Final Exam

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YouTube Link:

Problem 1.

Using R, generate a random variable X that has 10,000 random uniform numbers from 1 to N, where N can be any number of your choosing greater than or equal to 6. Then generate a random variable Y that has 10,000 random normal numbers with a mean of $\mu = \sigma = \frac{(N+1)}{2}$.

Probability. Calculate as a minimum the below probabilities a through c. Assume the small letter "x" is estimated as the median of the X variable, and the small letter "y" is estimated as the 1st quartile of the Y variable. Interpret the meaning of all probabilities.

5 points a. P(X>x | X>y) b. P(X>x, Y>y) c. P(X<x | X>y)

5 points. Investigate whether P(X>x and Y>y)=P(X>x)P(Y>y) by building a table and evaluating the marginal and joint probabilities.

5 points. Check to see if independence holds by using Fisher's Exact Test and the Chi Square Test. What is the difference between the two? Which is most appropriate?

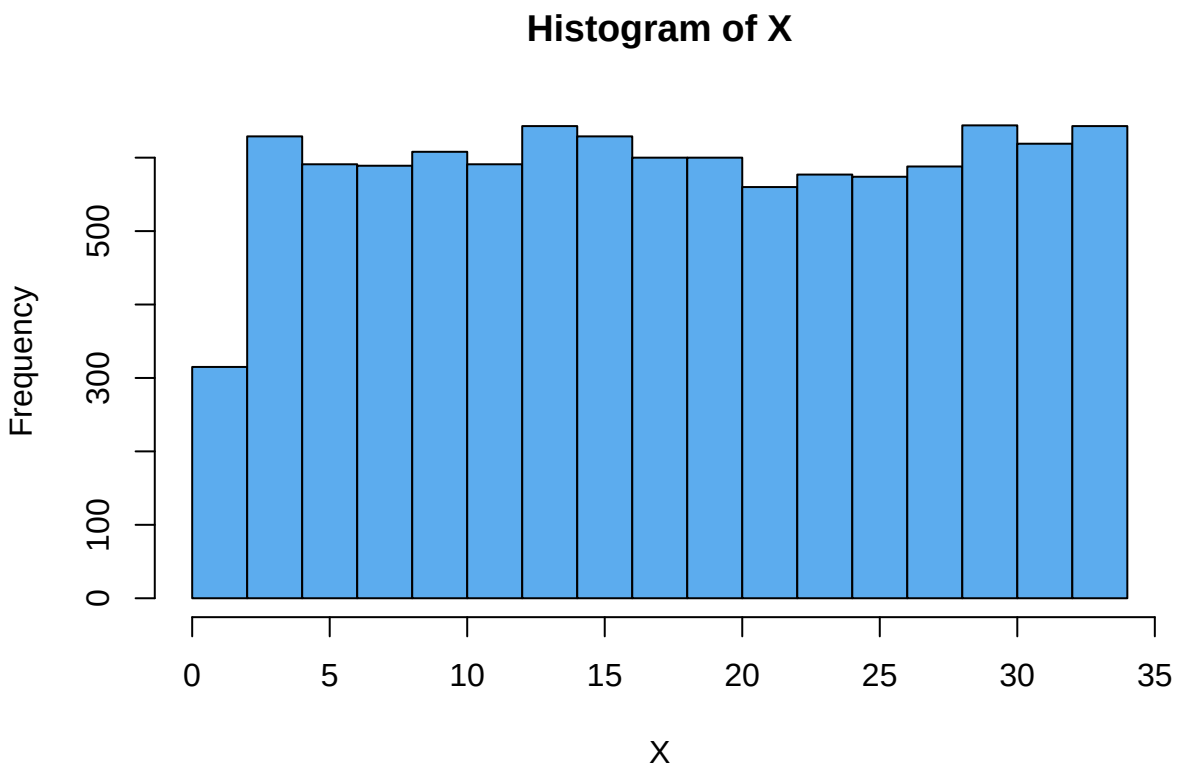
I. **Using R, generate a random variable X that has 10,000 random uniform numbers from 1 to N, where N can be any number of your choosing greater than or equal to 6. Then generate a random variable Y that has 10,000 random normal numbers with a mean of $\mu = \sigma = \frac{(N+1)}{2}$.**

Solution

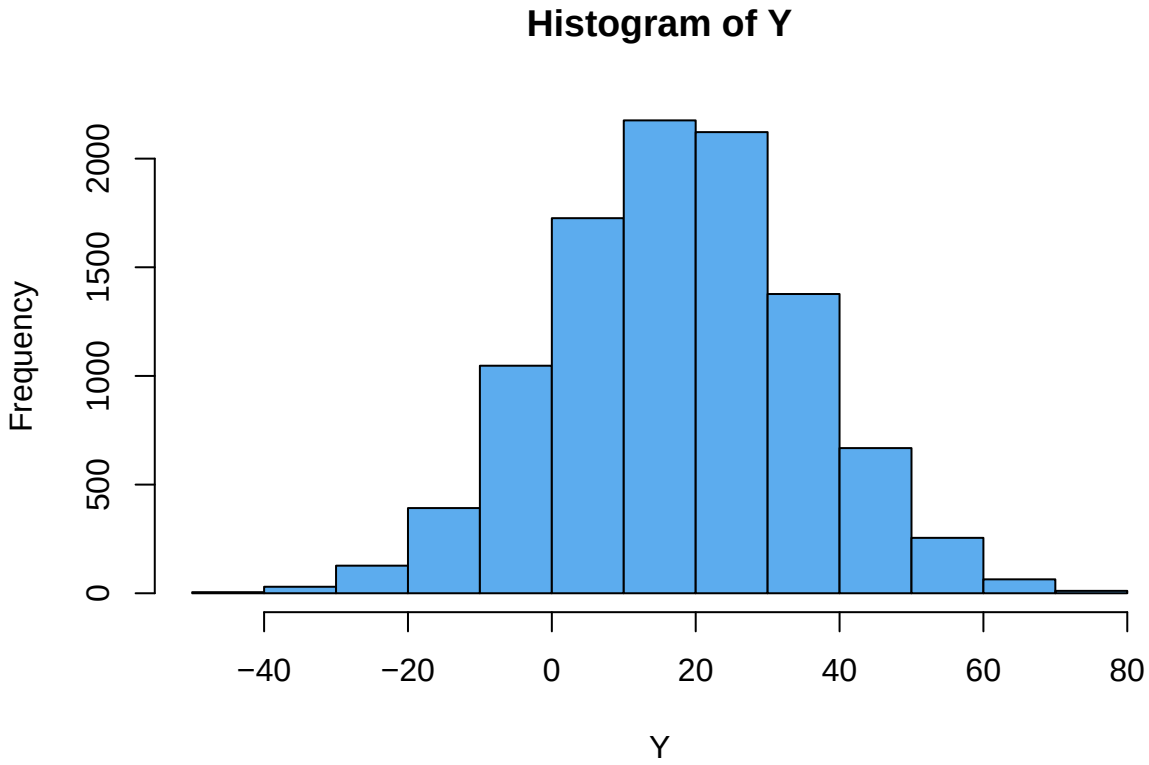
```
set.seed(1)
N <- round(runif(1, 10, 100))
mu <- (N+1)/2
sd <- (N+1)/2
X <- runif(10000,min=1,max=N)
summary(X)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.004   9.331  17.359  17.505  25.977  33.998
```

```
hist(X, col = "steelblue2")
```




```r
Y <- rnorm(10000,mean = mu,sd = sd)
hist(Y, col = "steelblue2")
```



```
summary(Y)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -44.017   5.652  17.684  17.572  29.359  79.942
```

Distribution of X showing almost uniform and distibution of Y showing mostly normal.

II. **Probability. Calculate as a minimum the below probabilities a through c. Assume the small letter "x" is estimated as the median of the X variable, and the small letter "y" is estimated as the 1st quartile of the Y variable.**

Solution

```
x<-median(X)
round(x,2)
```

```
## [1] 17.36
```

```
y<-quantile(Y,0.25)[[1]]
round(y,2)
```

```
## [1] 5.65
```

Interpret the meaning of all probabilities.

(*a*) **P(X>x | X>y)**

Solution

$$P(X > x|X > y) = \frac{P(X > x, X > y)}{P(X > y)}$$

```
Pxxandxy <- sum(X>x & X>y)/10000
Pxy <- sum(X>y)/10000
Pxx_xy <- Pxxandxy/Pxy
round(Pxx_xy,2)
```

```
## [1] 0.58
```

The probablity of a random number uniformly ranging from 1 to 34 being greater than 17.36 given that it is greater than 5.65 is 0.58

(*b*) **P(X>x, Y>y)**

Solution

```r
Pxxyy<-sum(X>x & Y>y)/10000
round(Pxxyy,2)
```

```
## [1] 0.38
```

The probablity of a random number uniformly ranging from 1 to 34 being greater than 17.36 and greater than 5.65 is 0.38

(*c*) **P(X<x | X>y)**

Solution

```r
Pxx_and_xy<-sum(X<x & X>y)/10000
round(Pxx_and_xy,2)
```

```
## [1] 0.36
```

The probablity of a random number uniformly ranging from 1 to 34 being less than 17.36 given that it is greater than 5.65 is 0.36

III. **Investigate whether P(X>x and Y>y)=P(X>x)P(Y>y) by building a table and evaluating the marginal and joint probabilities.**

Solution

```r
library(kableExtra)
Prob_X_x <- (length((X > x)[(X > x) == TRUE]))/(length((X > x)))
Prob_Y_y <- (length((Y > y)[(Y > y) == TRUE]))/(length((Y > y)))

X_x = c(Prob_X_x, Prob_Y_y, Prob_X_x*Prob_Y_y, Prob_X_x*Prob_Y_y)
Y_y = c(Prob_Y_y, Prob_X_x, Prob_X_x*Prob_Y_y, Prob_X_x*Prob_Y_y)

contingency_p <- as.data.frame(cbind(X_x, Y_y))
rownames(contingency_p) <-  c("(X>x)","(Y>y)","(X>x)*(Y>y)","(X>x and Y>y)")

kable(contingency_p) %>% kable_styling(bootstrap_options = c("striped", "hover", "condensed", "responsi
```

	X__x	Y__y
(X>x)	0.500	0.750
(Y>y)	0.750	0.500
(X>x)*(Y>y)	0.375	0.375
(X>x and Y>y)	0.375	0.375

Above table shows, P(X>x and Y>y) and P(X>x)P(Y>y) are equal.

IV. **Check to see if independence holds by using Fisher's Exact Test and the Chi Square Test. What is the difference between the two? Which is most appropriate?**

Solution

We will use above created conitingency table to perform these 2 tests - Ficher's and Chi Square test.

Null Hypothesis, H_0: X>x and Y>y are independent events

Alternate Hypothesis, H_A: Both of these are dependent events

```
fisher.test(contingency_p)
```

```
##
##  Fisher's Exact Test for Count Data
##
## data:  contingency_p
## p-value = 1
## alternative hypothesis: two.sided
```

```
chisq.test(contingency_p)
```

```
##
##  Pearson's Chi-squared test
##
## data:  contingency_p
## X-squared = 0.1, df = 3, p-value = 0.9918
```

Both test showing high p-value so, we cannot reject null hyposthesis that X>x and Y>y are independent events.

Problem 2

You are to register for Kaggle.com (free) and compete in the House Prices: Advanced Regression Techniques competition. https://www.kaggle.com/c/house-prices-advanced-regression-techniques **. I want you to do the following.**

Descriptive and Inferential Statistics. Provide univariate descriptive statistics and appropriate plots for the training data set. Provide a scatterplot matrix for at least two of the independent variables and the dependent variable. Derive a correlation matrix for any three quantitative variables in the dataset. Test the hypotheses that the correlations between each pairwise set of variables is 0 and provide an 80% confidence interval. Discuss the meaning of your analysis. Would you be worried about familywise error? Why or why not?

