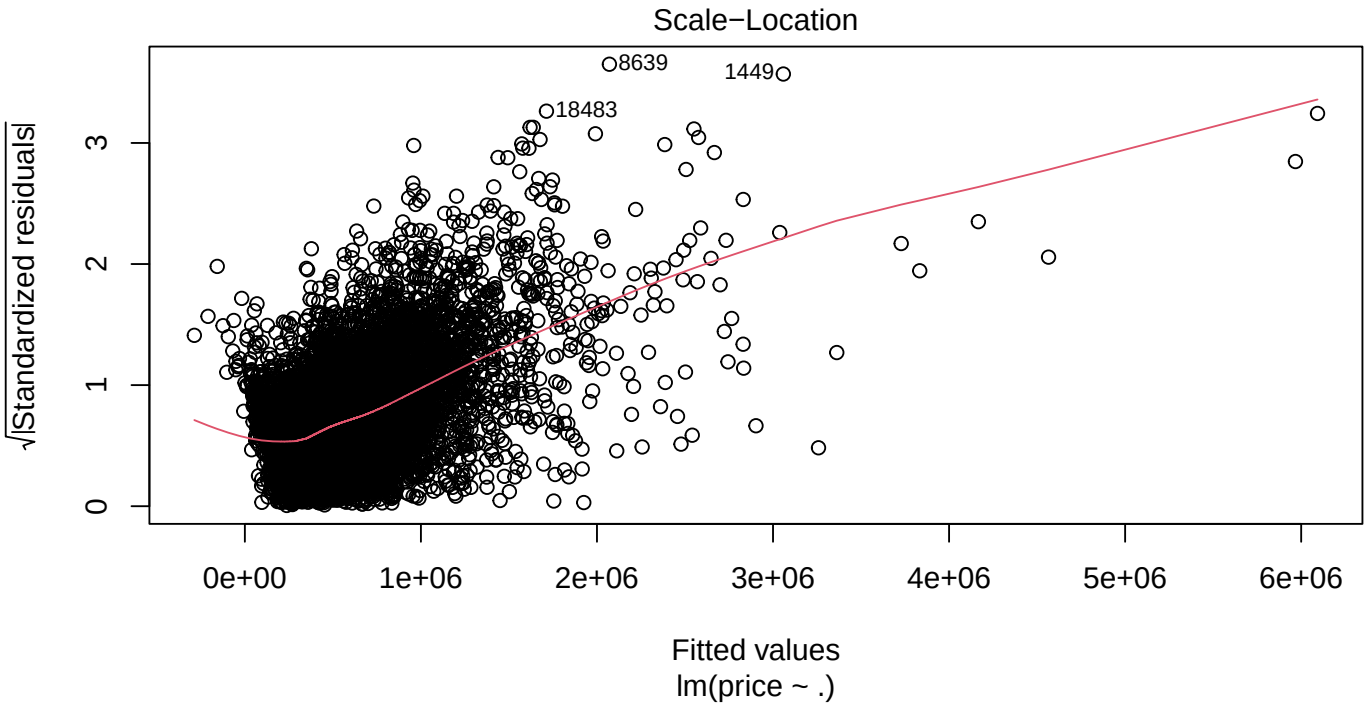
```
##               Variable        VIF
## 1            bathrooms   3.236310
## 2          sqft_living 301.396634
## 3                 view   1.381361
## 4                grade  32.743474
## 5                  lat   1.125627
## 6        sqft_living15   3.089565
## 7       sqft_adj_grade 121.362389
## 8   sqft_adj_condition  39.016026
## 9  sqft_adj_waterfront   5.604679
## 10 sqft_living_squared   5.796105
## 11          year_built   2.487072
## 12                year   1.324197
## 13        yr_renovated   1.151505
## 14              floors   2.044766
## 15                long   1.495650
## 16          waterfront   5.677761
## 17           month_Feb   1.189664
## 18           month_Jan   1.154349
## 19            bedrooms   1.732089
## 20          sqft_lot15   2.091251
## 21      floors_squared   1.556110
## 22            sqft_lot   2.076415
## 23           condition   5.407689
```

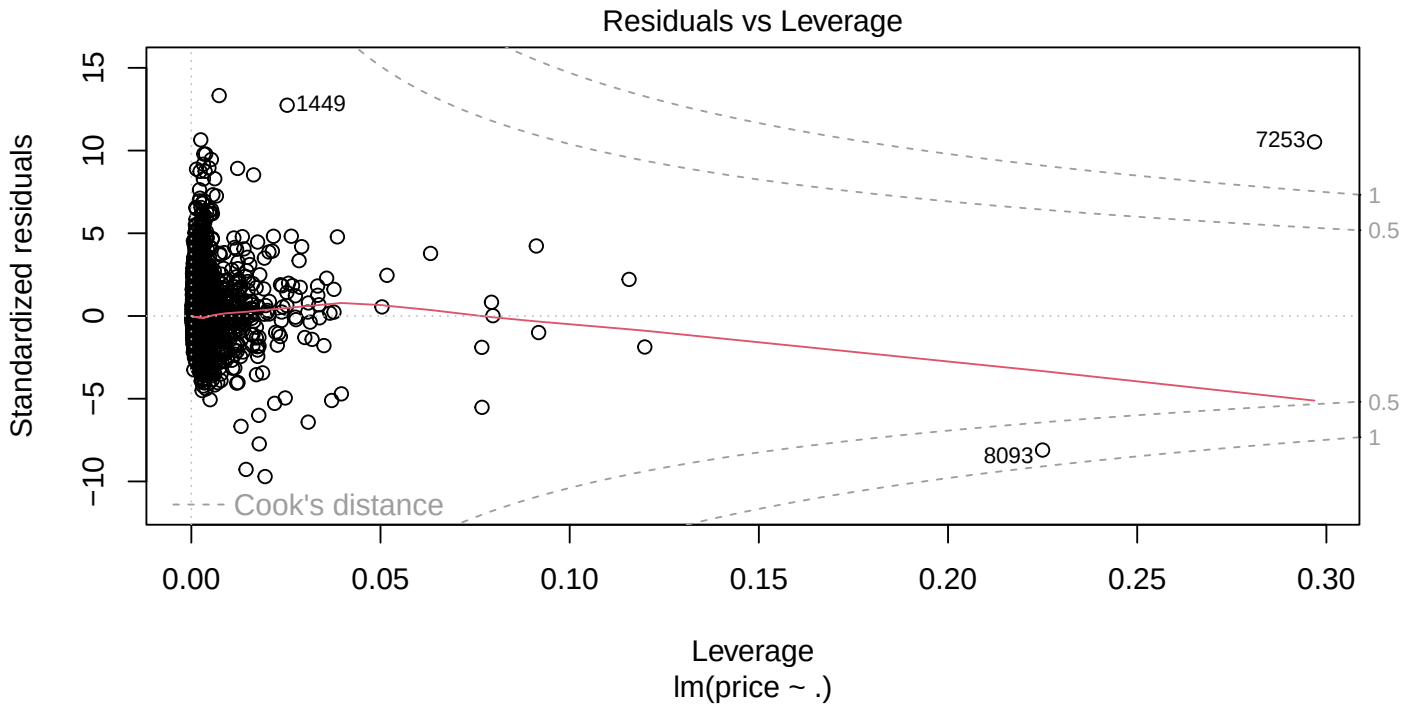
We got 4 variables above our cutoff 10 Vif value: sqft_living, grade, sqft_adj_grade and sqft_adj_condition.I don't think they add much to interpretability, so I'm excluding them for now (maybe returning them when we use other remedial measures, like ridge regression)

```
# First we eliminate the variables with high multicollinearity we just found out and fit a new linear model
#VIF_eliminated = c("sqft_adj_grade", "sqft_adj_condition")
#selected_train_df = selected_train_df[, !names(selected_train_df) %in% VIF_eliminated]
#selected_test_df = selected_test_df[, !names(selected_test_df) %in% VIF_eliminated]

#selected_linear_model = lm(price ~ . , data = cbind(price = kc.house.train.y, selected_train_df))

#pred_selected <- predict(selected_linear_model, selected_test_df)
#act_selected <- kc.house.test.y
#n_selected <- dim(model.matrix(selected_linear_model)[, -1])[1]
#p_selected <- dim(model.matrix(selected_linear_model)[, -1])[2]

#performance_selected = cbind(CalcTestMetrics(pred_selected, act_selected, n_selected, p_selected))
#print(performance_selected)

plot(selected_linear_model)
```




Normal Q−Q
Standardized residuals
Theoretical Quantiles
lm(price ~ .)
8639
1449
18483

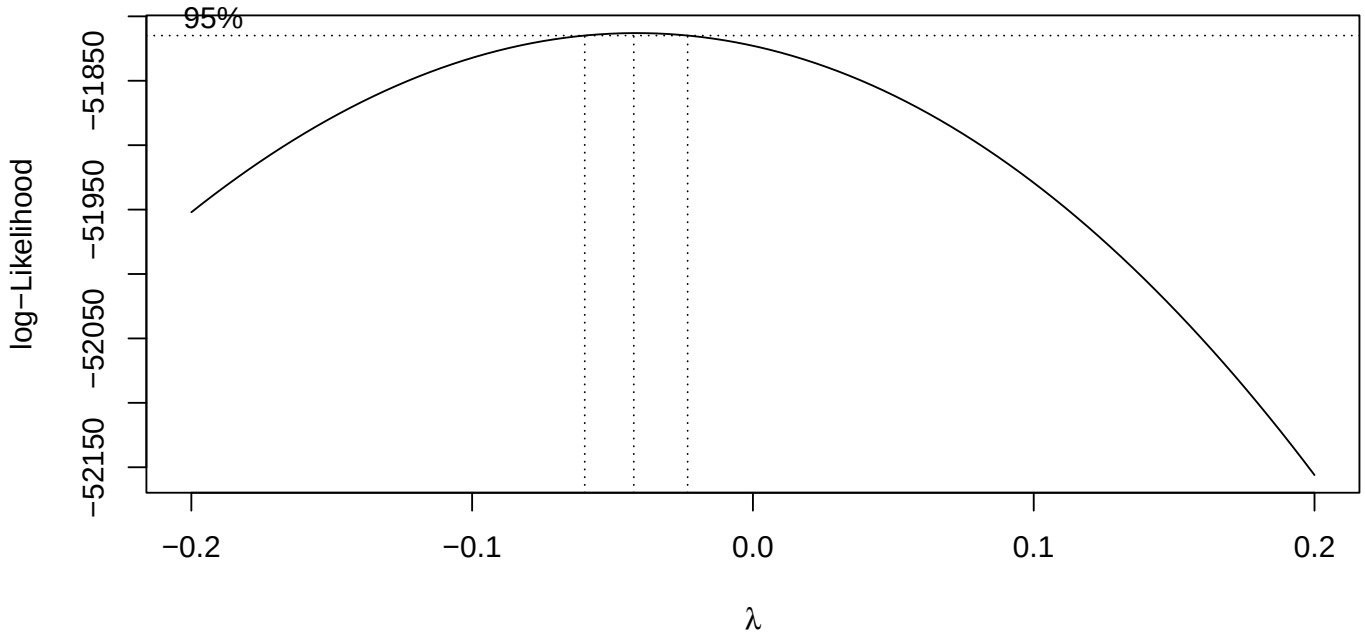

Scale−Location
√|Standardized residuals|
Fitted values
lm(price ~ .)
8639
1449
18483




```
library(MASS)
```

```
##
## Attaching package: 'MASS'

## The following object is masked from 'package:olsrr':
##
##     cement

## The following object is masked from 'package:dplyr':
##
##     select
```

```
boxcox(selected_linear_model,lambda=seq(-0.2,0.2,0.01))
```