Linear Algebra and Correlation. Invert your correlation matrix from above. (This is known as the precision matrix and contains variance inflation factors on the diagonal.) Multiply the correlation matrix by the precision matrix, and then multiply the precision matrix by the correlation matrix. Conduct LU decomposition on the matrix.

Calculus-Based Probability & Statistics. Many times, it makes sense to fit a closed form distribution to data. Select a variable in the Kaggle.com training dataset that is skewed to the right, shift it so that the minimum value is absolutely above zero if necessary. Then load the MASS package and run fitdistr to fit

an exponential probability density function. (See https://stat.ethz.ch/R-manual/R-devel/library/MASS/html/fitdistr.html). Find the optimal value of λ for this distribution, and then take 1000 samples from this exponential distribution using this value (e.g., rexp(1000, λ)). Plot a histogram and compare it with a histogram of your original variable. Using the exponential pdf, find the 5th and 95th percentiles using the cumulative distribution function (CDF). Also generate a 95% confidence interval from the empirical data, assuming normality. Finally, provide the empirical 5th percentile and 95th percentile of the data. Discuss.

Modeling. Build some type of multiple regression model and submit your model to the competition board. Provide your complete model summary and results with analysis. Report your Kaggle.com user name and score.

Solution

Download train and test csv file from kaggle and load these in R. The goal of this analysis is predict SalesPrice. We will do below steps.

- Load data and perform EDA (Exploratory Data Analysis)
  - Descriptive and Inferential Statistics
  - Linear Algebra and Correlation
  - Calculus-Based Probability & Statistics
- Clean data
- Build Models
- Select best model to predict salesprice on test dataset

Data Load and EDA Load all necessary libraries.

```
library(ggplot2)
library(kableExtra)
library(visdat)
library(corrplot)
library(MASS)
library(purrr)
```

Train dataset consists of 1460 obsevations and 81 features. Test dataset consists of 1459 obsevations and 80 features.

```
train <-
  read.csv("https://raw.githubusercontent.com/SubhalaxmiRout002/DATA-605/master/Final%20Project/train.cs
dim(train)
```

```
## [1] 1460   81
```

```
test <-
  read.csv("https://raw.githubusercontent.com/SubhalaxmiRout002/DATA-605/master/Final%20Project/test.csv
dim(test)
```

```
## [1] 1459   80
```

```
str(train)
```

```
## 'data.frame':    1460 obs. of  81 variables:
##  $ Id           : int  1 2 3 4 5 6 7 8 9 10 ...
##  $ MSSubClass   : int  60 20 60 70 60 50 20 60 50 190 ...
##  $ MSZoning     : chr  "RL" "RL" "RL" "RL" ...
##  $ LotFrontage  : int  65 80 68 60 84 85 75 NA 51 50 ...
##  $ LotArea      : int  8450 9600 11250 9550 14260 14115 10084 10382 6120 7420 ...
##  $ Street       : chr  "Pave" "Pave" "Pave" "Pave" ...
##  $ Alley        : chr  NA NA NA NA ...
##  $ LotShape     : chr  "Reg" "Reg" "IR1" "IR1" ...
##  $ LandContour  : chr  "Lvl" "Lvl" "Lvl" "Lvl" ...
##  $ Utilities    : chr  "AllPub" "AllPub" "AllPub" "AllPub" ...
##  $ LotConfig    : chr  "Inside" "FR2" "Inside" "Corner" ...
##  $ LandSlope    : chr  "Gtl" "Gtl" "Gtl" "Gtl" ...
##  $ Neighborhood : chr  "CollgCr" "Veenker" "CollgCr" "Crawfor" ...
##  $ Condition1   : chr  "Norm" "Feedr" "Norm" "Norm" ...
##  $ Condition2   : chr  "Norm" "Norm" "Norm" "Norm" ...
##  $ BldgType     : chr  "1Fam" "1Fam" "1Fam" "1Fam" ...
##  $ HouseStyle   : chr  "2Story" "1Story" "2Story" "2Story" ...
##  $ OverallQual  : int  7 6 7 7 8 5 8 7 7 5 ...
##  $ OverallCond  : int  5 8 5 5 5 5 5 6 5 6 ...
##  $ YearBuilt    : int  2003 1976 2001 1915 2000 1993 2004 1973 1931 1939 ...
##  $ YearRemodAdd : int  2003 1976 2002 1970 2000 1995 2005 1973 1950 1950 ...
##  $ RoofStyle    : chr  "Gable" "Gable" "Gable" "Gable" ...
##  $ RoofMatl     : chr  "CompShg" "CompShg" "CompShg" "CompShg" ...
##  $ Exterior1st  : chr  "VinylSd" "MetalSd" "VinylSd" "Wd Sdng" ...
##  $ Exterior2nd  : chr  "VinylSd" "MetalSd" "VinylSd" "Wd Shng" ...
##  $ MasVnrType   : chr  "BrkFace" "None" "BrkFace" "None" ...
##  $ MasVnrArea   : int  196 0 162 0 350 0 186 240 0 0 ...
##  $ ExterQual    : chr  "Gd" "TA" "Gd" "TA" ...
##  $ ExterCond    : chr  "TA" "TA" "TA" "TA" ...
##  $ Foundation   : chr  "PConc" "CBlock" "PConc" "BrkTil" ...
##  $ BsmtQual     : chr  "Gd" "Gd" "Gd" "TA" ...
##  $ BsmtCond     : chr  "TA" "TA" "TA" "Gd" ...
##  $ BsmtExposure : chr  "No" "Gd" "Mn" "No" ...
##  $ BsmtFinType1 : chr  "GLQ" "ALQ" "GLQ" "ALQ" ...
##  $ BsmtFinSF1   : int  706 978 486 216 655 732 1369 859 0 851 ...
##  $ BsmtFinType2 : chr  "Unf" "Unf" "Unf" "Unf" ...
##  $ BsmtFinSF2   : int  0 0 0 0 0 0 0 32 0 0 ...
##  $ BsmtUnfSF    : int  150 284 434 540 490 64 317 216 952 140 ...
##  $ TotalBsmtSF  : int  856 1262 920 756 1145 796 1686 1107 952 991 ...
##  $ Heating      : chr  "GasA" "GasA" "GasA" "GasA" ...
##  $ HeatingQC    : chr  "Ex" "Ex" "Ex" "Gd" ...
##  $ CentralAir   : chr  "Y" "Y" "Y" "Y" ...
##  $ Electrical   : chr  "SBrkr" "SBrkr" "SBrkr" "SBrkr" ...
##  $ X1stFlrSF    : int  856 1262 920 961 1145 796 1694 1107 1022 1077 ...
##  $ X2ndFlrSF    : int  854 0 866 756 1053 566 0 983 752 0 ...
##  $ LowQualFinSF : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ GrLivArea    : int  1710 1262 1786 1717 2198 1362 1694 2090 1774 1077 ...
##  $ BsmtFullBath : int  1 0 1 1 1 1 1 1 0 1 ...
##  $ BsmtHalfBath : int  0 1 0 0 0 0 0 0 0 0 ...
##  $ FullBath     : int  2 2 2 1 2 1 2 2 2 1 ...
```

```
##  $ HalfBath     : int  1 0 1 0 1 1 0 1 0 0 ...
##  $ BedroomAbvGr : int  3 3 3 3 4 1 3 3 2 2 ...
##  $ KitchenAbvGr : int  1 1 1 1 1 1 1 1 2 2 ...
##  $ KitchenQual  : chr  "Gd" "TA" "Gd" "Gd" ...
##  $ TotRmsAbvGrd : int  8 6 6 7 9 5 7 7 8 5 ...
##  $ Functional   : chr  "Typ" "Typ" "Typ" "Typ" ...
##  $ Fireplaces   : int  0 1 1 1 1 0 1 2 2 2 ...
##  $ FireplaceQu  : chr  NA "TA" "TA" "Gd" ...
##  $ GarageType   : chr  "Attchd" "Attchd" "Attchd" "Detchd" ...
##  $ GarageYrBlt  : int  2003 1976 2001 1998 2000 1993 2004 1973 1931 1939 ...
##  $ GarageFinish : chr  "RFn" "RFn" "RFn" "Unf" ...
##  $ GarageCars   : int  2 2 2 3 3 2 2 2 2 1 ...
##  $ GarageArea   : int  548 460 608 642 836 480 636 484 468 205 ...
##  $ GarageQual   : chr  "TA" "TA" "TA" "TA" ...
##  $ GarageCond   : chr  "TA" "TA" "TA" "TA" ...
##  $ PavedDrive   : chr  "Y" "Y" "Y" "Y" ...
##  $ WoodDeckSF   : int  0 298 0 0 192 40 255 235 90 0 ...
##  $ OpenPorchSF  : int  61 0 42 35 84 30 57 204 0 4 ...
##  $ EnclosedPorch: int  0 0 0 272 0 0 0 228 205 0 ...
##  $ X3SsnPorch   : int  0 0 0 0 0 320 0 0 0 0 ...
##  $ ScreenPorch  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ PoolArea     : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ PoolQC       : chr  NA NA NA NA ...
##  $ Fence        : chr  NA NA NA NA ...
##  $ MiscFeature  : chr  NA NA NA NA ...
##  $ MiscVal      : int  0 0 0 0 0 700 0 350 0 0 ...
##  $ MoSold       : int  2 5 9 2 12 10 8 11 4 1 ...
##  $ YrSold       : int  2008 2007 2008 2006 2008 2009 2007 2009 2008 2008 ...
##  $ SaleType     : chr  "WD" "WD" "WD" "WD" ...
##  $ SaleCondition: chr  "Normal" "Normal" "Normal" "Abnorml" ...
##  $ SalePrice    : int  208500 181500 223500 140000 250000 143000 307000 200000 129900 118000 ...
```

```
summary(train)
```

Descriptive and Inferential Statistics

```
##        Id           MSSubClass      MSZoning          LotFrontage
##  Min.   :   1.0   Min.   : 20.0   Length:1460        Min.   : 21.00
##  1st Qu.: 365.8   1st Qu.: 20.0   Class :character   1st Qu.: 59.00
##  Median : 730.5   Median : 50.0   Mode  :character   Median : 69.00
##  Mean   : 730.5   Mean   : 56.9                      Mean   : 70.05
##  3rd Qu.:1095.2   3rd Qu.: 70.0                      3rd Qu.: 80.00
##  Max.   :1460.0   Max.   :190.0                      Max.   :313.00
##                                                      NA's   :259
##     LotArea          Street             Alley             LotShape
##  Min.   :  1300   Length:1460        Length:1460        Length:1460
##  1st Qu.:  7554   Class :character   Class :character   Class :character
##  Median :  9478   Mode  :character   Mode  :character   Mode  :character
##  Mean   : 10517
##  3rd Qu.: 11602
##  Max.   :215245
```

```
##
##  LandContour         Utilities          LotConfig          LandSlope
##  Length:1460        Length:1460        Length:1460        Length:1460
##  Class :character   Class :character   Class :character   Class :character
##  Mode  :character   Mode  :character   Mode  :character   Mode  :character
##
##
##
##
##  Neighborhood        Condition1         Condition2          BldgType
##  Length:1460        Length:1460        Length:1460        Length:1460
##  Class :character   Class :character   Class :character   Class :character
##  Mode  :character   Mode  :character   Mode  :character   Mode  :character
##
##
##
##
##   HouseStyle         OverallQual      OverallCond      YearBuilt
##  Length:1460        Min.   : 1.000   Min.   :1.000   Min.   :1872
##  Class :character   1st Qu.: 5.000   1st Qu.:5.000   1st Qu.:1954
##  Mode  :character   Median : 6.000   Median :5.000   Median :1973
##                     Mean   : 6.099   Mean   :5.575   Mean   :1971
##                     3rd Qu.: 7.000   3rd Qu.:6.000   3rd Qu.:2000
##                     Max.   :10.000   Max.   :9.000   Max.   :2010
##
##   YearRemodAdd   RoofStyle           RoofMatl         Exterior1st
##  Min.   :1950   Length:1460        Length:1460        Length:1460
##  1st Qu.:1967   Class :character   Class :character   Class :character
##  Median :1994   Mode  :character   Mode  :character   Mode  :character
##  Mean   :1985
##  3rd Qu.:2004
##  Max.   :2010
##
##  Exterior2nd         MasVnrType          MasVnrArea      ExterQual
##  Length:1460        Length:1460        Min.   :   0.0   Length:1460
##  Class :character   Class :character   1st Qu.:   0.0   Class :character
##  Mode  :character   Mode  :character   Median :   0.0   Mode  :character
##                                        Mean   : 103.7
##                                        3rd Qu.: 166.0
##                                        Max.   :1600.0
##                                        NA's   :8
##   ExterCond          Foundation          BsmtQual           BsmtCond
##  Length:1460        Length:1460        Length:1460        Length:1460
##  Class :character   Class :character   Class :character   Class :character
##  Mode  :character   Mode  :character   Mode  :character   Mode  :character
##
##
##
##
##  BsmtExposure       BsmtFinType1         BsmtFinSF1     BsmtFinType2
##  Length:1460        Length:1460        Min.   :   0.0   Length:1460
##  Class :character   Class :character   1st Qu.:   0.0   Class :character
##  Mode  :character   Mode  :character   Median : 383.5   Mode  :character
##                                        Mean   : 443.6
```