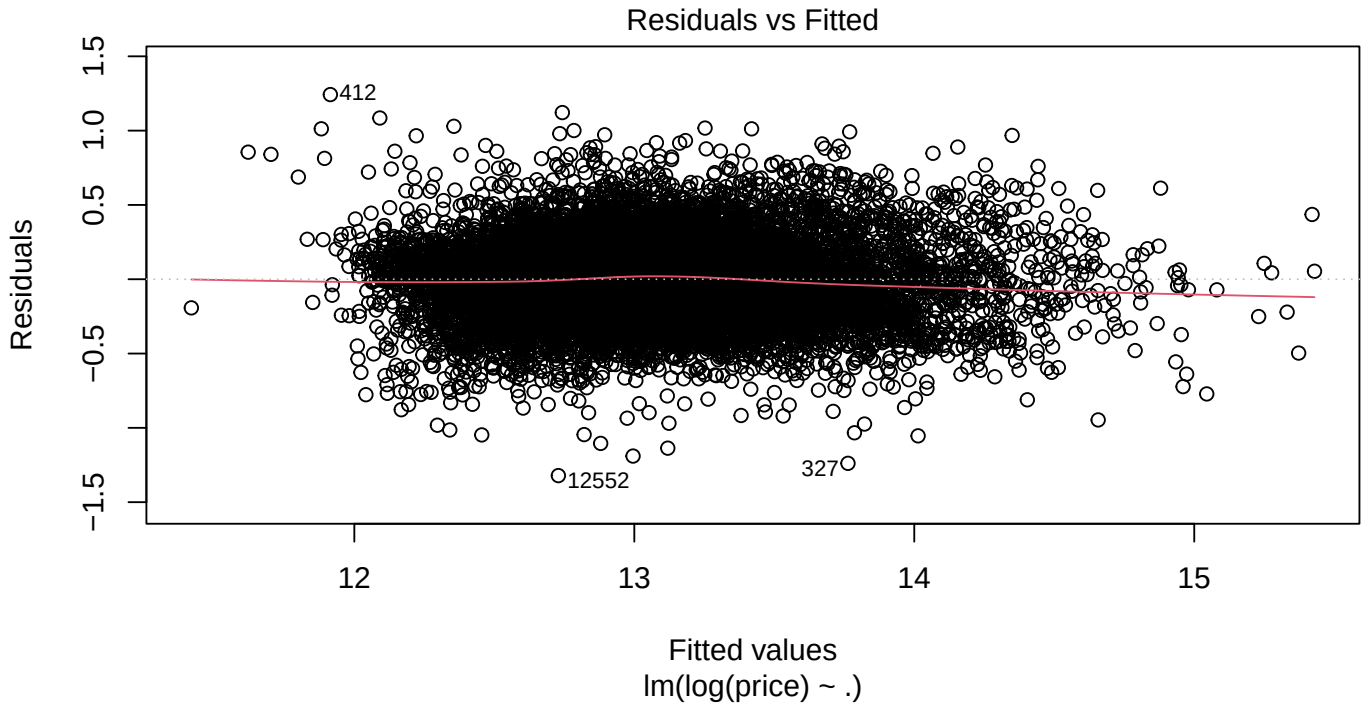


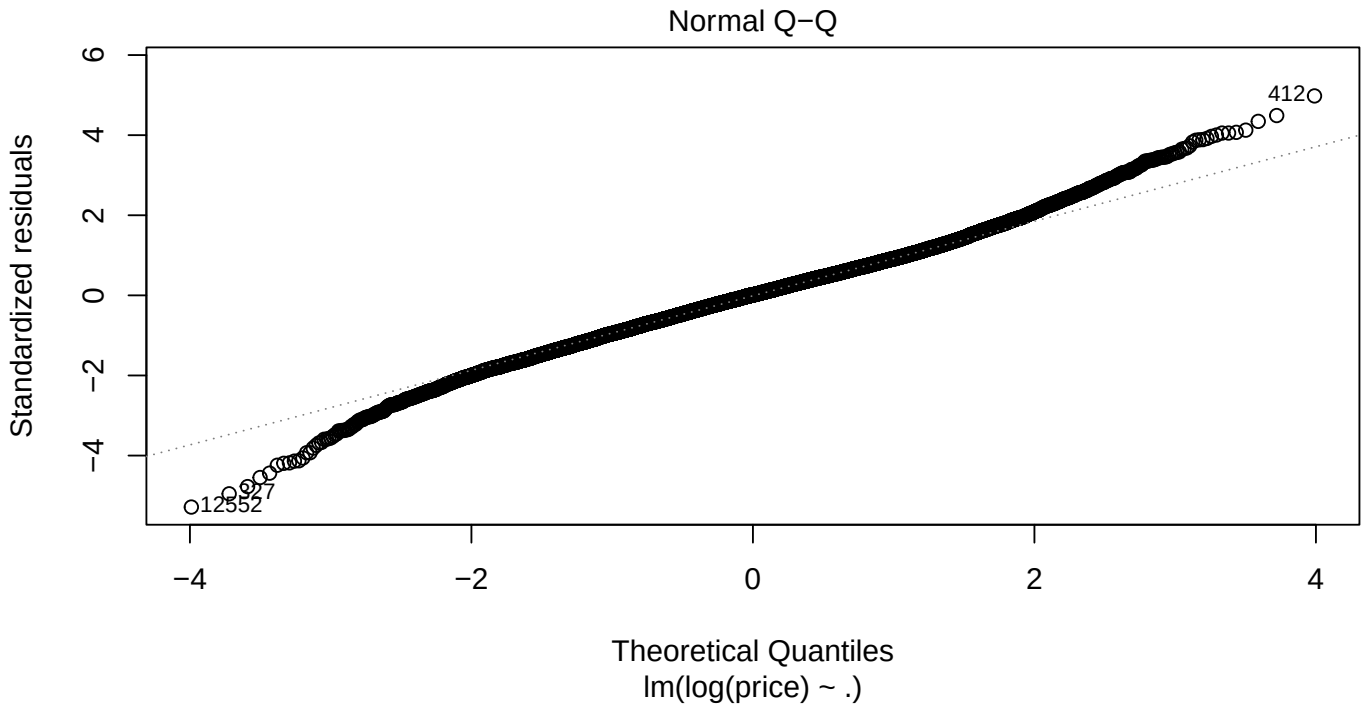

```
transformed_model = lm(log(price) ~ . , data = cbind(price = kc.house.train.y, selected_train_df))
summary(transformed_model)
```

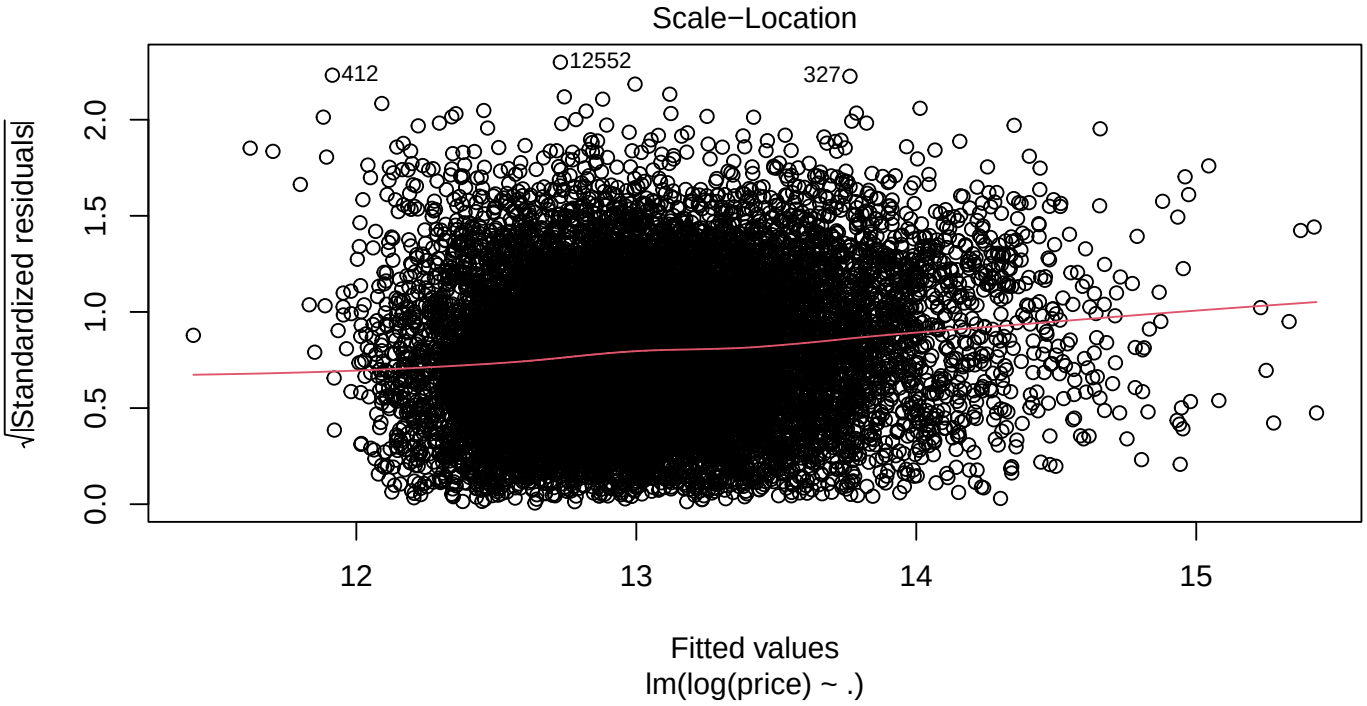
```
##
## Call:
## lm(formula = log(price) ~ ., data = cbind(price = kc.house.train.y,
##     selected_train_df))
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.32124 -0.15955  0.00329  0.15423  1.24245
##
## Coefficients:
##                         Estimate Std. Error t value Pr(>|t|)
## (Intercept)         -2.075e+02  1.034e+01 -20.072  < 2e-16 ***
## bathrooms            6.623e-02  4.750e-03  13.942  < 2e-16 ***
## sqft_living          1.613e-04  3.869e-05   4.169 3.08e-05 ***
## view                 6.069e-02  3.161e-03  19.201  < 2e-16 ***
## grade                1.660e-01  9.921e-03  16.736  < 2e-16 ***
## lat                  1.370e+00  1.561e-02  87.798  < 2e-16 ***
## sqft_living15        1.023e-04  5.192e-06  19.709  < 2e-16 ***
## sqft_adj_grade       3.766e-04  2.596e-04   1.451 0.146796
## sqft_adj_condition  -1.183e-04  4.165e-05  -2.841 0.004509 **
## sqft_adj_waterfront  1.824e-05  1.676e-05   1.088 0.276518
## sqft_living_squared -1.274e-08  2.413e-09  -5.278 1.32e-07 ***
## year_built          -3.219e-03  1.090e-04 -29.540  < 2e-16 ***
## year                 7.566e-02  5.001e-03  15.127  < 2e-16 ***
## yr_renovated         4.276e-05  5.413e-06   7.901 2.96e-15 ***
## floors               5.976e-02  5.388e-03  11.091  < 2e-16 ***
## long                -6.184e-02  1.761e-02  -3.512 0.000446 ***
## waterfront           3.052e-01  5.891e-02   5.181 2.24e-07 ***
## month_Feb           -5.714e-02  9.541e-03  -5.989 2.16e-09 ***
## month_Jan           -6.665e-02  1.043e-02  -6.388 1.73e-10 ***
```