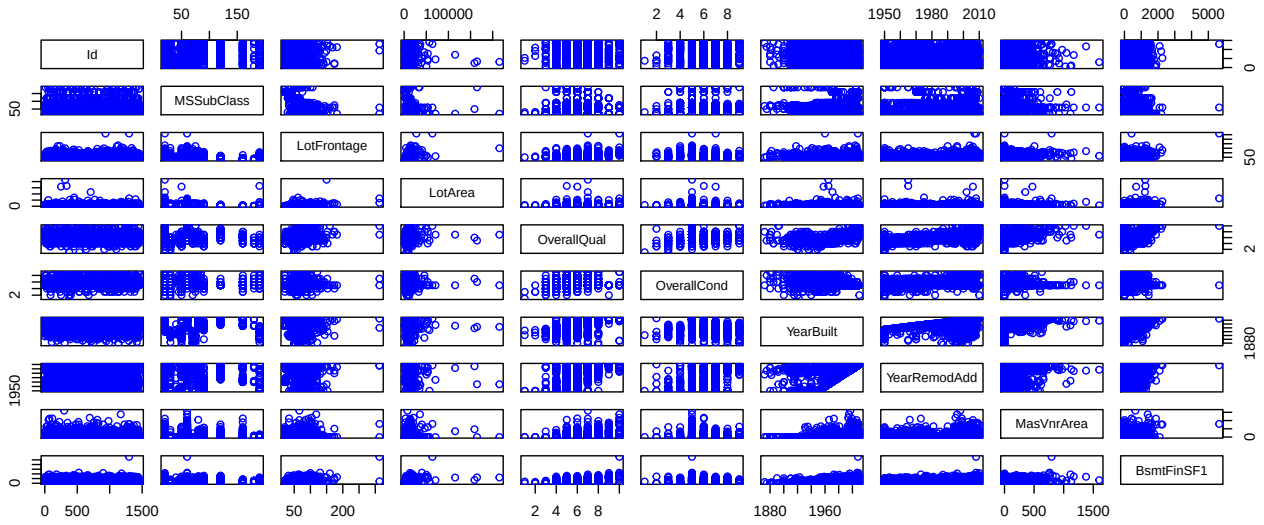
```
##                                      3rd Qu.: 712.2
##                                      Max.   :5644.0
##
##    BsmtFinSF2        BsmtUnfSF       TotalBsmtSF       Heating
##  Min.   :   0.00   Min.   :   0.0   Min.   :   0.0   Length:1460
##  1st Qu.:   0.00   1st Qu.: 223.0   1st Qu.: 795.8   Class :character
##  Median :   0.00   Median : 477.5   Median : 991.5   Mode  :character
##  Mean   :  46.55   Mean   : 567.2   Mean   :1057.4
##  3rd Qu.:   0.00   3rd Qu.: 808.0   3rd Qu.:1298.2
##  Max.   :1474.00   Max.   :2336.0   Max.   :6110.0
##
##   HeatingQC          CentralAir         Electrical          X1stFlrSF
##  Length:1460        Length:1460        Length:1460        Min.   : 334
##  Class :character   Class :character   Class :character   1st Qu.: 882
##  Mode  :character   Mode  :character   Mode  :character   Median :1087
##                                                           Mean   :1163
##                                                           3rd Qu.:1391
##                                                           Max.   :4692
##
##    X2ndFlrSF     LowQualFinSF       GrLivArea     BsmtFullBath
##  Min.   :   0   Min.   :  0.000   Min.   : 334   Min.   :0.0000
##  1st Qu.:   0   1st Qu.:  0.000   1st Qu.:1130   1st Qu.:0.0000
##  Median :   0   Median :  0.000   Median :1464   Median :0.0000
##  Mean   : 347   Mean   :  5.845   Mean   :1515   Mean   :0.4253
##  3rd Qu.: 728   3rd Qu.:  0.000   3rd Qu.:1777   3rd Qu.:1.0000
##  Max.   :2065   Max.   :572.000   Max.   :5642   Max.   :3.0000
##
##   BsmtHalfBath        FullBath        HalfBath       BedroomAbvGr
##  Min.   :0.00000   Min.   :0.000   Min.   :0.0000   Min.   :0.000
##  1st Qu.:0.00000   1st Qu.:1.000   1st Qu.:0.0000   1st Qu.:2.000
##  Median :0.00000   Median :2.000   Median :0.0000   Median :3.000
##  Mean   :0.05753   Mean   :1.565   Mean   :0.3829   Mean   :2.866
##  3rd Qu.:0.00000   3rd Qu.:2.000   3rd Qu.:1.0000   3rd Qu.:3.000
##  Max.   :2.00000   Max.   :3.000   Max.   :2.0000   Max.   :8.000
##
##   KitchenAbvGr   KitchenQual         TotRmsAbvGrd     Functional
##  Min.   :0.000   Length:1460        Min.   : 2.000   Length:1460
##  1st Qu.:1.000   Class :character   1st Qu.: 5.000   Class :character
##  Median :1.000   Mode  :character   Median : 6.000   Mode  :character
##  Mean   :1.047                      Mean   : 6.518
##  3rd Qu.:1.000                      3rd Qu.: 7.000
##  Max.   :3.000                      Max.   :14.000
##
##    Fireplaces    FireplaceQu         GarageType         GarageYrBlt
##  Min.   :0.000   Length:1460        Length:1460        Min.   :1900
##  1st Qu.:0.000   Class :character   Class :character   1st Qu.:1961
##  Median :1.000   Mode  :character   Mode  :character   Median :1980
##  Mean   :0.613                                         Mean   :1979
##  3rd Qu.:1.000                                         3rd Qu.:2002
##  Max.   :3.000                                         Max.   :2010
##                                                        NA's   :81
##  GarageFinish         GarageCars      GarageArea      GarageQual
##  Length:1460        Min.   :0.000   Min.   :   0.0   Length:1460
##  Class :character   1st Qu.:1.000   1st Qu.: 334.5   Class :character
```

```
##  Mode  :character   Median :2.000   Median : 480.0   Mode  :character
##                     Mean   :1.767   Mean   : 473.0
##                     3rd Qu.:2.000   3rd Qu.: 576.0
##                     Max.   :4.000   Max.   :1418.0
##
##   GarageCond         PavedDrive          WoodDeckSF      OpenPorchSF
##  Length:1460        Length:1460        Min.   :  0.00   Min.   :  0.00
##  Class :character   Class :character   1st Qu.:  0.00   1st Qu.:  0.00
##  Mode  :character   Mode  :character   Median :  0.00   Median : 25.00
##                                        Mean   : 94.24   Mean   : 46.66
##                                        3rd Qu.:168.00   3rd Qu.: 68.00
##                                        Max.   :857.00   Max.   :547.00
##
##  EnclosedPorch      X3SsnPorch      ScreenPorch        PoolArea
##  Min.   :  0.00   Min.   :  0.00   Min.   :  0.00   Min.   :  0.000
##  1st Qu.:  0.00   1st Qu.:  0.00   1st Qu.:  0.00   1st Qu.:  0.000
##  Median :  0.00   Median :  0.00   Median :  0.00   Median :  0.000
##  Mean   : 21.95   Mean   :  3.41   Mean   : 15.06   Mean   :  2.759
##  3rd Qu.:  0.00   3rd Qu.:  0.00   3rd Qu.:  0.00   3rd Qu.:  0.000
##  Max.   :552.00   Max.   :508.00   Max.   :480.00   Max.   :738.000
##
##     PoolQC             Fence           MiscFeature           MiscVal
##  Length:1460        Length:1460        Length:1460        Min.   :    0.00
##  Class :character   Class :character   Class :character   1st Qu.:    0.00
##  Mode  :character   Mode  :character   Mode  :character   Median :    0.00
##                                                           Mean   :   43.49
##                                                           3rd Qu.:    0.00
##                                                           Max.   :15500.00
##
##      MoSold           YrSold       SaleType         SaleCondition
##  Min.   : 1.000   Min.   :2006   Length:1460        Length:1460
##  1st Qu.: 5.000   1st Qu.:2007   Class :character   Class :character
##  Median : 6.000   Median :2008   Mode  :character   Mode  :character
##  Mean   : 6.322   Mean   :2008
##  3rd Qu.: 8.000   3rd Qu.:2009
##  Max.   :12.000   Max.   :2010
##
##    SalePrice
##  Min.   : 34900
##  1st Qu.:129975
##  Median :163000
##  Mean   :180921
##  3rd Qu.:214000
##  Max.   :755000
##
```

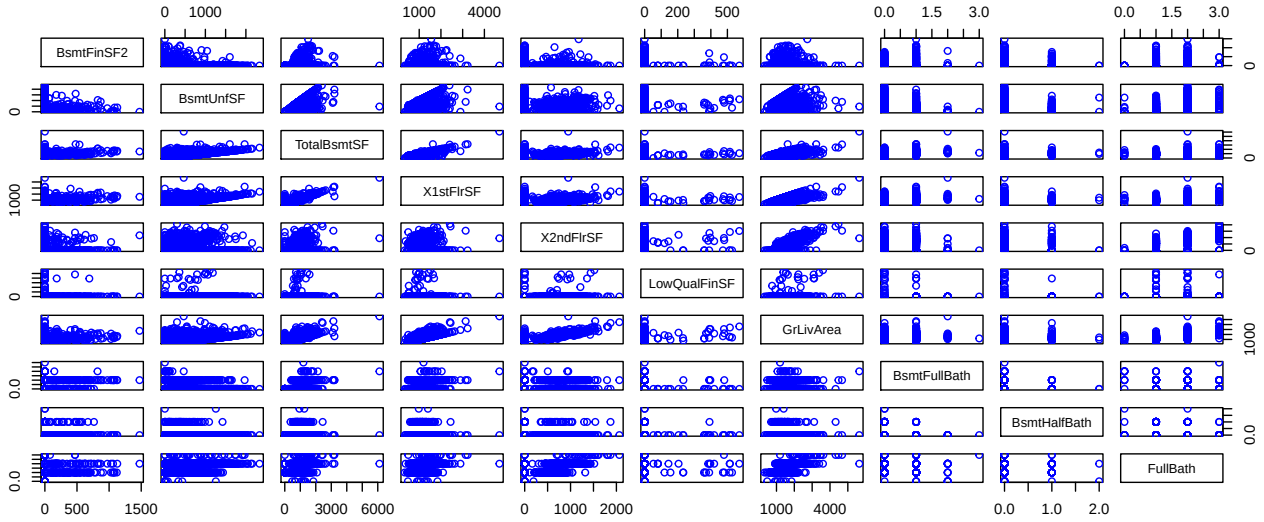
Provide univariate descriptive statistics and appropriate plots for the training data set.