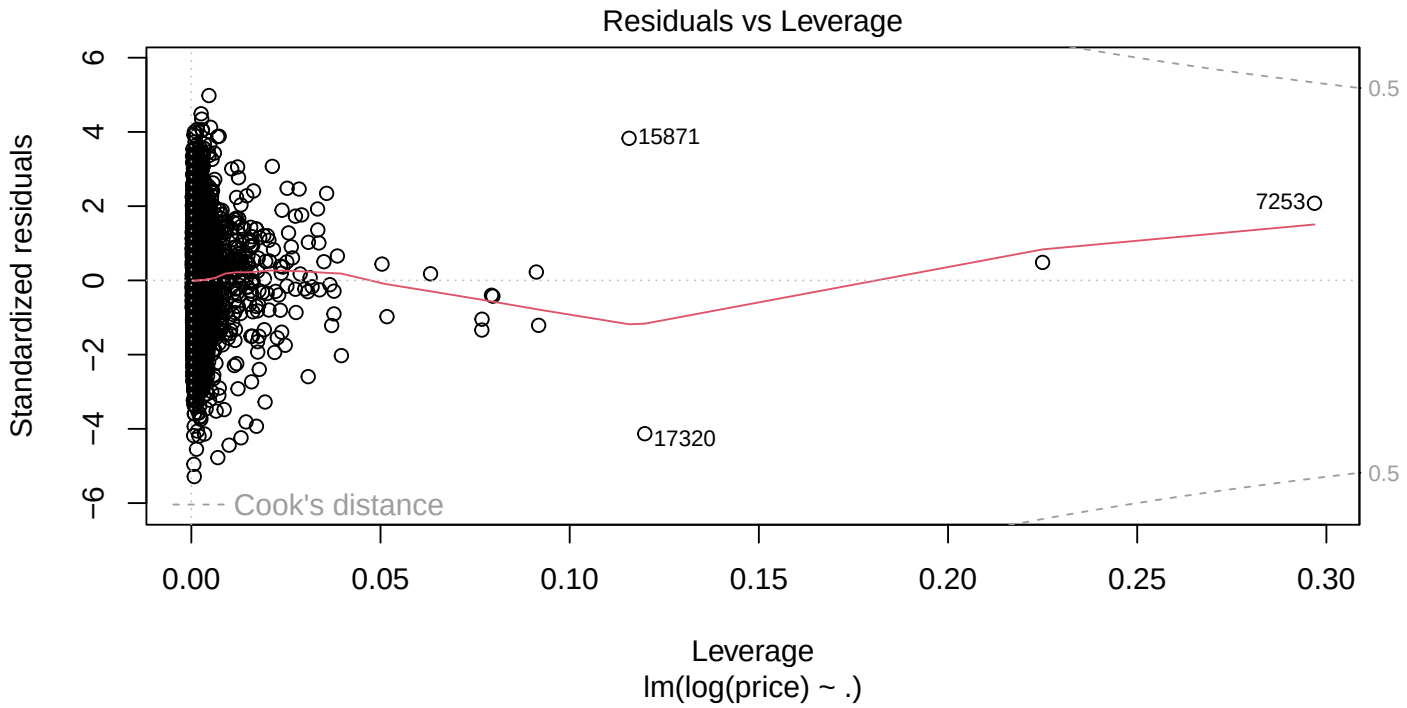
```
## bedrooms            -2.042e-02  2.848e-03  -7.171 7.81e-13 ***
## sqft_lot15          -1.728e-07  1.084e-07  -1.594 0.111006
## floors_squared       8.202e-03  7.038e-03   1.165 0.243876
## sqft_lot             4.955e-07  7.507e-08   6.600 4.24e-11 ***
## condition            5.098e-02  7.232e-03   7.049 1.88e-12 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2501 on 15105 degrees of freedom
## Multiple R-squared:  0.7729, Adjusted R-squared:  0.7726
## F-statistic:  2235 on 23 and 15105 DF,  p-value: < 2.2e-16
```

```
plot(transformed_model)
```




Normal Q−Q
Standardized residuals
Theoretical Quantiles
lm(log(price) ~ .)
412
327
12552


Scale−Location
√|Standardized residuals|
Fitted values
lm(log(price) ~ .)
412
12552
327



After transforming the model (log of the price), the assumptions seem to be fine. Just to be sure on normality, let's do some tests.

```
std_residuals = rstandard(transformed_model)

library(nortest)
ad.test(std_residuals)
```

```
##
##  Anderson-Darling normality test
##
## data:  std_residuals
## A = 14.501, p-value < 2.2e-16
```

```
lillie.test(std_residuals)
```

```
##
##  Lilliefors (Kolmogorov-Smirnov) normality test
##
## data:  std_residuals
## D = 0.022193, p-value < 2.2e-16
```

It seems like normality does not hold, even though the Q-Q plot looks much better after transformation. Looks like the standardized residuals are heavy on the tails, and normality tests shows that normality does not hold as well. It's up to question if this is a huge problem, considering the size of the data set. However, non-parametric models should (and will, in the next part) be tried for better results, since some does not need those assumptions to work.

```
y_test = log(kc.house.test.y)

# Coefficients
coeff.tr.df <- data.frame(Transformed = transformed_model$coefficients)
coeff.tr.df$Coefficients <- rownames(coeff.tr.df)
coeff.q1.df <-
```

```
  coeff.q1.df %>%
  dplyr::left_join(coeff.tr.df, by = "Coefficients") %>%
  dplyr::mutate(Transformed = ifelse(dplyr::coalesce(Transformed, 0) == 0, "--",
                                     scales::comma(Transformed, accuracy = 1e-4)))
knitr::kable(coeff.q1.df, caption = "Model Coefficients")
```

Table 6: Model Coefficients

Coefficients	Baseline	Stepwise	Transformed
(Intercept)	-166,310,707.6499	-122,358,944.4651	-207.4960
bedrooms	-8,027.4927	-7,901.2247	-0.0204
bathrooms	45,731.9969	45,428.4038	0.0662
sqft_living	484.3936	485.5559	0.0002
sqft_lot	0.1267	0.1268	0.0000
floors	23,921.4460	23,324.8806	0.0598
waterfront	-230,270.4560	-226,317.0611	0.3052
view	46,291.8461	45,648.1857	0.0607
condition	-12,652.0079	-11,688.0616	0.0510
grade	14,980.8525	14,824.3893	0.1660
sqft_above	1.4255	–	–
year_built	-2,135.2811	-2,092.6731	-0.0032
yr_renovated	39.2291	39.5648	0.0000
lat	567,973.0859	560,171.4178	1.3704
long	-102,082.8267	-84,063.5717	-0.0618
sqft_living15	55.8477	57.4640	0.0001
sqft_lot15	-0.2955	-0.2903	0.0000
year	70,145.6686	45,001.3459	0.0757
month_Jan	-58,367.4012	-35,117.1640	-0.0667
month_Feb	-57,628.3533	-34,367.8073	-0.0571
month_Mar	-26,845.5248	–	–
month_Apr	-26,687.3253	–	–
month_May	112.9928	–	–
month_Jun	2,738.1788	–	–
month_Jul	3,667.0506	–	–
month_Aug	3,723.3331	–	–
month_Sep	2,051.0150	–	–
month_Oct	1,903.1699	–	–
month_Nov	76.3270	–	–
month_Dec	NA	–	–
zipcode_start	-9,361.8650	–	–
sqft_adj_grade	-2,307.2998	-2,313.2728	0.0004
sqft_adj_condition	-348.5952	-347.1665	-0.0001
sqft_adj_waterfront	240.3149	239.5841	0.0000
sqft_living_squared	0.0228	0.0227	0.0000
floors_squared	12,819.2042	12,263.9547	0.0082

```
pred_transformed = predict(transformed_model, selected_test_df)
act_transformed <- y_test
n_transformed <- dim(model.matrix(transformed_model)[, -1])[1]
p_transformed <- dim(model.matrix(transformed_model)[, -1])[2]

performance_transformed = CalcTestMetrics(pred_transformed, act_transformed, n_transformed, p_transformed)
print(performance_transformed)
```

```
## adj.rsquared     rsquared          mse          mae
##   0.77430649   0.77464963   0.02738164   0.08374056
```

```
library(glmnet)
```

```
## Loading required package: Matrix
```

```
## Loaded glmnet 4.1-6
```

```
x= data.matrix(selected_train_df)
y= log(kc.house.train.y)

ridge_model = cv.glmnet(x,y,alpha=0, nlambda=100,lambda.min.ratio=0.0001)
best_lambda_ridge = ridge_model$lambda.min

# Coefficients Best Lambda
coeff.ridge.df <- stats::coef(ridge_model , s = best_lambda_ridge)
coeff.ridge.df <- data.frame(Coefficients = coeff.ridge.df@Dimnames[[1]],
                             Ridge = coeff.ridge.df@x)
coeff.q1.df <-
  coeff.q1.df %>%
  dplyr::left_join(coeff.ridge.df, by = "Coefficients") %>%
  dplyr::mutate(Ridge = ifelse(dplyr::coalesce(Ridge, 0) == 0, "--",
                               scales::comma(Ridge, accuracy = 1e-4)))
knitr::kable(coeff.q1.df, caption = "Model Coefficients")
```

Table 7: Model Coefficients

Coefficients	Baseline	Stepwise	Transformed	Ridge
(Intercept)	-166,310,707.6499	-122,358,944.4651	-207.4960	-189.7198
bedrooms	-8,027.4927	-7,901.2247	-0.0204	-0.0137
bathrooms	45,731.9969	45,428.4038	0.0662	0.0637
sqft_living	484.3936	485.5559	0.0002	0.0001
sqft_lot	0.1267	0.1268	0.0000	0.0000
floors	23,921.4460	23,324.8806	0.0598	0.0597
waterfront	-230,270.4560	-226,317.0611	0.3052	0.2487
view	46,291.8461	45,648.1857	0.0607	0.0622
condition	-12,652.0079	-11,688.0616	0.0510	0.0809
grade	14,980.8525	14,824.3893	0.1660	0.1466
sqft_above	1.4255	–	–	–
year_built	-2,135.2811	-2,092.6731	-0.0032	-0.0027
yr_renovated	39.2291	39.5648	0.0000	0.0000
lat	567,973.0859	560,171.4178	1.3704	1.3067
long	-102,082.8267	-84,063.5717	-0.0618	-0.0934
sqft_living15	55.8477	57.4640	0.0001	0.0001
sqft_lot15	-0.2955	-0.2903	0.0000	0.0000
year	70,145.6686	45,001.3459	0.0757	0.0659
month_Jan	-58,367.4012	-35,117.1640	-0.0667	-0.0571
month_Feb	-57,628.3533	-34,367.8073	-0.0571	-0.0485
month_Mar	-26,845.5248	–	–	–
month_Apr	-26,687.3253	–	–	–
month_May	112.9928	–	–	–
month_Jun	2,738.1788	–	–	–
month_Jul	3,667.0506	–	–	–
month_Aug	3,723.3331	–	–	–
month_Sep	2,051.0150	–	–	–
month_Oct	1,903.1699	–	–	–
month_Nov	76.3270	–	–	–
month_Dec	NA	–	–	–
zipcode_start	-9,361.8650	–	–	–

Coefficients	Baseline	Stepwise	Transformed	Ridge
sqft_adj_grade	-2,307.2998	-2,313.2728	0.0004	0.0004
sqft_adj_condition	-348.5952	-347.1665	-0.0001	0.0001
sqft_adj_waterfront	240.3149	239.5841	0.0000	0.0000
sqft_living_squared	0.0228	0.0227	0.0000	0.0000
floors_squared	12,819.2042	12,263.9547	0.0082	0.0089

```
#Performance
pred_ridge = predict(ridge_model, s = best_lambda_ridge,
                  newx = data.matrix(selected_test_df))[,1]
act_ridge <- y_test
n_ridge <- dim(model.matrix(transformed_model)[, -1])[1]
p_ridge <- dim(model.matrix(transformed_model)[, -1])[2]

performance_ridge = CalcTestMetrics(pred_ridge, act_ridge, n_ridge, p_ridge)
print(performance_ridge)
```

```
## adj.rsquared     rsquared          mse          mae
##   0.77184230   0.77218918   0.02768060   0.08437574
```

```
library(glmnet)
lasso_model = cv.glmnet(x,y,alpha=1, nlambda=100,lambda.min.ratio=0.0001)
best_lambda_lasso = lasso_model$lambda.min

# Coefficients
coeff.lasso <- stats::coef(lasso_model, s = "lambda.min")
coeff.lasso.names <- coeff.lasso@Dimnames[[1]]
coeff.lasso.df <- data.frame()
for (i in 1:length(coeff.lasso)) {
  df <- data.frame(Coefficients = coeff.lasso.names[i],
                   Lasso = coeff.lasso[i])
  coeff.lasso.df <- rbind(df, coeff.lasso.df)
}
coeff.q1.df <-
  coeff.q1.df %>%
  dplyr::left_join(coeff.lasso.df, by = "Coefficients") %>%
  dplyr::mutate(Lasso = ifelse(dplyr::coalesce(Lasso, 0) == 0, "--",
                               scales::comma(Lasso, accuracy = 1e-4)))
knitr::kable(coeff.q1.df, caption = "Model Coefficients")
```

Table 8: Model Coefficients

Coefficients	Baseline	Stepwise	Transformed	Ridge	Lasso
(Intercept)	-166,310,707.6499	-122,358,944.4651	-207.4960	-189.7198	-202.1087
bedrooms	-8,027.4927	-7,901.2247	-0.0204	-0.0137	-0.0186
bathrooms	45,731.9969	45,428.4038	0.0662	0.0637	0.0649
sqft_living	484.3936	485.5559	0.0002	0.0001	0.0001
sqft_lot	0.1267	0.1268	0.0000	0.0000	0.0000
floors	23,921.4460	23,324.8806	0.0598	0.0597	0.0586
waterfront	-230,270.4560	-226,317.0611	0.3052	0.2487	0.3052
view	46,291.8461	45,648.1857	0.0607	0.0622	0.0614
condition	-12,652.0079	-11,688.0616	0.0510	0.0809	0.0681
grade	14,980.8525	14,824.3893	0.1660	0.1466	0.1808
sqft_above	1.4255	–	–	–	–
year_built	-2,135.2811	-2,092.6731	-0.0032	-0.0027	-0.0032
yr_renovated	39.2291	39.5648	0.0000	0.0000	0.0000

Coefficients	Baseline	Stepwise	Transformed	Ridge	Lasso
lat	567,973.0859	560,171.4178	1.3704	1.3067	1.3687
long	-102,082.8267	-84,063.5717	-0.0618	-0.0934	-0.0596
sqft_living15	55.8477	57.4640	0.0001	0.0001	0.0001
sqft_lot15	-0.2955	-0.2903	0.0000	0.0000	0.0000
year	70,145.6686	45,001.3459	0.0757	0.0659	0.0730
month_Jan	-58,367.4012	-35,117.1640	-0.0667	-0.0571	-0.0621
month_Feb	-57,628.3533	-34,367.8073	-0.0571	-0.0485	-0.0526
month_Mar	-26,845.5248	–	–	–	–
month_Apr	-26,687.3253	–	–	–	–
month_May	112.9928	–	–	–	–
month_Jun	2,738.1788	–	–	–	–
month_Jul	3,667.0506	–	–	–	–
month_Aug	3,723.3331	–	–	–	–
month_Sep	2,051.0150	–	–	–	–
month_Oct	1,903.1699	–	–	–	–
month_Nov	76.3270	–	–	–	–
month_Dec	NA	–	–	–	–
zipcode_start	-9,361.8650	–	–	–	–
sqft_adj_grade	-2,307.2998	-2,313.2728	0.0004	0.0004	0.0008
sqft_adj_condition	-348.5952	-347.1665	-0.0001	0.0001	–
sqft_adj_waterfront	240.3149	239.5841	0.0000	0.0000	0.0000
sqft_living_squared	0.0228	0.0227	0.0000	0.0000	0.0000
floors_squared	12,819.2042	12,263.9547	0.0082	0.0089	0.0070

```
#Performance
pred_lasso = predict(lasso_model, s = best_lambda_lasso,
                 newx = data.matrix(selected_test_df))[,1]
act_lasso <- y_test
n_lasso <- dim(model.matrix(transformed_model)[, -1])[1]
p_lasso <- dim(model.matrix(transformed_model)[, -1])[2]

performance_lasso = CalcTestMetrics(pred_lasso, act_lasso, n_lasso, p_lasso)
print(performance_lasso)
```

```
## adj.rsquared     rsquared          mse          mae
##   0.77459960   0.77494229   0.02734608   0.08374378
```

```
enet_model = cv.glmnet(x,y,alpha=0.5, nlambda=100,lambda.min.ratio=0.0001)
best_lambda_enet = enet_model$lambda.min

# Coefficients
coeff.en <- stats::coef(enet_model, s = best_lambda_enet)
coeff.en.names <- coeff.en@Dimnames[[1]]
coeff.en.df <- data.frame()
for (i in 1:length(coeff.en)) {
  df <- data.frame(Coefficients = coeff.en.names[i],
                   ElasticNet = coeff.en[i])
  coeff.en.df <- rbind(df, coeff.en.df)
}
coeff.q1.df <-
  coeff.q1.df %>%
  dplyr::left_join(coeff.en.df, by = "Coefficients") %>%
  dplyr::mutate(ElasticNet = ifelse(dplyr::coalesce(ElasticNet, 0) == 0, "--",
                                    scales::comma(ElasticNet, accuracy = 1e-4)))
knitr::kable(coeff.q1.df, caption = "Model Coefficients")
```

Table 9: Model Coefficients

Coefficients	Baseline	Stepwise	Transformed	Ridge	Lasso	ElasticNet
(Intercept)	-166,310,707.6499	-122,358,944.4651	-207.4960	-189.7198	-202.1087	-201.7399
bedrooms	-8,027.4927	-7,901.2247	-0.0204	-0.0137	-0.0186	-0.0184
bathrooms	45,731.9969	45,428.4038	0.0662	0.0637	0.0649	0.0649
sqft_living	484.3936	485.5559	0.0002	0.0001	0.0001	0.0001
sqft_lot	0.1267	0.1268	0.0000	0.0000	0.0000	0.0000
floors	23,921.4460	23,324.8806	0.0598	0.0597	0.0586	0.0588
waterfront	-230,270.4560	-226,317.0611	0.3052	0.2487	0.3052	0.3037
view	46,291.8461	45,648.1857	0.0607	0.0622	0.0614	0.0614
condition	-12,652.0079	-11,688.0616	0.0510	0.0809	0.0681	0.0681
grade	14,980.8525	14,824.3893	0.1660	0.1466	0.1808	0.1721
sqft_above	1.4255	–	–	–	–	–
year_built	-2,135.2811	-2,092.6731	-0.0032	-0.0027	-0.0032	-0.0032
yr_renovated	39.2291	39.5648	0.0000	0.0000	0.0000	0.0000
lat	567,973.0859	560,171.4178	1.3704	1.3067	1.3687	1.3684
long	-102,082.8267	-84,063.5717	-0.0618	-0.0934	-0.0596	-0.0609
sqft_living15	55.8477	57.4640	0.0001	0.0001	0.0001	0.0001
sqft_lot15	-0.2955	-0.2903	0.0000	0.0000	0.0000	0.0000
year	70,145.6686	45,001.3459	0.0757	0.0659	0.0730	0.0728
month_Jan	-58,367.4012	-35,117.1640	-0.0667	-0.0571	-0.0621	-0.0619
month_Feb	-57,628.3533	-34,367.8073	-0.0571	-0.0485	-0.0526	-0.0525
month_Mar	-26,845.5248	–	–	–	–	–
month_Apr	-26,687.3253	–	–	–	–	–
month_May	112.9928	–	–	–	–	–
month_Jun	2,738.1788	–	–	–	–	–
month_Jul	3,667.0506	–	–	–	–	–
month_Aug	3,723.3331	–	–	–	–	–
month_Sep	2,051.0150	–	–	–	–	–
month_Oct	1,903.1699	–	–	–	–	–
month_Nov	76.3270	–	–	–	–	–
month_Dec	NA	–	–	–	–	–
zipcode_start	-9,361.8650	–	–	–	–	–
sqft_adj_grade	-2,307.2998	-2,313.2728	0.0004	0.0004	0.0008	0.0005
sqft_adj_condition	-348.5952	-347.1665	-0.0001	0.0001	–	0.0000
sqft_adj_waterfront	240.3149	239.5841	0.0000	0.0000	0.0000	0.0000
sqft_living_squared	0.0228	0.0227	0.0000	0.0000	0.0000	0.0000
floors_squared	12,819.2042	12,263.9547	0.0082	0.0089	0.0070	0.0073

```
#Performance
pred_enet = predict(enet_model, s = best_lambda_enet,
                    newx = data.matrix(selected_test_df))[,1]
act_enet <- y_test
n_enet <- dim(model.matrix(transformed_model)[, -1])[1]
p_enet <- dim(model.matrix(transformed_model)[, -1])[2]

performance_enet = CalcTestMetrics(pred_enet, act_enet, n_enet, p_enet)
print(performance_enet)
```

```
## adj.rsquared     rsquared          mse          mae
##   0.77456142   0.77490417   0.02735071   0.08376233
```

```
x1= data.matrix(selected_train_df)
y1= kc.house.train.y

enet_model1 = cv.glmnet(x1,y1,alpha=0.5, nlambda=100,lambda.min.ratio=0.0001)
best_lambda_enet = enet_model$lambda.min
```

```r
# Coefficients
coeff.en <- stats::coef(enet_model1, s = best_lambda_enet)
coeff.en.names <- coeff.en@Dimnames[[1]]
coeff.en.df <- data.frame()
for (i in 1:length(coeff.en)) {
  df <- data.frame(Coefficients = coeff.en.names[i],
                   ElasticNetNonTrans = coeff.en[i])
  coeff.en.df <- rbind(df, coeff.en.df)
}
coeff.q1.df <-
  coeff.q1.df %>%
  dplyr::left_join(coeff.en.df, by = "Coefficients") %>%
  dplyr::mutate(ElasticNetNonTrans = ifelse(dplyr::coalesce(ElasticNetNonTrans, 0) == 0, "--",
                                    scales::comma(ElasticNetNonTrans, accuracy = 1e-4)))
knitr::kable(coeff.q1.df, caption = "Model Coefficients")
```