Pairplot shows the relationship between variables.

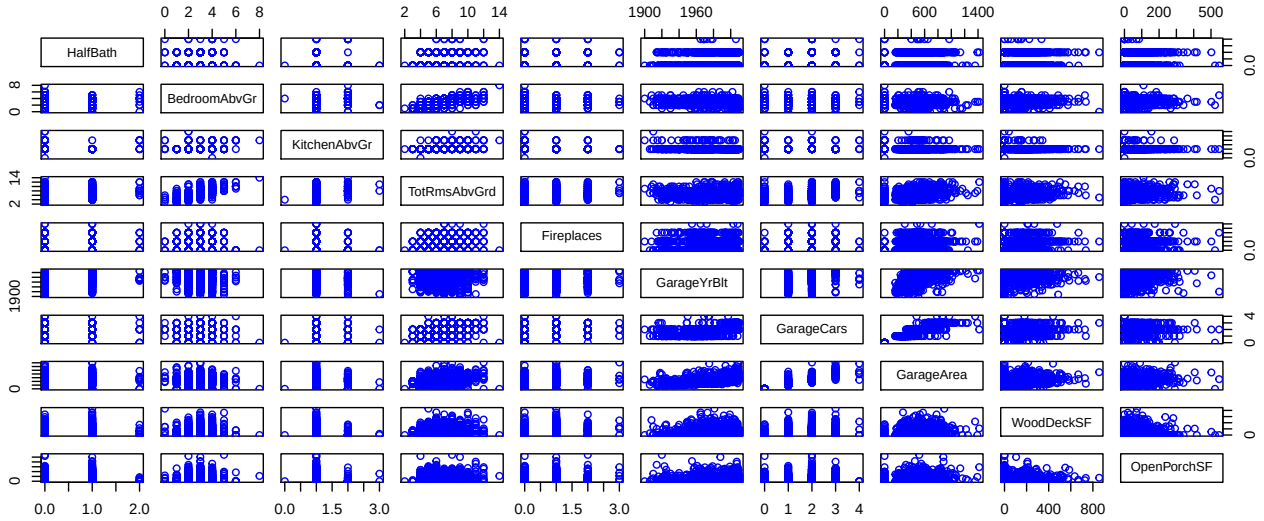
```
train_2 <- dplyr::select_if(train, is.numeric) %>% keep(is.numeric)

plot(train_2[1:10], col="blue")
```



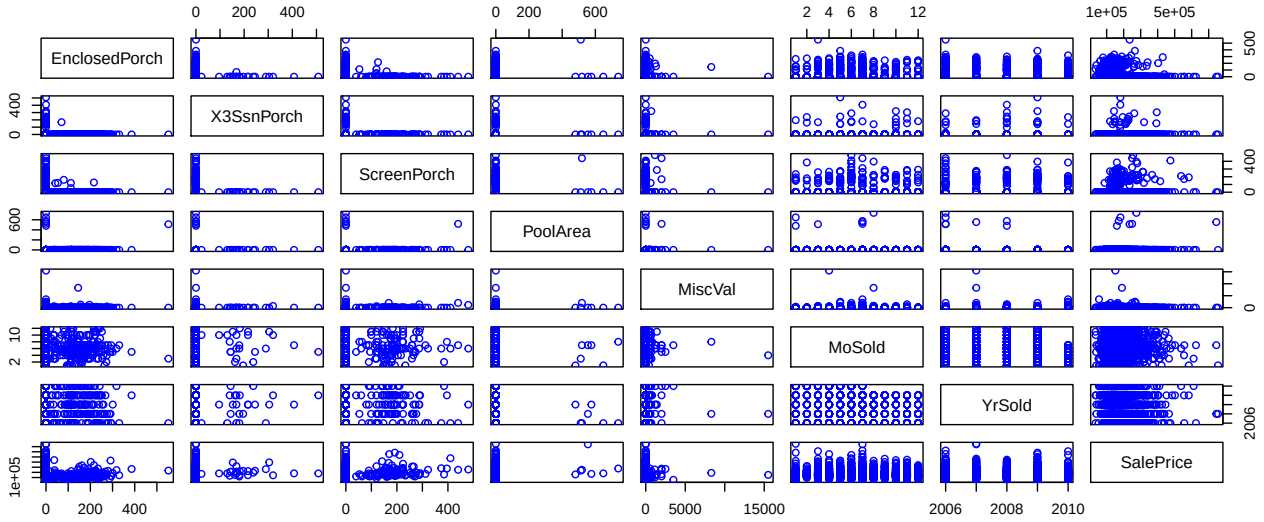

```
plot(train_2[11:20], col="blue")
```




```
plot(train_2[21:30], col="blue")
```

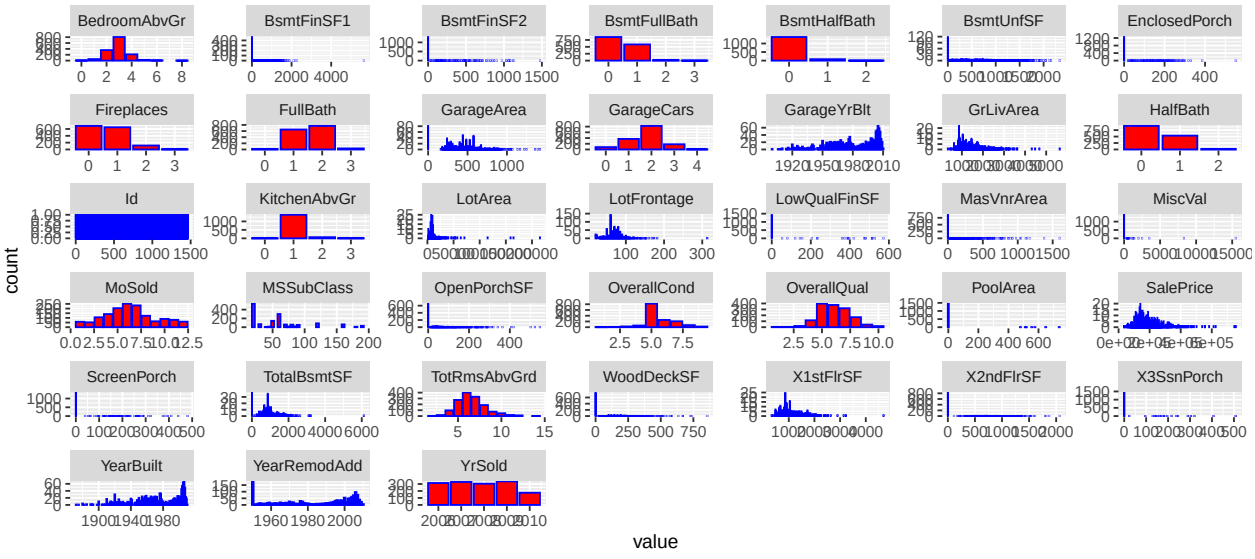



```
plot(train_2[31:38], col="blue")
```



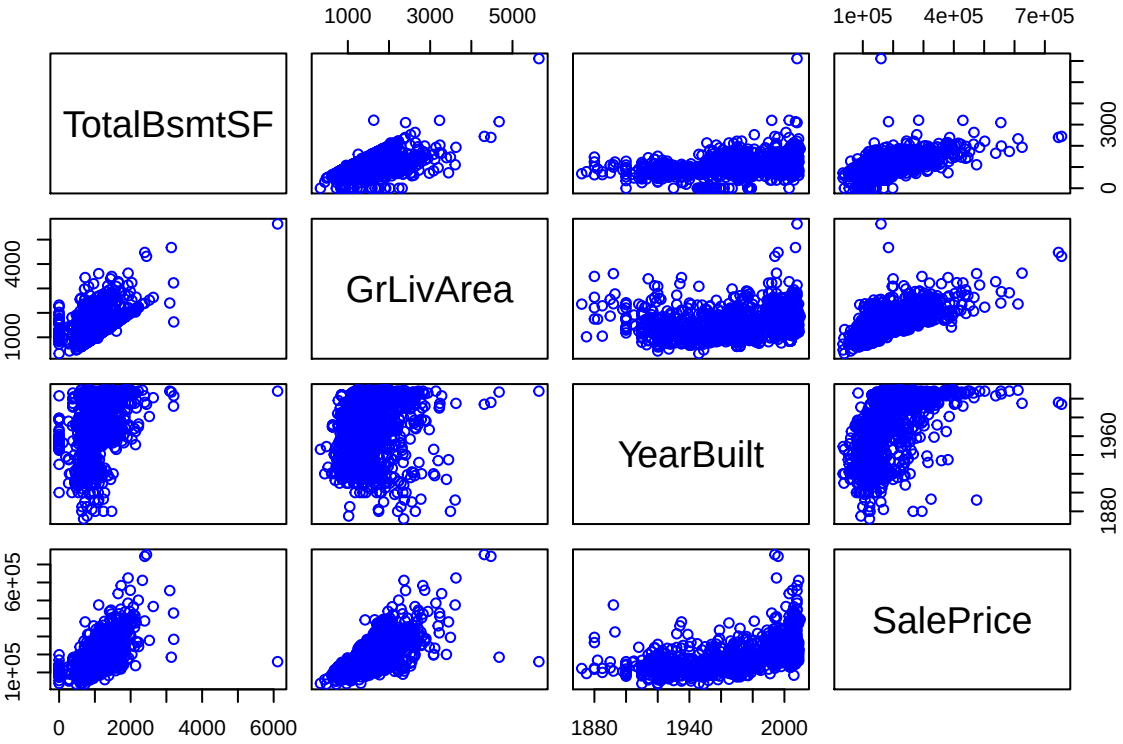
Below plot shows the distribution of data.

```
ggplot(dplyr::select_if(train, is.numeric) %>% keep(is.numeric) %>% tidyr::gather() , aes(value)) +
    facet_wrap(~ key, scales = "free") +
    geom_bar(color = "blue", fill = "red")
```



Provide a scatterplot matrix for at least two of the independent variables and the dependent variable.

```
plot(train %>%
  dplyr::select(TotalBsmtSF, GrLivArea, YearBuilt, SalePrice), col="blue")
```



Derive a correlation matrix for any three quantitative variables in the dataset.

```
correlation_matrix <- train %>%
  dplyr::select(TotalBsmtSF, GrLivArea, YearBuilt) %>%
  cor() %>%
```

```
  as.matrix()

kable(correlation_matrix) %>% kable_styling(bootstrap_options = c("striped", "hover", "condensed", "resp
```

	TotalBsmtSF	GrLivArea	YearBuilt
TotalBsmtSF	1.0000000	0.4548682	0.3914520
GrLivArea	0.4548682	1.0000000	0.1990097
YearBuilt	0.3914520	0.1990097	1.0000000

Test the hypothesis that the correlations between each pairwise set of variables is 0 and provide an 80% confidence interval.

```
cor.test(train$TotalBsmtSF, train$SalePrice, method = "pearson", conf.level = 0.8)
```

```
##
##  Pearson's product-moment correlation
##
## data:  train$TotalBsmtSF and train$SalePrice
## t = 29.671, df = 1458, p-value < 2.2e-16
## alternative hypothesis: true correlation is not equal to 0
## 80 percent confidence interval:
##  0.5922142 0.6340846
## sample estimates:
##       cor
## 0.6135806
```

```
cor.test(train$GrLivArea, train$SalePrice, method = "pearson", conf.level = 0.8)
```

```
##
##  Pearson's product-moment correlation
##
## data:  train$GrLivArea and train$SalePrice
## t = 38.348, df = 1458, p-value < 2.2e-16
## alternative hypothesis: true correlation is not equal to 0
## 80 percent confidence interval:
##  0.6915087 0.7249450
## sample estimates:
##       cor
## 0.7086245
```

```
cor.test(train$YearBuilt, train$SalePrice, method = "pearson", conf.level = 0.8)
```

```
##
##  Pearson's product-moment correlation
##
## data:  train$YearBuilt and train$SalePrice
```

```
## t = 23.424, df = 1458, p-value < 2.2e-16
## alternative hypothesis: true correlation is not equal to 0
## 80 percent confidence interval:
##  0.4980766 0.5468619
## sample estimates:
##       cor
## 0.5228973
```

The p-values for all three variables are less than 0.05 and the correlation coefficient between TotalBsmtSF, GrLivArea, YearBuilt with respect to SalePrice is 0.6135806, 0.7086245 , 0.5228973 respectively. The correlation falls within the 80% CI.