Table 10: Model Coefficients

Coefficients	Baseline	Stepwise	Transformed	Ridge	Lasso	ElasticNet	ElasticNetNonTrans
(Intercept)	-166,310,707.6499	-122,358,944.4651	-207.4960	-189.7198	-202.1087	-201.7399	-121,004,536.0034
bedrooms	-8,027.4927	-7,901.2247	-0.0204	-0.0137	-0.0186	-0.0184	-8,161.6683
bathrooms	45,731.9969	45,428.4038	0.0662	0.0637	0.0649	0.0649	44,448.6935
sqft_living	484.3936	485.5559	0.0002	0.0001	0.0001	0.0001	325.8519
sqft_lot	0.1267	0.1268	0.0000	0.0000	0.0000	0.0000	0.1191
floors	23,921.4460	23,324.8806	0.0598	0.0597	0.0586	0.0588	21,998.5498
waterfront	-230,270.4560	-226,317.0611	0.3052	0.2487	0.3052	0.3037	-198,508.2980
view	46,291.8461	45,648.1857	0.0607	0.0622	0.0614	0.0614	45,964.6615
condition	-12,652.0079	-11,688.0616	0.0510	0.0809	0.0681	0.0681	152.6320
grade	14,980.8525	14,824.3893	0.1660	0.1466	0.1808	0.1721	51,403.7604
sqft_above	1.4255	–	–	–	–	–	–
year_built	-2,135.2811	-2,092.6731	-0.0032	-0.0027	-0.0032	-0.0032	-2,118.9915
yr_renovated	39.2291	39.5648	0.0000	0.0000	0.0000	0.0000	37.8144
lat	567,973.0859	560,171.4178	1.3704	1.3067	1.3687	1.3684	557,387.7536
long	-102,082.8267	-84,063.5717	-0.0618	-0.0934	-0.0596	-0.0609	-81,552.9321
sqft_living15	55.8477	57.4640	0.0001	0.0001	0.0001	0.0001	60.1423
sqft_lot15	-0.2955	-0.2903	0.0000	0.0000	0.0000	0.0000	-0.2791
year	70,145.6686	45,001.3459	0.0757	0.0659	0.0730	0.0728	44,251.8896
month_Jan	-58,367.4012	-35,117.1640	-0.0667	-0.0571	-0.0621	-0.0619	-33,993.6275
month_Feb	-57,628.3533	-34,367.8073	-0.0571	-0.0485	-0.0526	-0.0525	-32,999.4280
month_Mar	-26,845.5248	–	–	–	–	–	–
month_Apr	-26,687.3253	–	–	–	–	–	–
month_May	112.9928	–	–	–	–	–	–
month_Jun	2,738.1788	–	–	–	–	–	–
month_Jul	3,667.0506	–	–	–	–	–	–
month_Aug	3,723.3331	–	–	–	–	–	–
month_Sep	2,051.0150	–	–	–	–	–	–
month_Oct	1,903.1699	–	–	–	–	–	–
month_Nov	76.3270	–	–	–	–	–	–
month_Dec	NA	–	–	–	–	–	–
zipcode_start	-9,361.8650	–	–	–	–	–	–
sqft_adj_grade	-2,307.2998	-2,313.2728	0.0004	0.0004	0.0008	0.0005	-1,313.3999
sqft_adj_condition	-348.5952	-347.1665	-0.0001	0.0001	–	0.0000	-264.5459
sqft_adj_waterfront	240.3149	239.5841	0.0000	0.0000	0.0000	0.0000	231.0851
sqft_living_squared	0.0228	0.0227	0.0000	0.0000	0.0000	0.0000	0.0307
floors_squared	12,819.2042	12,263.9547	0.0082	0.0089	0.0070	0.0073	11,225.0751

```r
#Performance

y_test1 = kc.house.test.y

pred_enet = predict(enet_model1, s = best_lambda_enet,
                    newx = data.matrix(selected_test_df))[,1]
act_enet <- y_test1
n_enet <- dim(model.matrix(transformed_model)[, -1])[1]
p_enet <- dim(model.matrix(transformed_model)[, -1])[2]

performance_enet = CalcTestMetrics(pred_enet, act_enet, n_enet, p_enet)
print(performance_enet)
```

```
## adj.rsquared     rsquared          mse          mae
## 7.335420e-01 7.339471e-01 1.644849e+10 5.050140e+04
```

```r
robust_model = rlm(log(price) ~ . , data = cbind(price = kc.house.train.y, selected_train_df), psi = psi.huber
summary(robust_model)
```

```
##
## Call: rlm(formula = log(price) ~ ., data = cbind(price = kc.house.train.y,
##     selected_train_df), psi = psi.huber)
## Residuals:
##       Min        1Q    Median        3Q       Max
## -1.328906 -0.157710  0.003441  0.154057  1.260301
##
## Coefficients:
##                       Value     Std. Error t value
## (Intercept)         -202.6587   10.0244   -20.2166
## bathrooms              0.0711    0.0046    15.4287
## sqft_living            0.0001    0.0000     3.9817
## view                   0.0654    0.0031    21.3494
## grade                  0.1718    0.0096    17.8623
## lat                    1.3687    0.0151    90.4252
## sqft_living15          0.0001    0.0000    18.4384
## sqft_adj_grade         0.0005    0.0003     2.0790
## sqft_adj_condition    -0.0002    0.0000    -3.8909
## sqft_adj_waterfront    0.0000    0.0000     1.4099
## sqft_living_squared    0.0000    0.0000    -5.0808
## year_built            -0.0035    0.0001   -32.6579
## year                   0.0758    0.0048    15.6283
## yr_renovated           0.0000    0.0000     7.5771
## floors                 0.0666    0.0052    12.7427
## long                  -0.0243    0.0171    -1.4232
## waterfront             0.3084    0.0571     5.3975
## month_Feb             -0.0594    0.0093    -6.4255
## month_Jan             -0.0713    0.0101    -7.0454
## bedrooms              -0.0220    0.0028    -7.9593
## sqft_lot15             0.0000    0.0000    -2.2537
## floors_squared         0.0051    0.0068     0.7412
## sqft_lot               0.0000    0.0000     7.5468
## condition              0.0403    0.0070     5.7442
##
## Residual standard error: 0.2312 on 15105 degrees of freedom
```

```r
# Coefficients
coeff.huber.df <- data.frame(Robust = robust_model$coefficients)
coeff.huber.df$Coefficients <- rownames(coeff.huber.df)
```

```
coeff.q1.df <-
  coeff.q1.df %>%
  dplyr::left_join(coeff.huber.df, by = "Coefficients") %>%
  dplyr::mutate(Robust = ifelse(dplyr::coalesce(Robust, 0) == 0, "--",
                                scales::comma(Robust, accuracy = 1e-4)))
knitr::kable(coeff.q1.df, caption = "Model Coefficients")
```

Table 11: Model Coefficients

Coefficients	Baseline	Stepwise	Transformed	Ridge	Lasso	ElasticNet	ElasticNetNonTrans	Robust
(Intercept)	-166,310,707.6499	-122,358,944.4651	-207.4960	-189.7198	-202.1087	-201.7399	-121,004,536.0034	-202.6587
bedrooms	-8,027.4927	-7,901.2247	-0.0204	-0.0137	-0.0186	-0.0184	-8,161.6683	-0.0220
bathrooms	45,731.9969	45,428.4038	0.0662	0.0637	0.0649	0.0649	44,448.6935	0.0711
sqft_living	484.3936	485.5559	0.0002	0.0001	0.0001	0.0001	325.8519	0.0001
sqft_lot	0.1267	0.1268	0.0000	0.0000	0.0000	0.0000	0.1191	0.0000
floors	23,921.4460	23,324.8806	0.0598	0.0597	0.0586	0.0588	21,998.5498	0.0666
waterfront	-230,270.4560	-226,317.0611	0.3052	0.2487	0.3052	0.3037	-198,508.2980	0.3084
view	46,291.8461	45,648.1857	0.0607	0.0622	0.0614	0.0614	45,964.6615	0.0654
condition	-12,652.0079	-11,688.0616	0.0510	0.0809	0.0681	0.0681	152.6320	0.0403
grade	14,980.8525	14,824.3893	0.1660	0.1466	0.1808	0.1721	51,403.7604	0.1718
sqft_above	1.4255	–	–	–	–	–	–	–
year_built	-2,135.2811	-2,092.6731	-0.0032	-0.0027	-0.0032	-0.0032	-2,118.9915	-0.0035
yr_renovated	39.2291	39.5648	0.0000	0.0000	0.0000	0.0000	37.8144	0.0000
lat	567,973.0859	560,171.4178	1.3704	1.3067	1.3687	1.3684	557,387.7536	1.3687
long	-102,082.8267	-84,063.5717	-0.0618	-0.0934	-0.0596	-0.0609	-81,552.9321	-0.0243
sqft_living15	55.8477	57.4640	0.0001	0.0001	0.0001	0.0001	60.1423	0.0001
sqft_lot15	-0.2955	-0.2903	0.0000	0.0000	0.0000	0.0000	-0.2791	0.0000
year	70,145.6686	45,001.3459	0.0757	0.0659	0.0730	0.0728	44,251.8896	0.0758
month_Jan	-58,367.4012	-35,117.1640	-0.0667	-0.0571	-0.0621	-0.0619	-33,993.6275	-0.0713
month_Feb	-57,628.3533	-34,367.8073	-0.0571	-0.0485	-0.0526	-0.0525	-32,999.4280	-0.0594
month_Mar	-26,845.5248	–	–	–	–	–	–	–
month_Apr	-26,687.3253	–	–	–	–	–	–	–
month_May	112.9928	–	–	–	–	–	–	–
month_Jun	2,738.1788	–	–	–	–	–	–	–
month_Jul	3,667.0506	–	–	–	–	–	–	–
month_Aug	3,723.3331	–	–	–	–	–	–	–
month_Sep	2,051.0150	–	–	–	–	–	–	–
month_Oct	1,903.1699	–	–	–	–	–	–	–
month_Nov	76.3270	–	–	–	–	–	–	–
month_Dec	NA	–	–	–	–	–	–	–
zipcode_start	-9,361.8650	–	–	–	–	–	–	–
sqft_adj_grade	-2,307.2998	-2,313.2728	0.0004	0.0004	0.0008	0.0005	-1,313.3999	0.0005
sqft_adj_condition	-348.5952	-347.1665	-0.0001	0.0001	–	0.0000	-264.5459	-0.0002
sqft_adj_waterfront	240.3149	239.5841	0.0000	0.0000	0.0000	0.0000	231.0851	0.0000
sqft_living_squared	0.0228	0.0227	0.0000	0.0000	0.0000	0.0000	0.0307	0.0000
floors_squared	12,819.2042	12,263.9547	0.0082	0.0089	0.0070	0.0073	11,225.0751	0.0051

```
#Performance
pred_robust = predict(robust_model, selected_test_df)
act_robust <- y_test
n_robust <- dim(model.matrix(robust_model)[, -1])[1]
p_robust <- dim(model.matrix(robust_model)[, -1])[2]

performance_robust = CalcTestMetrics(pred_robust, act_robust, n_robust, p_robust)
print(performance_robust)
```

```
## adj.rsquared     rsquared          mse          mae
```

```
##    0.77409514    0.77443860    0.02740728    0.08353808
```

With robust performance, it does not seem that outliers matter much (after transformation at least)

```
library(knitr)
library(dplyr)

results_df <- data.frame(
  Model = c('Baseline', 'Stepwise', 'Transformed', 'Ridge', 'Lasso', 'Elastic Net', 'Robust'),
  Adj.RSquared = c(performance_baseline["adj.rsquared"], performance_selected["adj.rsquared"], performance_tra
  RSquared = c(performance_baseline["rsquared"], performance_selected["rsquared"], performance_transformed["rs
  MSE = c(performance_baseline["mse"], performance_selected["mse"], performance_transformed["mse"],performance
  MAE = c(performance_baseline["mae"], performance_selected["mae"], performance_transformed["mae"],performance
)

# Sort and display the table
sorted_results_df <- dplyr::arrange(results_df, desc(Adj.RSquared))
knitr::kable(sorted_results_df, caption = "Model Metrics")
```

Table 12: Model Metrics

Model	Adj.RSquared	RSquared	MSE	MAE
Lasso	0.7745996	0.7749423	2.734610e-02	8.374380e-02
Transformed	0.7743065	0.7746496	2.738160e-02	8.374060e-02
Robust	0.7740951	0.7744386	2.740730e-02	8.353810e-02
Ridge	0.7718423	0.7721892	2.768060e-02	8.437570e-02
Stepwise	0.7374118	0.7378110	1.620961e+10	5.057684e+04
Baseline	0.7373025	0.7379102	1.621635e+10	5.065398e+04
Elastic Net	0.7335420	0.7339471	1.644849e+10	5.050140e+04

V. Challenger Models (15 points)

Build an alternative model based on one of the following approaches to predict price: regression tree, NN, or SVM. Explore using a logistic regression. Check the applicable model assumptions. Apply in-sample and out-of-sample testing, backtesting and review the comparative goodness of fit of the candidate models. Describe step by step your procedure to get to the best model and why you believe it is fit for purpose.

```
# Load libraries
library(caret)
library(rpart)
library(nnet)
library(knitr)
library(dplyr)
library(stringr)
library(readr)

HouseSales <- read.csv('KC_House_Sales.csv')

# Step a: Data Splitting
set.seed(123)  #
split_ratio <- 0.7  # 70% training, 30% testing
index <- sample(1:nrow(HouseSales), size = round(split_ratio * nrow(HouseSales)))
train_data <- HouseSales[index, ]
test_data <- HouseSales[-index, ]

# Step b: Model Building

# Model 1: Logistic Regression

# Create a binary variable 'high_price' based on the chosen percentile
logisticdf <- HouseSales
logisticdf$price <- parse_number(logisticdf$price)
logisticdf$high_price <- ifelse(logisticdf$price >= 1000000, 1, 0)

# Create a new dataframe with 'high_price' column
logisticdf <- logisticdf %>%
  dplyr::select(-price)

# Split data for logistic regrssion model
set.seed(123)  #
split_ratio <- 0.7  # 70% training, 30% testing
index <- sample(1:nrow(logisticdf), size = round(split_ratio * nrow(logisticdf)))
train_data_logistic <- logisticdf[index, ]
test_data_logistic <- logisticdf[-index, ]

#Build basic logistic regrssion model
logistic_model <- glm(high_price ~ ., data = train_data_logistic, family = binomial)
summary(logistic_model)

# Model 2: Regression Tree
tree_model <- rpart(price ~ ., data = train_data)
printcp(tree_model)  # Display complexity parameter plot
plot(tree_model)  # Visualize the decision tree

# Model 3: Neural Network
nn_model <- neuralnet(price ~ ., data = train_data, hidden = c(5, 2), linear.output = TRUE)

# Tune neural network hyperparameters - placehlder

# Step c: Model Evaluation
```

```r
# Model 1: Logistic Regression
logistic_predictions <- predict(logistic_model, newdata = test_data, type = 'response')
logistic_accuracy <- sum((logistic_predictions > 0.5) == test_data$high_price) / length(test_data$high_price)
cat("Logistic Regression Accuracy:", logistic_accuracy, "\n")

# Model 2: Regression Tree
tree_predictions <- predict(tree_model, newdata = test_data)
tree_rmse <- sqrt(mean((tree_predictions - test_data$price)^2))
cat("Regression Tree RMSE:", tree_rmse, "\n")

# Model 3: Neural Network
nn_predictions <- predict(nn_model, newdata = test_data)
# Calculate relevant performance metrics for the neural network model

# Step d: Model Comparison (Choose the best model based on evaluation metrics)

# Calculate evaluation metrics for all models
logistic_predictions <- predict(logistic_model, newdata = test_data, type = 'response')
logistic_accuracy <- sum((logistic_predictions > 0.5) == test_data$high_price) / length(test_data$high_price)
cat("Logistic Regression Accuracy:", logistic_accuracy, "\n")

tree_predictions <- predict(tree_model, newdata = test_data)
tree_rmse <- sqrt(mean((tree_predictions - test_data$price)^2))
cat("Regression Tree RMSE:", tree_rmse, "\n")

nn_predictions <- predict(nn_model, newdata = test_data)
cat("NN RMSE:", tree_rmse, "\n")

# Step e: Backtesting - placeholder

# Function to compare model performance
compare_model_performance <- function(models, model_names, data_train, data_test) {
  rmse_values <- c()
  rsquared_values <- c()
  mape_values <- c()

  for (i in 1:length(models)) {
    model <- models[[i]]
    predictions <- predict(model, newdata = data_test)
    rmse <- sqrt(mean((data_test$price - predictions)^2))
    rsquared <- cor(data_test$price, predictions)^2
    mape <- mean(abs((data_test$price - predictions) / data_test$price)) * 100

    rmse_values <- c(rmse_values, rmse)
    rsquared_values <- c(rsquared_values, rsquared)
    mape_values <- c(mape_values, mape)
  }

  # Create a data frame to hold the results
  model_results <- data.frame(Model = model_names, RMSE = rmse_values, R_squared = rsquared_values, MAPE = map

  # Create a table to compare model results
  kable(model_results, format = "markdown")
}
```

VI. Model Limitation and Assumptions (15 points)

Based on the performances on both train and test data sets, determine your primary (champion) model and the other model which would be your benchmark model. Validate your models using the test sample. Do the residuals look normal? Does it matter given your technique? How is the prediction performance using Pseudo R^2, SSE, RMSE? Benchmark the model against alternatives. How good is the relative fit? Are there any serious violations of the model assumptions? Has the model had issues or limitations that the user must know? (Which assumptions are needed to support the Champion model?)

VII. Ongoing Model Monitoring Plan (5 points)

How would you picture the model needing to be monitored, which quantitative thresholds and triggers would you set to decide when the model needs to be replaced? What are the assumptions that the model must comply with for its continuous use?

Overview

For model monitoring there are four areas to track 1) model stability, 2) prediction performance, 3) incremental data quality and 4) data pipeline failures.

1. Prediction Stability

This subsection concerns itself with stability of predictions. Price predictions often are used by loan originators to size a loan or as an input to a consumer product. For example, assume the product is a home price recommendation for homeowners looking to see. If the homeowners aka the customers get highly variable sale price recommendations month to month, it'll result in subpar user experience, creating distrust between the customer and the firm.

To check for prediction stability the approach is to store last month's prediction values in a database table and the model itself in an S3 bucket as an RDS file. We are assuming new data arrives in monthly batches because that is the frequency of our data set.

```
adjust_months <- function(date, num_months) {
  # Convert to character for easier manipulation
  date_str <- as.character(date)

  # Extract year and month components
  year <- substr(date_str, 1, 4)
  month <- substr(date_str, 5, 6)

  # Convert to numeric and adjust months
  result_month <- as.numeric(month) + num_months
  result_year <- as.numeric(year) + floor((result_month - 1) / 12)
  result_month <- (result_month - 1) %% 12 + 1  # Ensure the month is within 1 to 12

  # Create the result as "yyyymm"
  result <- paste0(result_year, sprintf("%02d", result_month))
  result <- as.double(result)

  return(result)
}
```

Since we do not have infrastructure stood up we use the following code block to simulate pulling in previous month's model and corresponding predictions. We sample the data using a sliding window approach. The past 12 months of data are used to train the model and the subsequent month is the test set. This different from the world in previous parts because here we are simulating the arrival of new data.

```
concat_date <- year*100 + month
kc.house.df$yyyymm <- concat_date

set.seed(1023)

lookback.window <- 12 #one year lookback window
#Any data before this date is in the training set
#Any data after is in the test set
cutoff_date <- 201501
train_start <- adjust_months(cutoff_date, -lookback.window)

prev_train_data <- kc.house.df[
  which(
```

```
    kc.house.df$yyyymm < cutoff_date &
    kc.house.df$yyyymm >= train_start
  ),
]

#horizon is the size of the test set
#Here one means the subsequent month, so 201501
#If it was 2 then the test set will include [201501-201502] so forth
horizon <- 1
test_start <- cutoff_date
test_end <- adjust_months(test_start, horizon)

prev_test_data <- kc.house.df[
  which(
    (kc.house.df$yyyymm < test_end) &
    (kc.house.df$yyyymm >= test_start)
  ),
]
prev_train_data <- prev_train_data %>% dplyr::select(-contains("Month"))
prev_test_data <- prev_test_data %>% dplyr::select(-contains("Month"))

previous.model <- lm(price ~ . -year, data = prev_train_data)
previous.pred <- predict(previous.model, prev_test_data)
```

Now we simulate getting a new batch of data and fitting the model on new data. We compare the new model predictions against the old model using

1. T-test on the means of the predictions

- To determine if prediction means are drifting from month to month

2. F-test for the variance of the predictions

- To determine if prediction variance is drifiting from month to month

3. T-test on the mean squared error.

- To determine if mean squared error is drifting from month to month

For assumption checking, we use Anderson-Darling test to check normality of predictions. Shapiro-Wilk test will not work due to the large sample size.

In practice, model stability tests tend to be overly sensitive so we will trigger Slack warnings when the p-values of the test are less than 0.01.

```
library(nortest)

#Current Model
cutoff_date <- adjust_months(cutoff_date, 1)
train_start <- adjust_months(cutoff_date, -lookback.window)

curr_train_data <- kc.house.df[
  which(
    kc.house.df$yyyymm < cutoff_date &
    kc.house.df$yyyymm >= train_start
  ),
]
```

```r
horizon <- 1
test_start <- cutoff_date
test_end <- adjust_months(test_start, horizon)

curr_test_data <- kc.house.df[
  which(
    (kc.house.df$yyyymm < test_end) &
    (kc.house.df$yyyymm >= test_start)

  ),
]
curr_train_data <- curr_train_data %>% dplyr::select(-contains("Month"))
curr_test_data <- curr_test_data %>% dplyr::select(-contains("Month"))

current.model <- lm(price ~ . -year, data = curr_train_data)
curr.pred <- predict(current.model, curr_test_data)

# H0: same means
# H1: means are not the same
t.test(previous.pred, curr.pred)
```

```
##
##  Welch Two Sample t-test
##
## data:  previous.pred and curr.pred
## t = 2.3105, df = 1989.2, p-value = 0.02096
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##   4569.016 55869.126
## sample estimates:
## mean of x mean of y
##  528469.4  498250.3
```

```r
# H0: same variance
# H1: variance are not the same
var.test(previous.pred, curr.pred)
```

```
##
##  F test to compare two variances
##
## data:  previous.pred and curr.pred
## F = 1.2245, num df = 977, denom df = 1249, p-value = 0.0007646
## alternative hypothesis: true ratio of variances is not equal to 1
## 95 percent confidence interval:
##  1.088160 1.379034
## sample estimates:
## ratio of variances
##           1.224461
```

```r
#Check if mean squared error is equivalent
prev_sq_error <- (prev_test_data[, "price"] - previous.pred)^2
curr_sq_error <- (curr_test_data[, "price"] - curr.pred)^2
t.test(prev_sq_error, curr_sq_error)
```

```
##
##  Welch Two Sample t-test
##
```

```
## data:  prev_sq_error and curr_sq_error
## t = -0.79995, df = 2222.4, p-value = 0.4238
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -16403044247   6898007004
## sample estimates:
##   mean of x   mean of y
## 32334011442 37086530064
```

```
#Check predictions are normal
ad.test(current.model$residuals)
```

```
##
##  Anderson-Darling normality test
##
## data:  current.model$residuals
## A = 462.67, p-value < 2.2e-16
```

Looks like in our case, the tests will trigger and warn us that the variance of the predictions have deviated (increased), means have not, MSE has not and the AD test will trigger an assumption violation alert. Variance of predictions deviating is worth notifying because we want to ensure stakeholders and customers a consistent experience.

The most important of these is MSE as we do not want our model to fluctuate in terms of error. We certainly do not want MSE to deviate downwards to significant degree (alert can adjusted to trigger when difference is negative and significant). Normality is important for inference in the case that model coefficients become part of a product. However it is not as important currently since we are only concerned with predictive power.

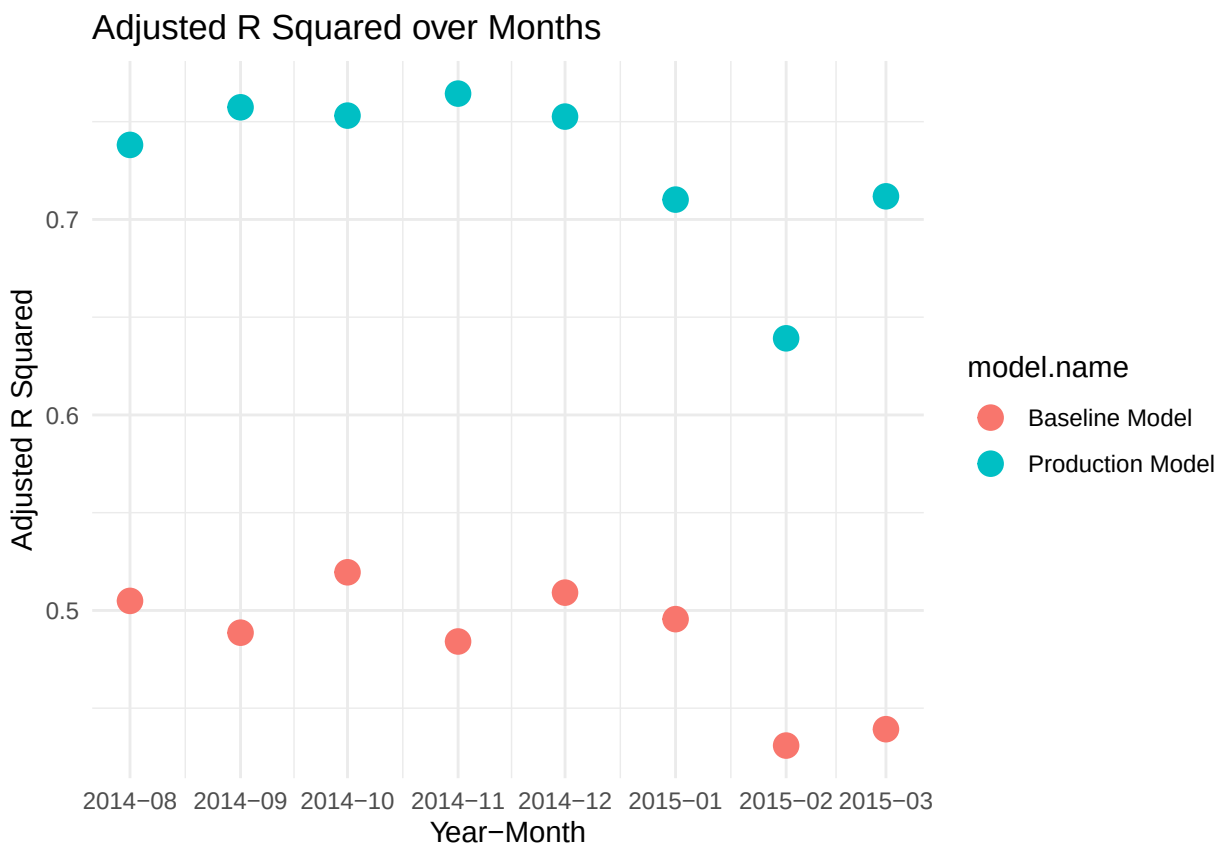
2. Prediction Performance over Time

For this section we track model metrics over time to ensure the model continues to be on par. Metrics we choose are adjusted R^2 and RMSE. We apply a function to create a rolling window for the model to train on and then test with data outside the window. We collect the metrics and plot them over time.