Would you be worried about familywise error? Why or why not?

Familywise error:

The familywise error rate is the probability of a coming to at least one false conclusion in a series of hypothesis tests. Familywise error is that of making at least one "type I error", or a false positive, rejection of a true null.

In our above 3 cases, the P value is extremely small (is less than 0.05) and rejects null hypothesis. So, I would not be worried about committing a type I error.

Linear Algebra and Correlation

Invert your correlation matrix from above. (This is known as the precision matrix and contains variance inflation factors on the diagonal.)

```
library(pracma)

precision_matrix <- pracma::inv(correlation_matrix)
kable(precision_matrix) %>% kable_styling(bootstrap_options = c("striped", "hover", "condensed", "respo
```

	TotalBsmtSF	GrLivArea	YearBuilt
TotalBsmtSF	1.4310199	-0.5616907	-0.4483937
GrLivArea	-0.5616907	1.2617078	-0.0312171
YearBuilt	-0.4483937	-0.0312171	1.1817371

Multiply the correlation matrix by the precision matrix, and then multiply the precision matrix by the correlation matrix.

```
kable(round(correlation_matrix %*% precision_matrix)) %>% kable_styling(bootstrap_options = c("striped"
```

	TotalBsmtSF	GrLivArea	YearBuilt
TotalBsmtSF	1	0	0
GrLivArea	0	1	0
YearBuilt	0	0	1

```
kable(round(precision_matrix %*% correlation_matrix)) %>% kable_styling(bootstrap_options = c("striped"
```

	TotalBsmtSF	GrLivArea	YearBuilt
TotalBsmtSF	1	0	0
GrLivArea	0	1	0
YearBuilt	0	0	1

Conduct LU decomposition on the matrix.

Below find out L and U matrix, and as per the LU decomposition, LU = A Here A is the correlation matrix we created above. So, if we multiply L and U above, it should give correlation matrix.

```
correlation_L <- lu(correlation_matrix)$L
correlation_U <- lu(correlation_matrix)$U

kable(correlation_L %*% correlation_U) %>%
  kable_styling(bootstrap_options =
                  c("striped", "hover", "condensed", "responsive"),
                latex_options="scale_down")
```

	TotalBsmtSF	GrLivArea	YearBuilt
TotalBsmtSF	1.0000000	0.4548682	0.3914520
GrLivArea	0.4548682	1.0000000	0.1990097
YearBuilt	0.3914520	0.1990097	1.0000000

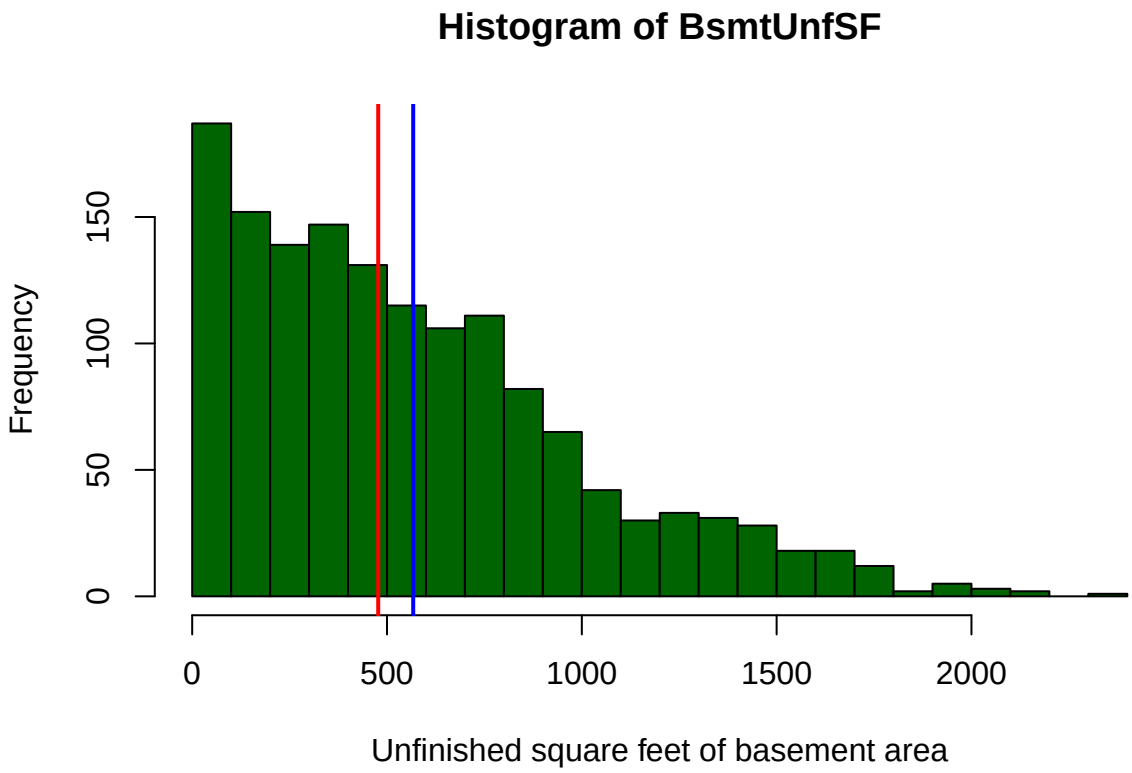
```
correlation_matrix == correlation_L %*% correlation_U
```

```
##             TotalBsmtSF GrLivArea YearBuilt
## TotalBsmtSF        TRUE      TRUE      TRUE
## GrLivArea          TRUE      TRUE      TRUE
## YearBuilt          TRUE      TRUE      TRUE
```

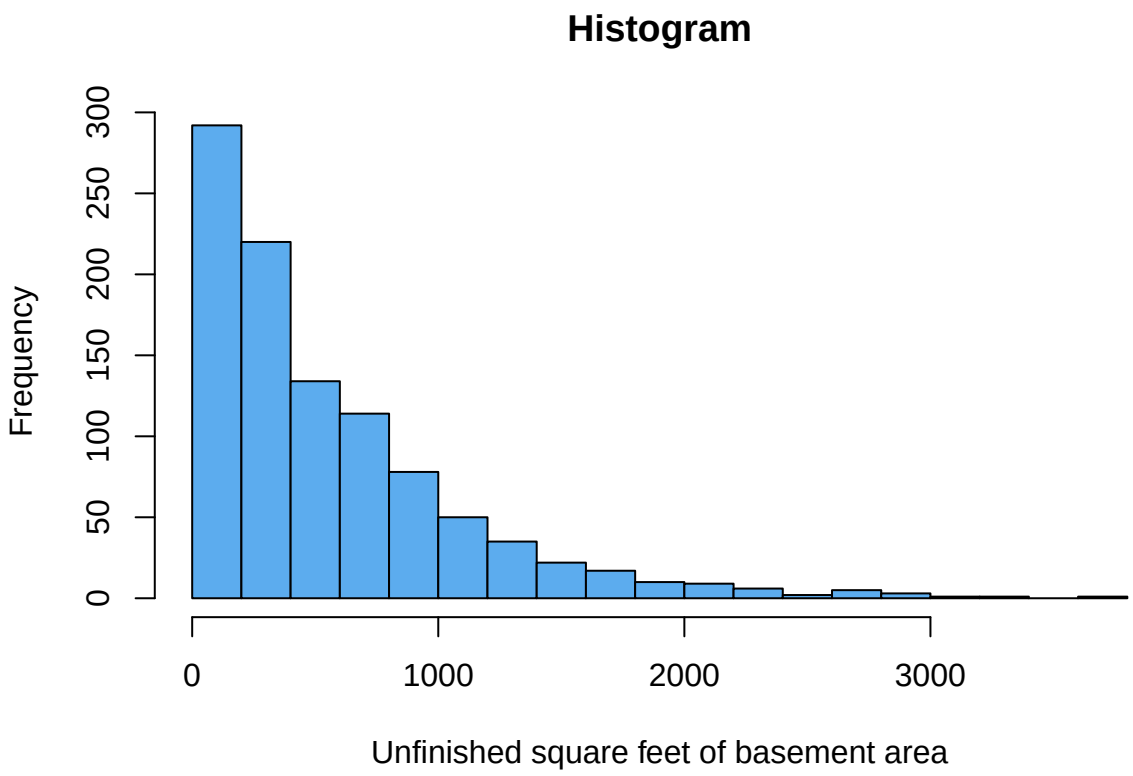
Calculus-Based Probability & Statistics

Many times, it makes sense to fit a closed form distribution to data. Select a variable in the Kaggle.com training dataset that is skewed to the right, shift it so that the minimum value is absolutely above zero if necessary. Then load the MASS package and run fitdistr to fit an exponential probability density function. (See https://stat.ethz.ch/R-manual/R-devel/library/MASS/html/fitdistr.html). Find the optimal value of λ for this distribution, and then take 1000 samples from this exponential distribution using this value (e.g., rexp(1000, λ)). Plot a histogram and compare it with a histogram of your original variable.

```r
hist(train$BsmtUnfSF, main = "Histogram of BsmtUnfSF"
     , col = "darkgreen",
     xlab = "Unfinished square feet of basement area", breaks = 20)
abline(v = mean(train$BsmtUnfSF), col = "blue", lwd = 2)
abline(v = median(train$BsmtUnfSF), col = "red", lwd = 2)
```




```r
lambda <- fitdistr(train$BsmtUnfSF,"exponential")[[1]]
sample <- rexp(1000, lambda)
hist(sample , main="Histogram",xlab="Unfinished square feet of basement area",
     breaks = 20, col = "steelblue2")
```

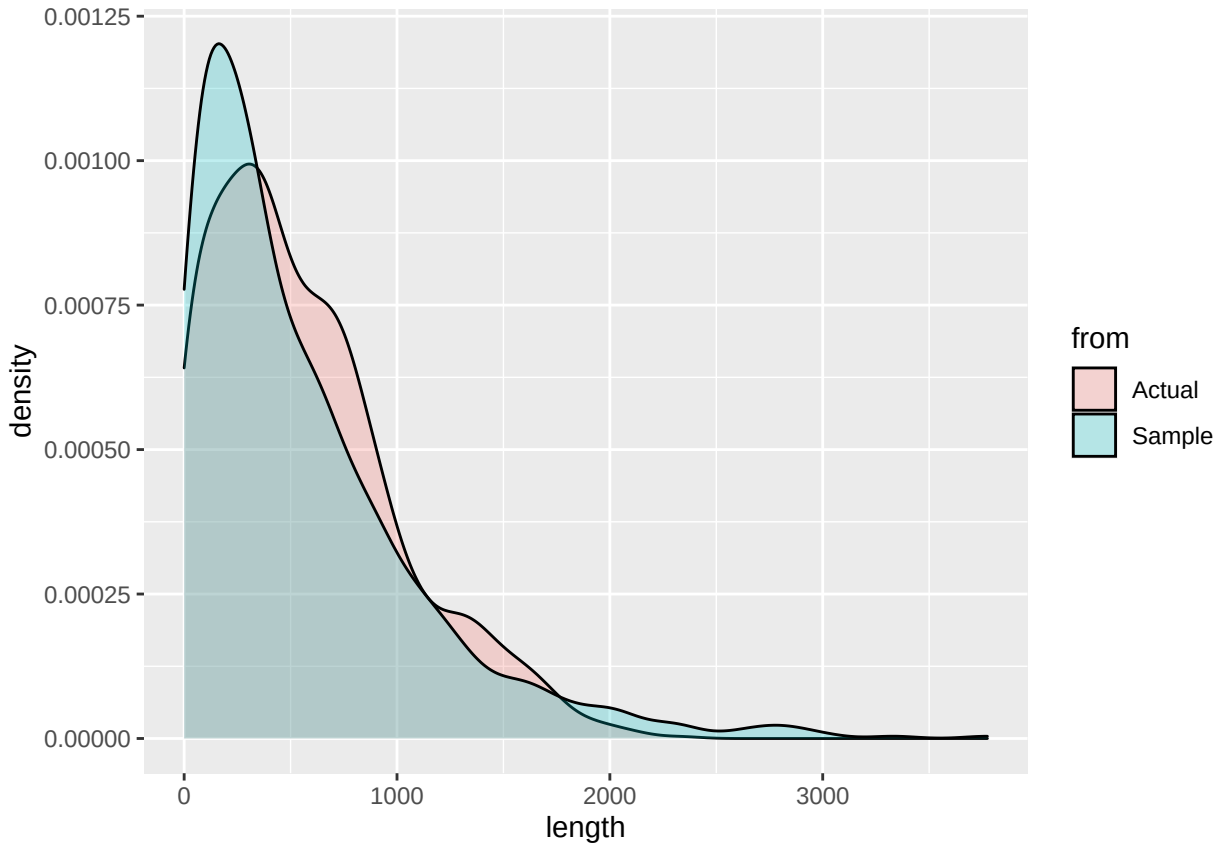



```
summary(sample)
```

```
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
##    0.556  169.404  383.793  556.042  782.351 3773.592
```

The optimal value for λ is 0.0017629.

```
sample.df <- data.frame(length = sample)
Actual.df <- data.frame(length = train$BsmtUnfSF)

sample.df$from <- 'Sample'
Actual.df$from <- 'Actual'

both.df <- rbind(sample.df,Actual.df)

ggplot(both.df, aes(length, fill = from)) + geom_density(alpha = 0.25)
```



The exponential distribution data has a longer tail than the basement square footage data.

Using the exponential pdf, find the 5th and 95th percentiles using the cumulative distribution function (CDF).Also generate a 95% confidence interval from the empirical data, assuming normality. Finally, provide the empirical 5th percentile and 95th percentile of the data. Discuss.

Generating the 5th and 95th percentiles

```
qexp(c(0.05,0.95), lambda)
```

```
## [1]   29.09563 1699.30041
```

Generating 95% confidence level from the data, assuming that the distribution is normal.

```
qnorm(c(0.05, 0.95), mean = mean(train$BsmtUnfSF), sd = sd(train$BsmtUnfSF))
```

```
## [1] -159.5661 1294.0469
```

Now using the actual data to get 5th and 95th percentile

```
quantile(train$BsmtUnfSF, c(0.05, 0.95))
```

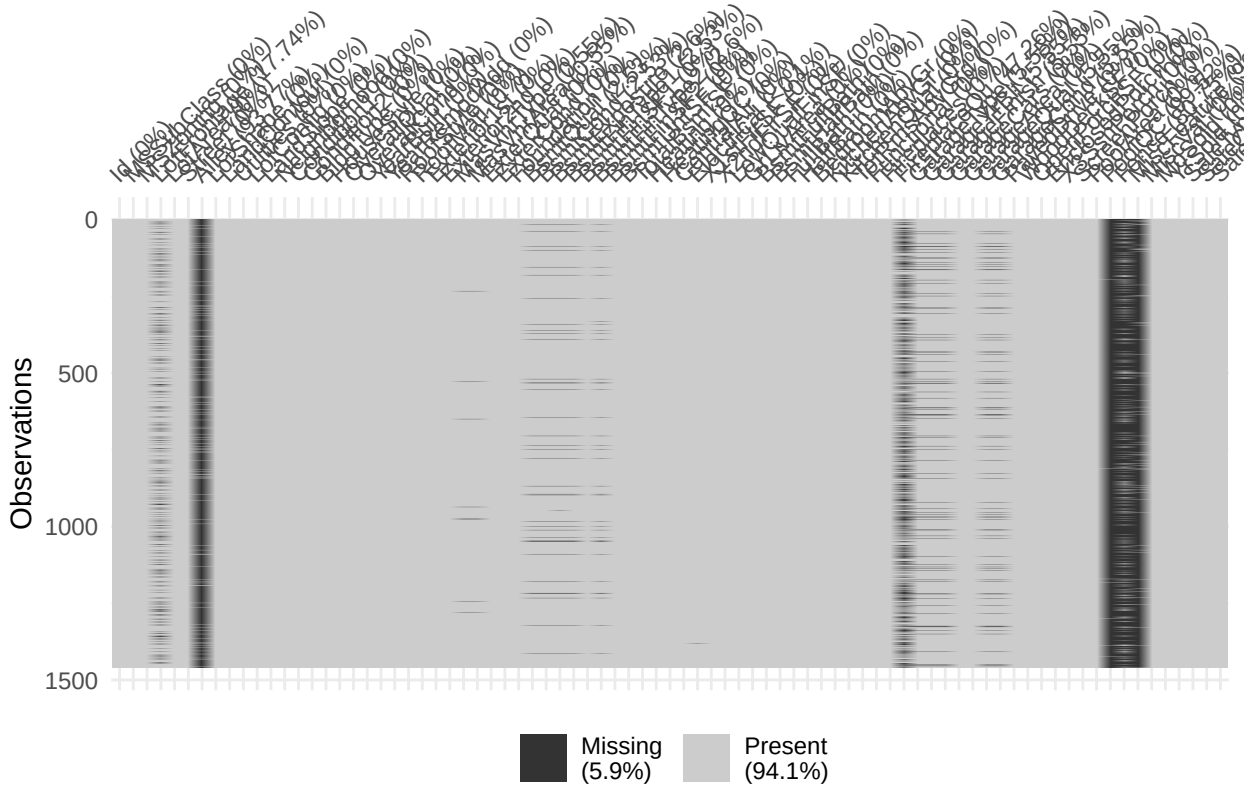
```
##   5%  95%
##    0 1468
```

If we model the data as exponentially distributed the 5th percentile is 29.0956294. If we model it as normally distributed the 5th is at -159.5660531. Actual data distributed the 5th percentile is 0.If we look at the 95th percentile we have 1699.300406 if the data are exponentially distributed, 1294.046875 if it is normally distributed and 1468 in actual data.

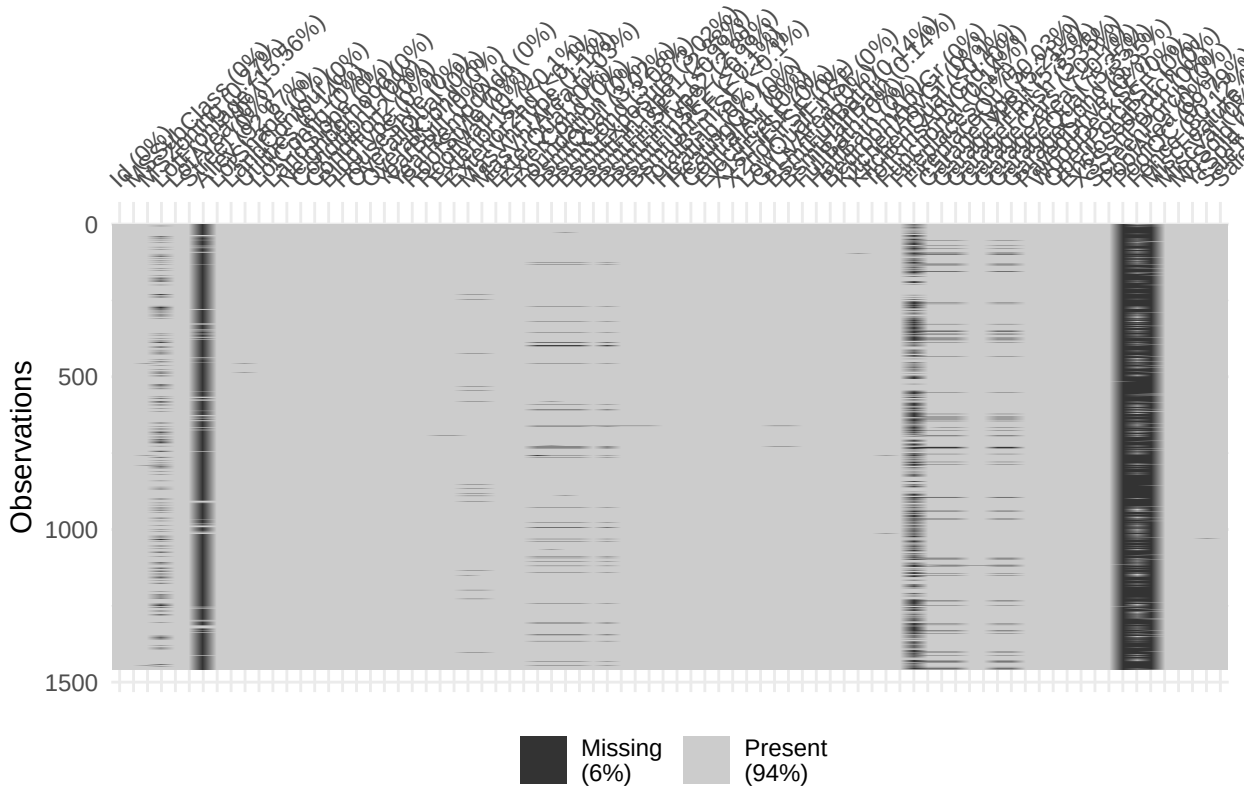
Data Cleaning

To check null values, if available replace with 0.

```
visdat::vis_miss(train)
```




```
visdat::vis_miss(test)
```