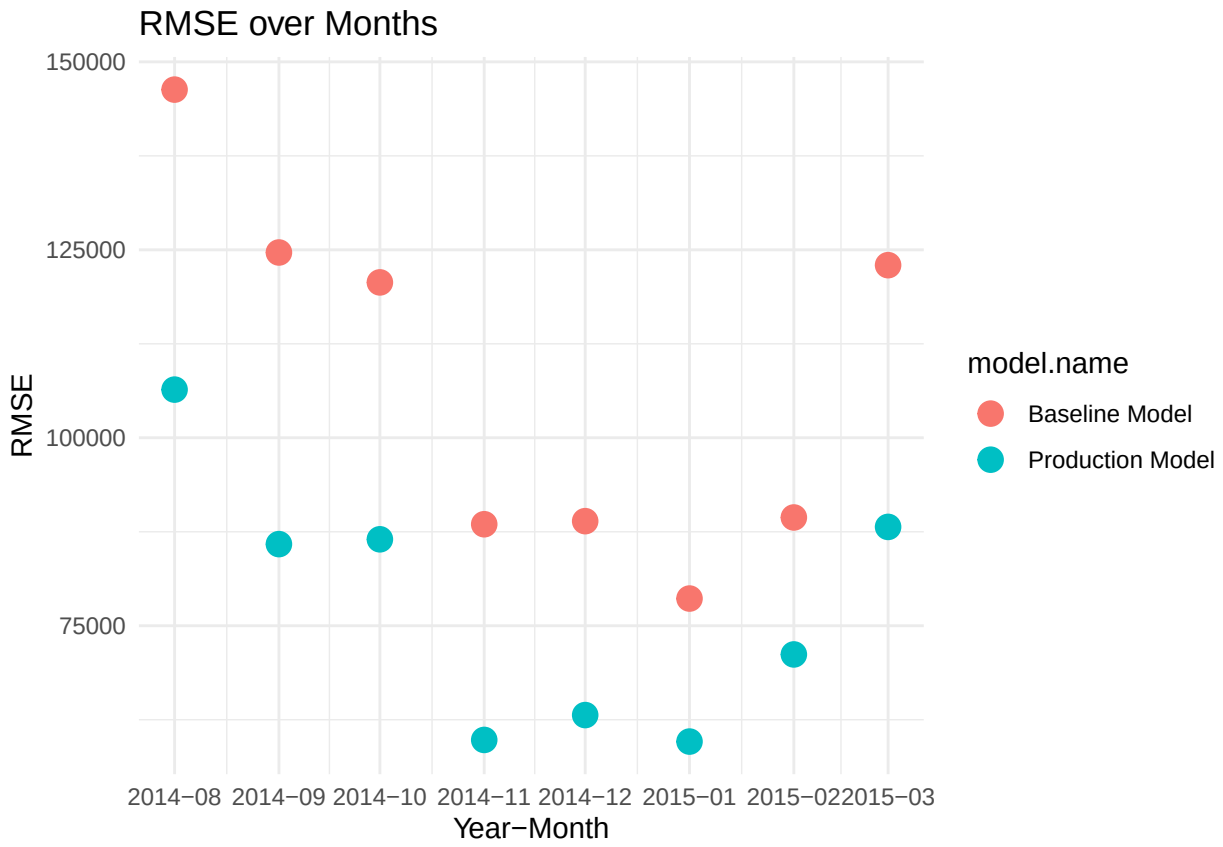
If any metrics fall below the baseline production model, we will trigger a slack message.

```
library(ggplot2)

#Iterate over folds
roll_model <- function(cutoff_date, form){

  lookback.window <- 6 #six month lookback
  train_start <- adjust_months(cutoff_date, -lookback.window)

  train_data <- kc.house.df[
    which(
      kc.house.df$yyyymm < cutoff_date &
      kc.house.df$yyyymm >= train_start
    ),
  ]
  train_data <- train_data %>% dplyr::select(-contains("Month"))

  horizon <- 1
  test_start <- cutoff_date
  test_end <- adjust_months(test_start, horizon)

  test_data <- kc.house.df[
    which(
      (kc.house.df$yyyymm < test_end) &
      (kc.house.df$yyyymm >= test_start)
```

```
    ),
  ]
  test_data <- test_data %>% dplyr::select(-contains("Month"))

  model <- lm(form, data = train_data)
  pred <- predict(model, test_data)

  act <- test_data[, "price"]
  n <- dim(model.matrix(model))[1]
  p <- dim(model.matrix(model))[2]

  metric <- CalcTestMetrics(pred, act, n, p)

  return (metric)
}

years <- c(201408, 201409, 201410, 201411, 201412, 201501, 201502, 201503)

ols_form <- as.formula("price ~ . -year")
metrics_table <- do.call(rbind, lapply(years, roll_model, form = ols_form))
metrics_table <- as.data.frame(metrics_table)
metrics_table$years <- years
metrics_table$rmse <- sqrt(as.numeric(metrics_table$mse))
metrics_table$model.name <- "Production Model"

#assume this it the baseline model
null_form <- as.formula("price ~ sqft_living")
null_metrics_table <- do.call(rbind, lapply(years, roll_model, form = null_form))
null_metrics_table <- as.data.frame(null_metrics_table)
null_metrics_table$years <- years
null_metrics_table$rmse <- sqrt(as.numeric(null_metrics_table$mse))
null_metrics_table$model.name <- "Baseline Model"



metrics_table <- dplyr::union(metrics_table, null_metrics_table)

# Convert date to Date class
metrics_table$date <- as.Date(paste0(metrics_table$years, "01"), format = "%Y%m%d")

# Create the ggplot
ggplot(metrics_table, aes(x = date, y = as.numeric(adj.rsquared), color = model.name)) +
  geom_point(size = 4) +
  labs(x = "Year-Month", y = "Adjusted R Squared", title = "Adjusted R Squared over Months") +
  scale_x_date(date_labels = "%Y-%m", date_breaks = "1 month") +
  theme_minimal()
```




```
ggplot(metrics_table, aes(x = date, y = as.numeric(rmse), color = model.name)) +
  geom_point(size = 4) +
  labs(x = "Year-Month", y = "RMSE", title = "RMSE over Months") +
  scale_x_date(date_labels = "%Y-%m", date_breaks = "1 month") +
  theme_minimal()
```

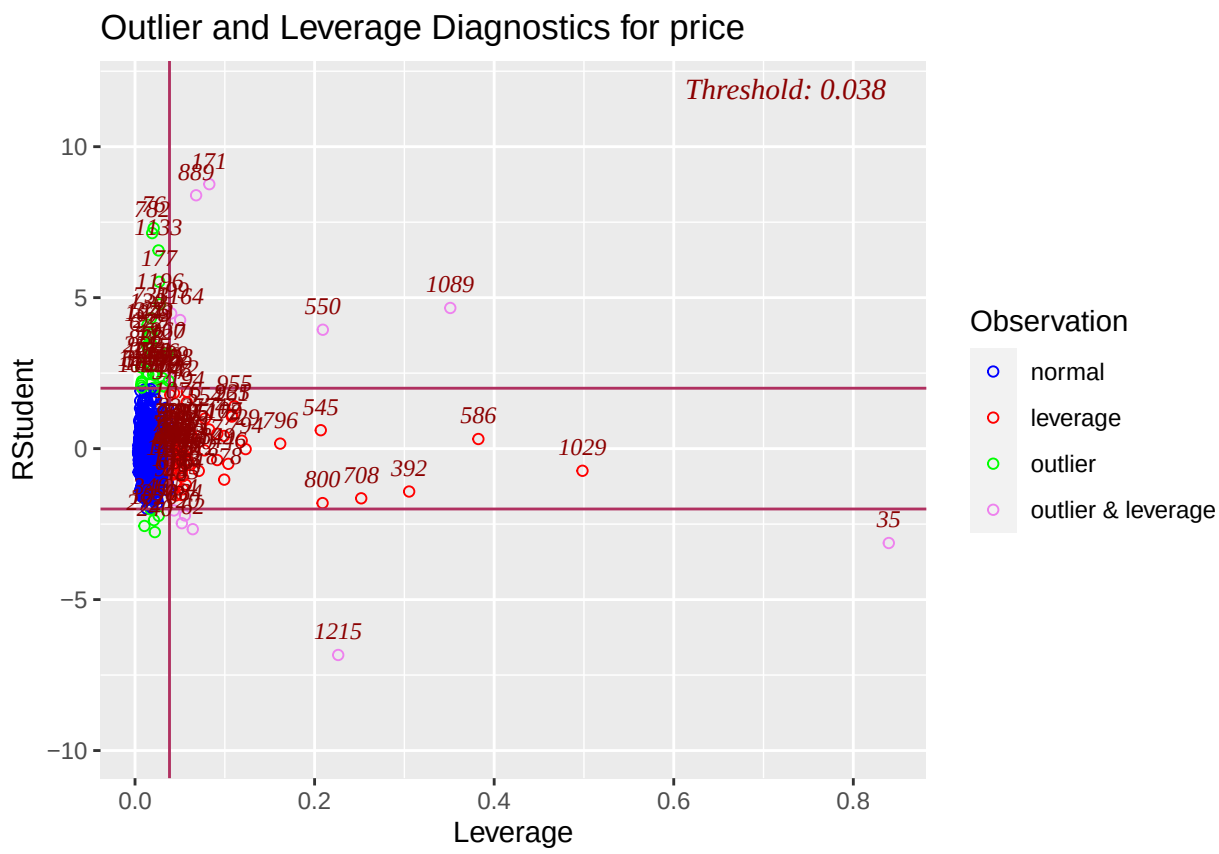


The `Adjusted R Squared over Months` plot will have no triggers. `RMSE over Months` will trigger on every month.