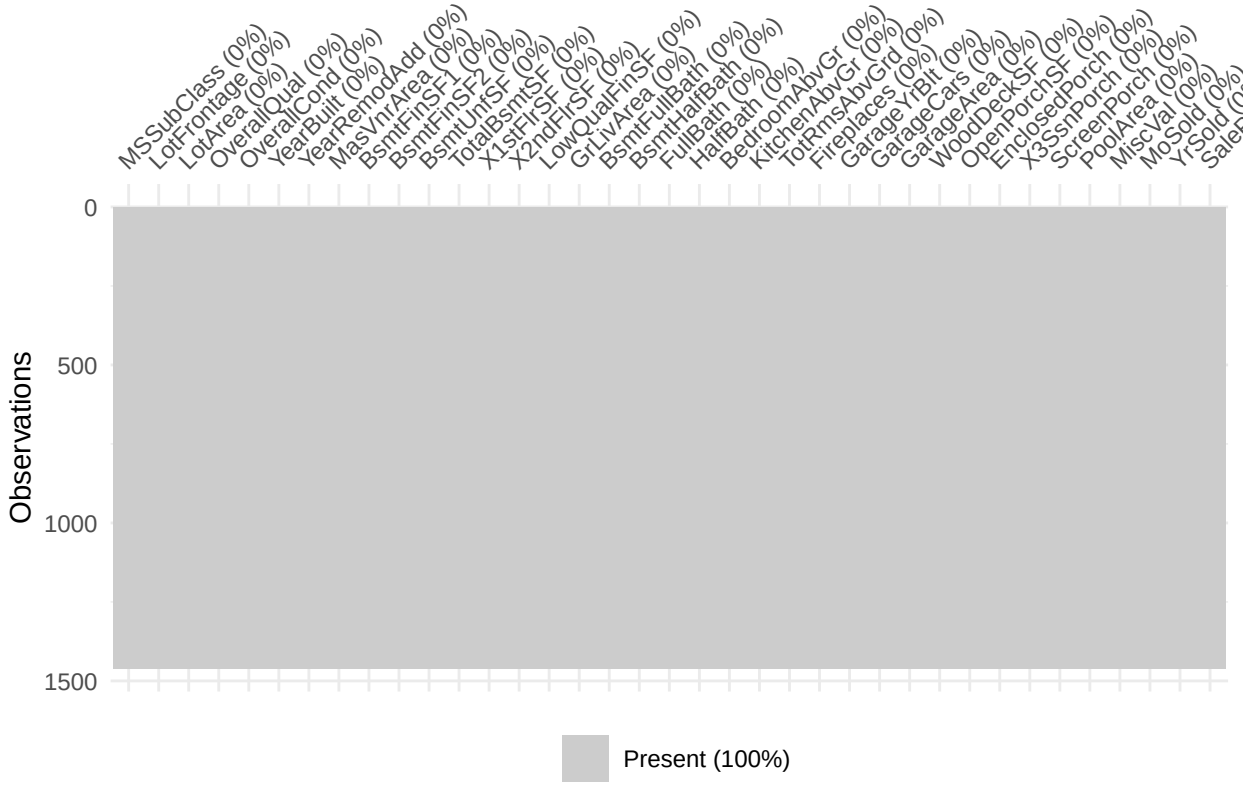



```
train$LotFrontage[is.na(train$LotFrontage)] <- median(train$LotFrontage,na.rm=T)
train$GarageYrBlt[is.na(train$GarageYrBlt)] <- median(train$GarageYrBlt,na.rm=T)
train$MasVnrArea[is.na(train$MasVnrArea)] <- median(train$MasVnrArea,na.rm=T)

train$LotFrontage <- as.integer(train$LotFrontage)
train$MasVnrArea <- as.integer(train$MasVnrArea)
train$TotalBsmtSF <- as.integer(train$TotalBsmtSF)
train$GrLivArea <- as.integer(train$GrLivArea)
train$GarageYrBlt <- as.integer(train$GarageYrBlt)

test$LotFrontage[is.na(test$LotFrontage)] <- median(test$LotFrontage,na.rm=T)
test$GarageYrBlt[is.na(test$GarageYrBlt)] <- median(test$GarageYrBlt,na.rm=T)
test$MasVnrArea[is.na(test$MasVnrArea)] <- median(test$MasVnrArea,na.rm=T)
test$LotFrontage[is.na(test$LotFrontage)] <- median(test$LotFrontage,na.rm=T)
test$BsmtFinSF1[is.na(test$BsmtFinSF1)] <- median(test$BsmtFinSF1,na.rm=T)
test$BsmtFullBath[is.na(test$BsmtFullBath)] <- median(test$BsmtFullBath,na.rm=T)
test$BsmtHalfBath[is.na(test$BsmtHalfBath)] <- median(test$BsmtHalfBath,na.rm=T)
test$GarageYrBlt[is.na(test$GarageYrBlt)] <- median(test$GarageYrBlt,na.rm=T)
test$GarageCars[is.na(test$GarageCars)] <- median(test$GarageCars,na.rm=T)
test$BsmtFinSF2[is.na(test$BsmtFinSF2)] <- median(test$BsmtFinSF2,na.rm=T)
test$BsmtUnfSF[is.na(test$BsmtUnfSF)] <- median(test$BsmtUnfSF,na.rm=T)
test$TotalBsmtSF[is.na(test$TotalBsmtSF)] <- median(test$TotalBsmtSF,na.rm=T)
test$GarageArea[is.na(test$GarageArea)] <- median(test$GarageArea,na.rm=T)



test$LotFrontage <- as.integer(test$LotFrontage)
test$MasVnrArea <- as.integer(test$MasVnrArea)
```

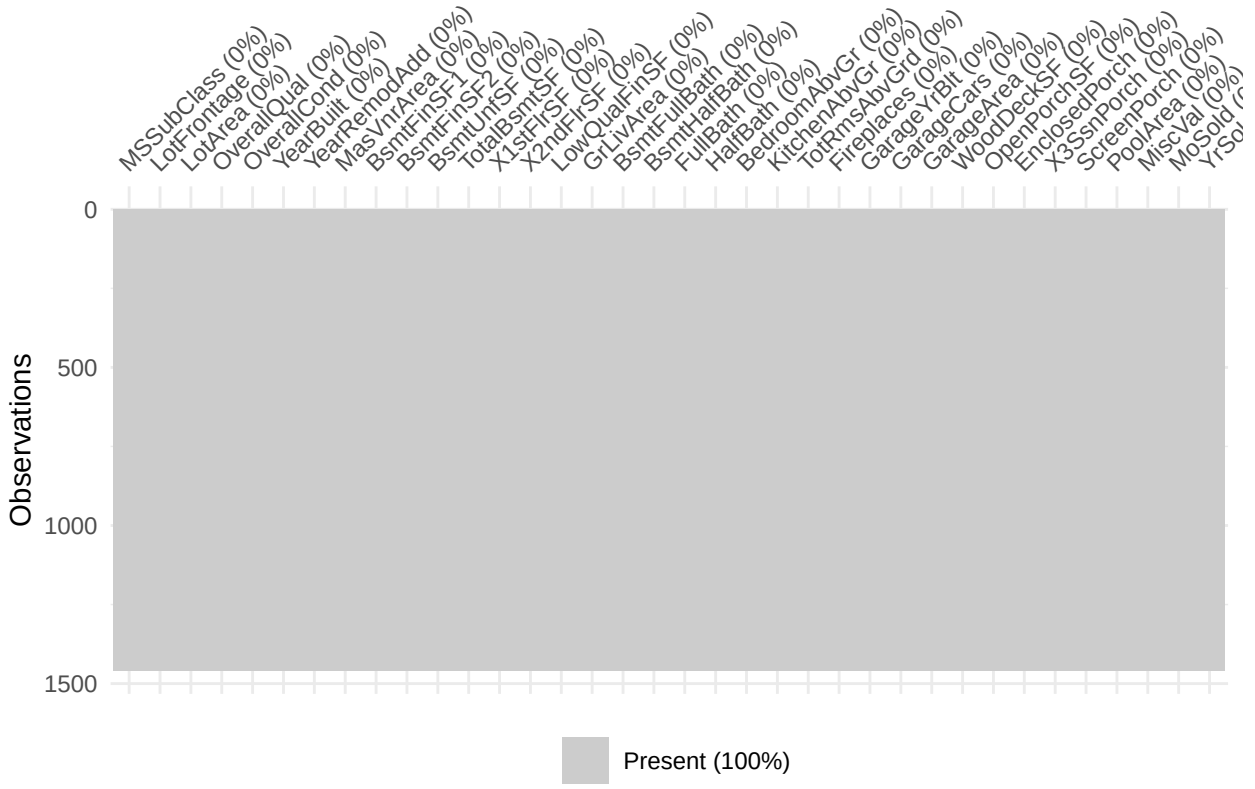
```
test$TotalBsmtSF <- as.integer(test$TotalBsmtSF)
test$GrLivArea <- as.integer(test$GrLivArea)
test$GarageYrBlt <- as.integer(test$GarageYrBlt)
```

Dropping variables with charecter types.

```
train_4 <- train %>%
  dplyr::select(-Id, -Alley, -MasVnrType, -BsmtQual, -BsmtCond, -BsmtExposure, -BsmtFinType1, -BsmtFinTy

test_4 <- test %>%
  dplyr::select(-Id, -Alley, -MasVnrType, -BsmtQual, -BsmtCond, -BsmtExposure, -BsmtFinType1, -BsmtFinTy

visdat::vis_miss(train_4)
```




```
visdat::vis_miss(test_4)
```