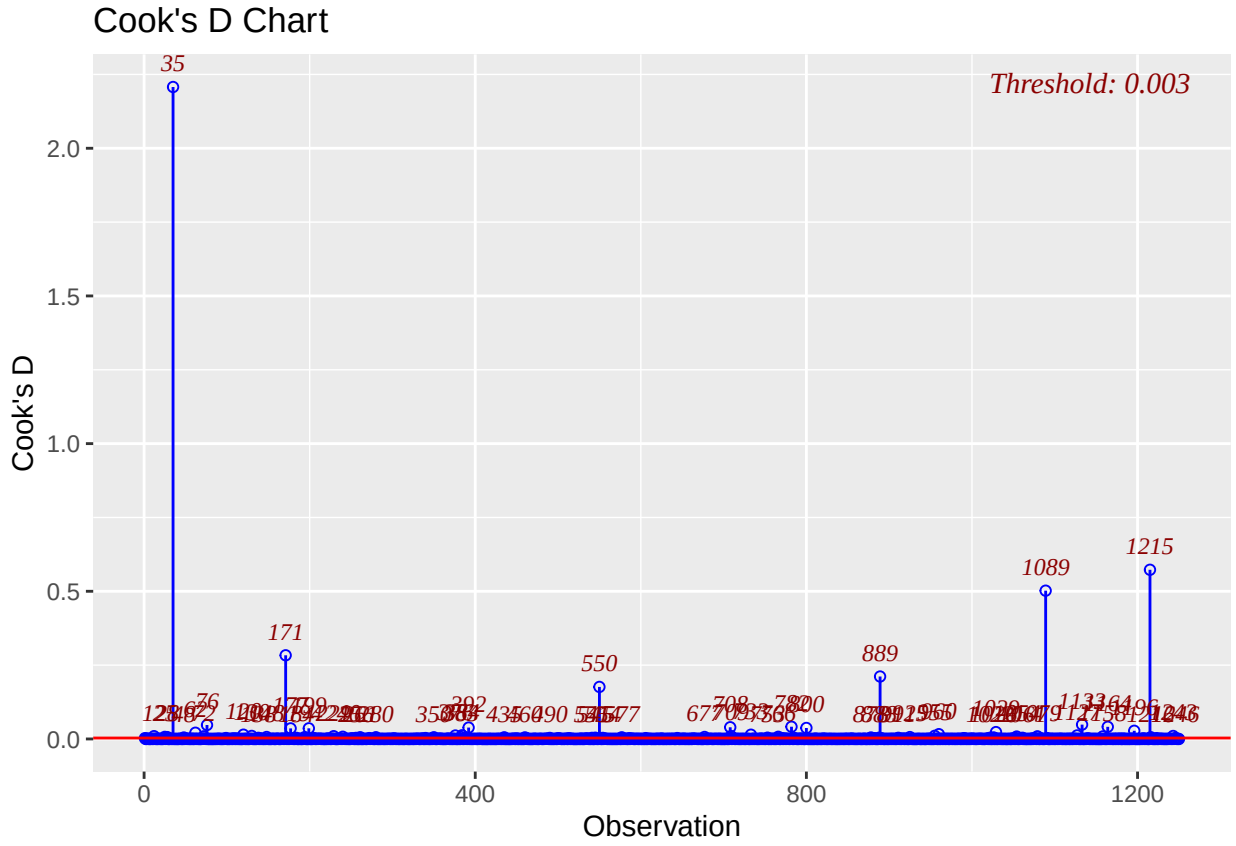
3. Incremental Data Quality Check

When new data comes in at monthly interval we will perform checks to prevent malformed data from entering the model. First we create graphs to add to a dashboard for visual inspection. These are the `Residuals vs Leverage` plot to detect outliers, leverage points or both and the `Cook's Distance` chart to detect influential points. The hope is to catch problematic points early, before they reach the model.

```
library(olsrr)
incremental_data <- curr_test_data
incremental.model <- lm(price ~ . -year, data = incremental_data)

#Residual vs Leverage
ols_plot_resid_lev(incremental.model)
```




```
#Cook's Distance Visualized
ols_plot_cooksd_chart(incremental.model)
```



To compare the old data with the new incremental data batch we perform a Kolmogorov-Smirnov test for continuous features

and Chi-Square Goodness of Fit test for categorical data. The threshold we set will be a conservative 0.01 because these tests tend to be overly sensitive due to the variable nature of real data.

```
old_data <- curr_train_data

continuous_features <- c(
  "price",
  "sqft_living",
  "sqft_lot",
  "sqft_above",
  "year_built",
  "yr_renovated",
  "sqft_living15",
  "sqft_lot15"
)
discrete_features <- c(
  "bedrooms",
  "bathrooms",
  "floors",
  "waterfront",
  "view",
  "condition",
  "grade",
  "zipcode_start"
)

#H0: Same Distribution
#H1: Not same distribution
ks_pvalues <- c()
for (feature in continuous_features){
  pval <- ks.test(
    old_data[, feature],
    incremental_data[, feature],
    simulate.p.value = TRUE
  )$p.value

  ks_pvalues <- c(ks_pvalues, pval)
}

#H0: Same Proportions
#H1: Not same proportions
chisq_pvalues <- c()
for (feature in discrete_features){
  # Extract the column data
  old_feature_data <- old_data[[feature]]
  n <- length(old_feature_data)
  expected_probabilities <- table(old_feature_data) / n

  incremental_feature_data <- incremental_data[[feature]]
  n <- length(incremental_feature_data)
  observed_probabilities <- table(old_feature_data) / n

  #want to compare new to old
  pval <- chisq.test(
    observed_probabilities,
    expected_probabilities,
    simulate.p.value = TRUE
  )$p.value

  chisq_pvalues <- c(chisq_pvalues, pval)
```

```
}

cbind(continuous_features, ks_pvalues)
```

```
##      continuous_features ks_pvalues
## [1,] "price"             "0.00499750124937526"
## [2,] "sqft_living"       "0.00599700149925032"
## [3,] "sqft_lot"          "0.19640179910045"
## [4,] "sqft_above"        "0.00299850074962513"
## [5,] "year_built"        "0.529735132433783"
## [6,] "yr_renovated"      "0.000999500249875007"
## [7,] "sqft_living15"     "0.217891054472764"
## [8,] "sqft_lot15"        "0.432783608195902"
```

```
cbind(discrete_features, chisq_pvalues)
```

```
##      discrete_features chisq_pvalues
## [1,] "bedrooms"        "0.0104947526236882"
## [2,] "bathrooms"       "0.000499750124937531"
## [3,] "floors"          "1"
## [4,] "waterfront"      "1"
## [5,] "view"            "1"
## [6,] "condition"       "1"
## [7,] "grade"           "0.0154922538730635"
## [8,] "zipcode_start"   "1"
```

Looks like `sqft_living`, `bedrooms`, `bathrooms` and deviated in our incremental data batch.

4. Pipeline Fail Safes

Note: No examples are shown here because we do not have data infrastructure

The plan to handle pipeline failures is to persist every production model and every test and training set of data. It is ok to store large amounts of data because storage is cheap in the modern day. Models RDS files will be stored in an S3 bucket. The data sets will be stored as compressed parquet files because production database tables usually only contain the most updated version (upserted records) and in this case we want to revert to data before any updates were made. When the pipeline fails, we can use old data and the old model to continue to generate predictions. This ensures downstream stakeholders are free from breaking changes and free from work disruption.

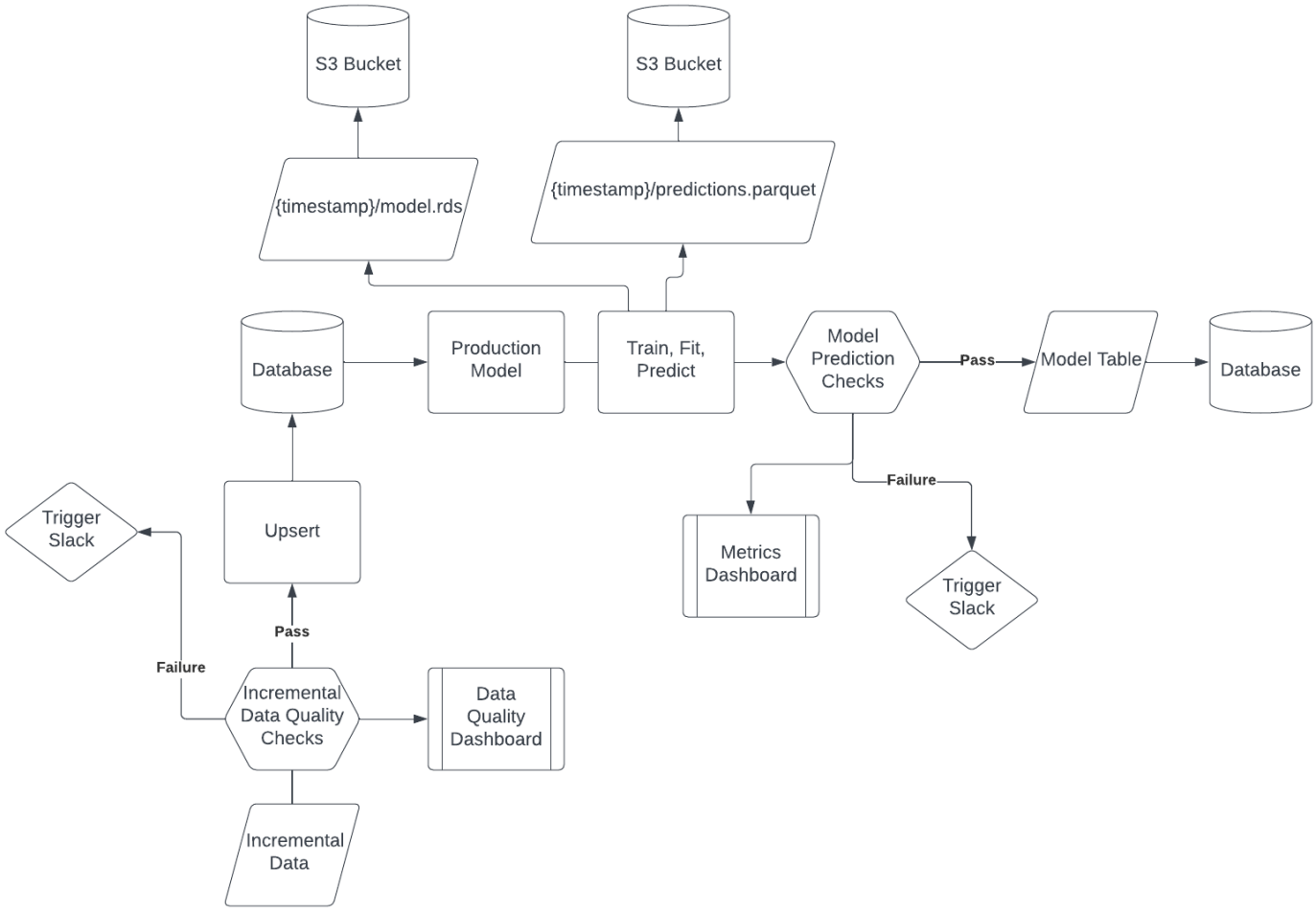


Figure 1: Model Monitoring Architecture

VIII. Conclusion (5 points)

Summarize your results here. What is the best model for the data and why?

Bibliography (7 points)

Please include all references, articles and papers in this section.

1. McGill University

- http://www.med.mcgill.ca/epidemiology/joseph/courses/EPIB-621/centered_var.pdf

2. Zip Code List in Washington https://www.ciclt.net/sn/clt/capitolimpact/gw_ziplist.aspx?zip=980&stfips=&state=wa&stname=washington
3. Anderson Darling Test

- https://www.rdocumentation.org/packages/nortest/versions/1.0-4/topics/ad.test

4. ggplot2

- https://cran.r-project.org/web/packages/ggplot2/ggplot2.pdf

5. CSCI E-106 Homework 7 Solutions

- Cloud/project/Homework Solutions/

6. dispRegFunc()

- Rafael Gomez

7. CSCI E-106 Homework 9 Solutions

- Cloud/project/Homework Solutions/

8. Kolmogorov-Smirnov Test

- https://www.rdocumentation.org/packages/dgof/versions/1.4/topics/ks.test
- https://en.wikipedia.org/wiki/Kolmogorov%E2%80%93Smirnov_test

Lastly, we would like to express our sincere appreciation for the instructors and teaching assistants of CSCI E-106 for sharing their knowledge and support for this project.

Appendix (3 points)

Please add any additional supporting graphs, plots and data analysis.