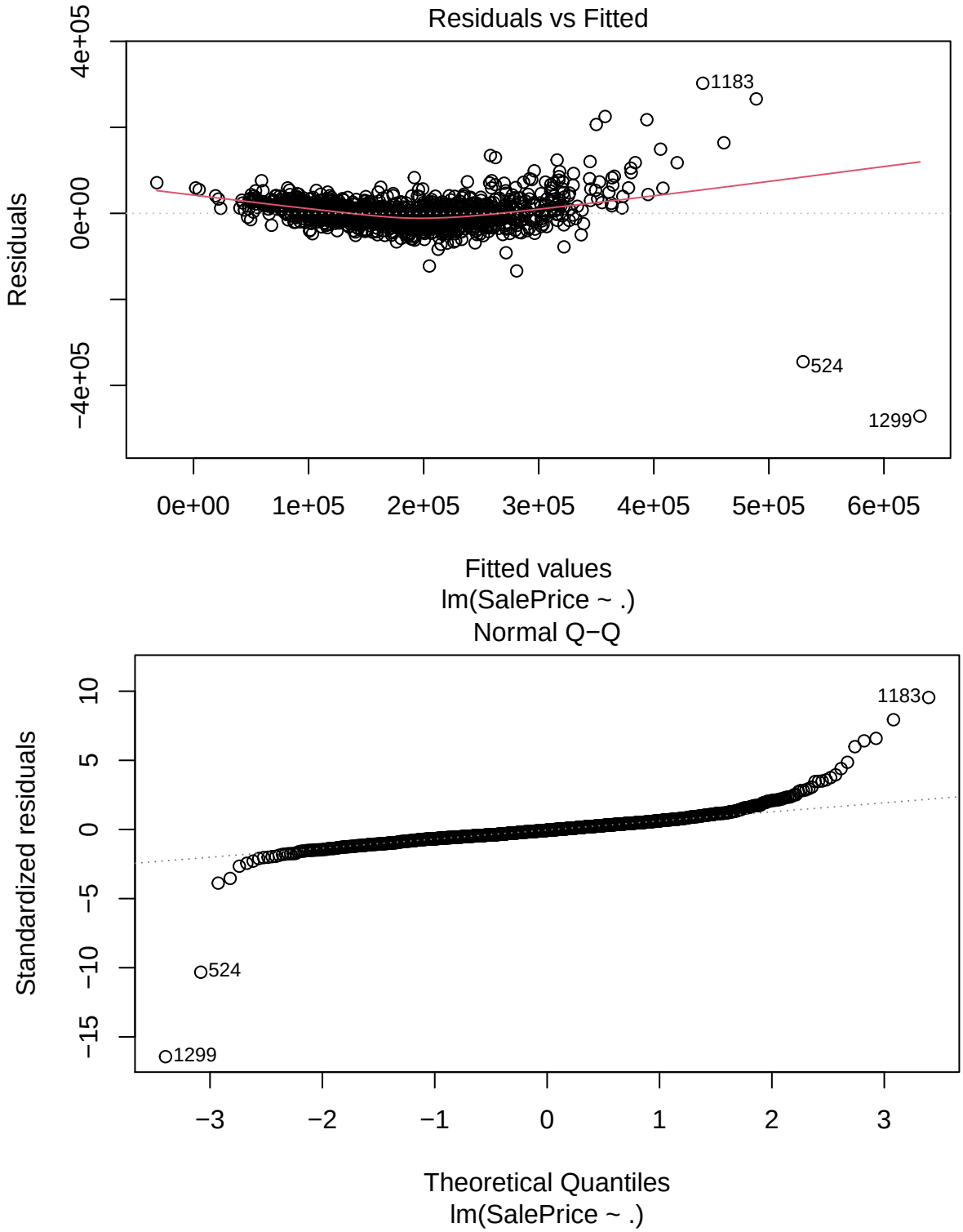
Model1 with all variables

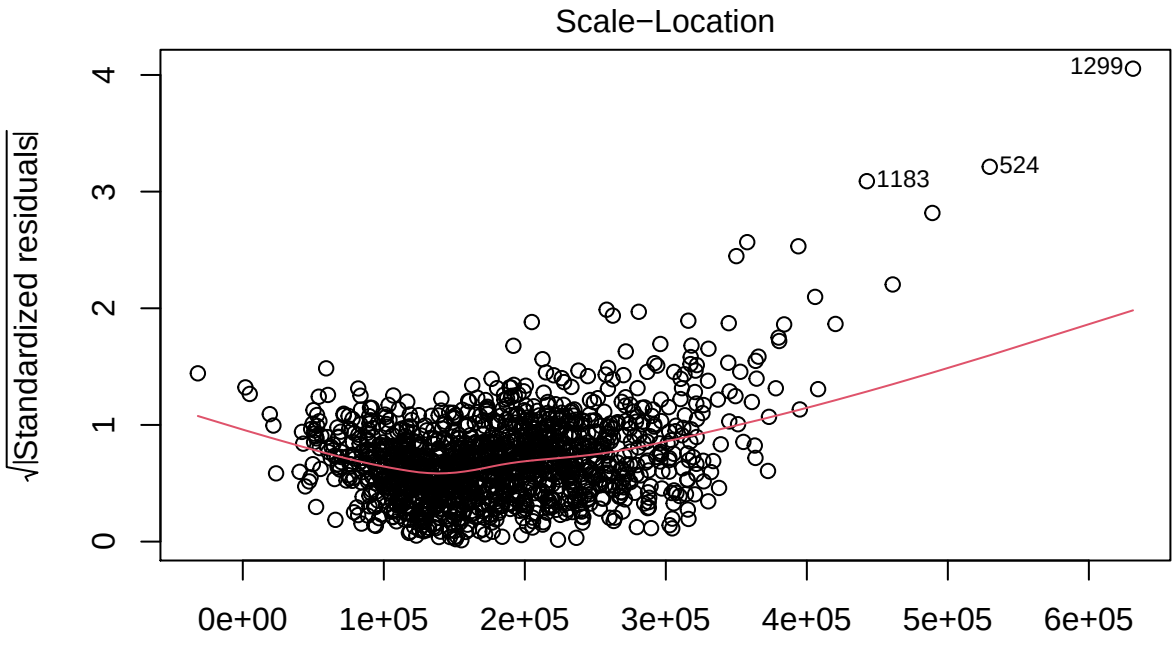
```
model1 <- lm(SalePrice ~ ., data = train_4)
summary(model1)
```

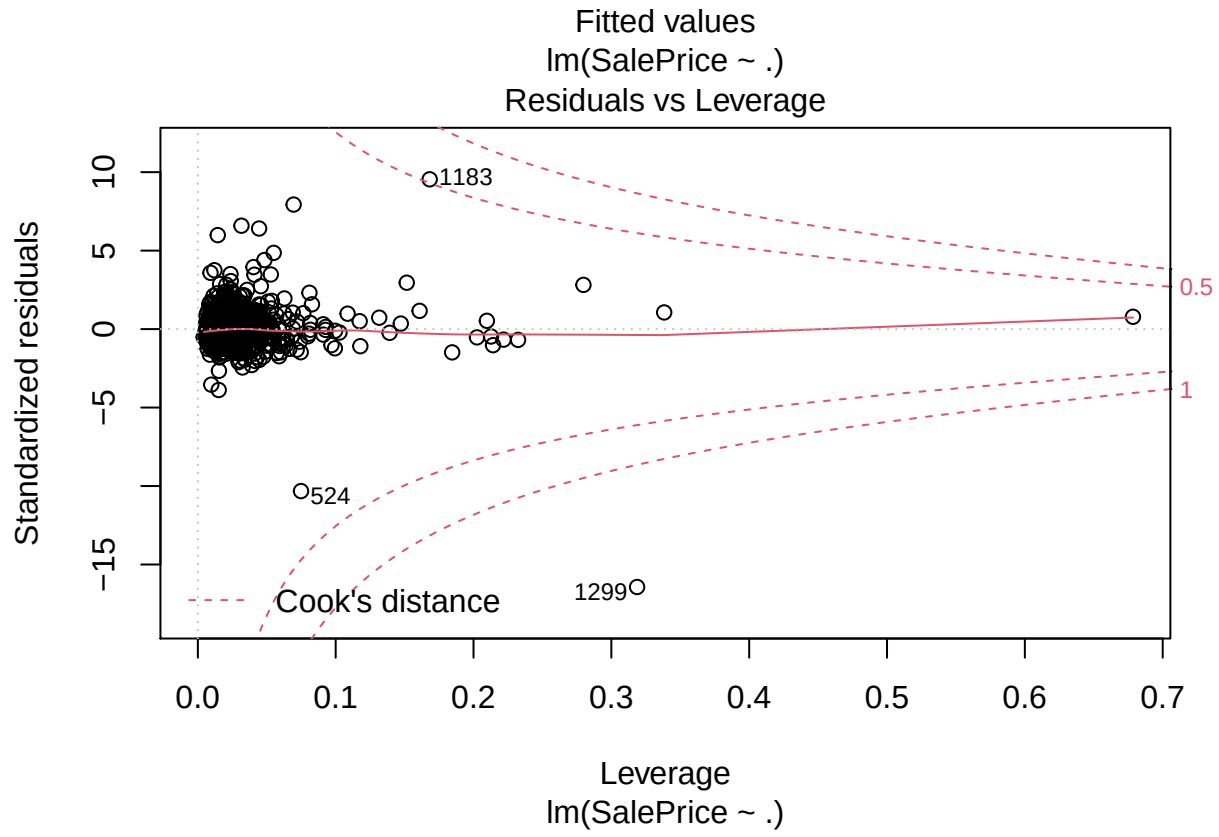
```
##
## Call:
## lm(formula = SalePrice ~ ., data = train_4)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -471312  -16510   -2011   13793  302440
##
## Coefficients: (2 not defined because of singularities)
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)    4.628e+05  1.414e+06   0.327 0.743435
## MSSubClass    -1.817e+02  2.767e+01  -6.566 7.22e-11 ***
## LotFrontage   -5.444e+01  5.171e+01  -1.053 0.292680
## LotArea        4.297e-01  1.021e-01   4.209 2.72e-05 ***
## OverallQual    1.733e+04  1.187e+03  14.597  < 2e-16 ***
## OverallCond    4.674e+03  1.033e+03   4.526 6.51e-06 ***
## YearBuilt      2.692e+02  6.741e+01   3.993 6.85e-05 ***
## YearRemodAdd   1.346e+02  6.859e+01   1.962 0.049921 *
## MasVnrArea     3.134e+01  5.933e+00   5.283 1.47e-07 ***
## BsmtFinSF1     1.921e+01  4.667e+00   4.116 4.07e-05 ***
## BsmtFinSF2     8.274e+00  7.057e+00   1.172 0.241220
## BsmtUnfSF      9.304e+00  4.194e+00   2.218 0.026687 *
## TotalBsmtSF           NA         NA      NA       NA
```

```
## X1stFlrSF      4.898e+01  5.809e+00   8.432  < 2e-16 ***
## X2ndFlrSF      4.901e+01  4.983e+00   9.835  < 2e-16 ***
## LowQualFinSF   2.530e+01  1.997e+01   1.267 0.205442
## GrLivArea             NA         NA      NA       NA
## BsmtFullBath   9.372e+03  2.612e+03   3.588 0.000344 ***
## BsmtHalfBath   2.055e+03  4.091e+03   0.502 0.615546
## FullBath       3.447e+03  2.837e+03   1.215 0.224513
## HalfBath      -1.872e+03  2.663e+03  -0.703 0.482212
## BedroomAbvGr  -1.009e+04  1.702e+03  -5.931 3.77e-09 ***
## KitchenAbvGr  -1.217e+04  5.212e+03  -2.335 0.019676 *
## TotRmsAbvGrd   5.045e+03  1.237e+03   4.078 4.79e-05 ***
## Fireplaces     3.979e+03  1.777e+03   2.239 0.025278 *
## GarageYrBlt    1.269e+02  6.898e+01   1.840 0.065965 .
## GarageCars     1.129e+04  2.876e+03   3.927 9.03e-05 ***
## GarageArea    -4.410e+00  9.941e+00  -0.444 0.657435
## WoodDeckSF     2.389e+01  8.012e+00   2.982 0.002914 **
## OpenPorchSF   -2.891e+00  1.518e+01  -0.190 0.848996
## EnclosedPorch  1.191e+01  1.686e+01   0.706 0.480195
## X3SsnPorch     2.032e+01  3.139e+01   0.647 0.517617
## ScreenPorch    5.599e+01  1.719e+01   3.257 0.001153 **
## PoolArea      -2.919e+01  2.381e+01  -1.226 0.220457
## MiscVal       -7.336e-01  1.855e+00  -0.395 0.692545
## MoSold        -4.840e+01  3.448e+02  -0.140 0.888392
## YrSold        -7.807e+02  7.025e+02  -1.111 0.266589
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 34750 on 1425 degrees of freedom
## Multiple R-squared:  0.8132, Adjusted R-squared:  0.8087
## F-statistic: 182.4 on 34 and 1425 DF,  p-value: < 2.2e-16
```

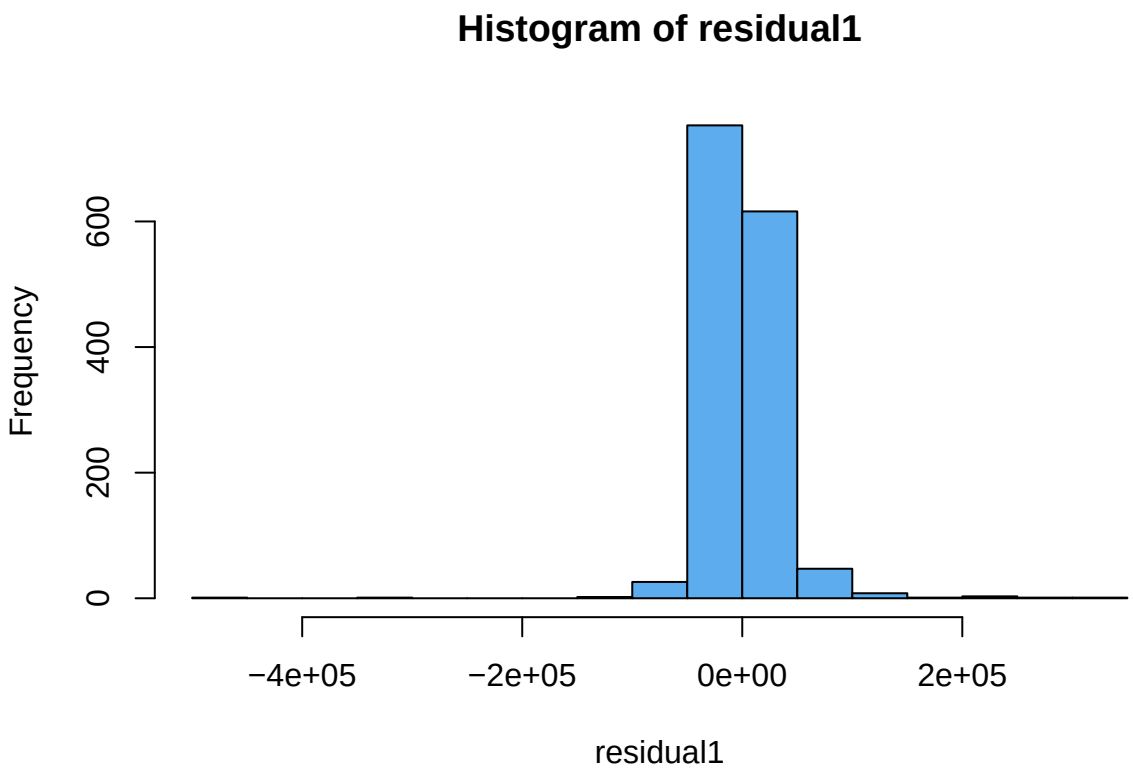
```
plot(model1)
```


Residuals vs Fitted
Residuals
4e+05
0e+00
−4e+05
1183
524
1299
0e+00
1e+05
2e+05
3e+05
4e+05
5e+05
6e+05
Fitted values
lm(SalePrice ~ .)
Normal Q−Q
Standardized residuals
10
5
0
−5
−10
−15
1183
524
1299
−3
−2
−1
0
1
2
3
Theoretical Quantiles
lm(SalePrice ~ .)

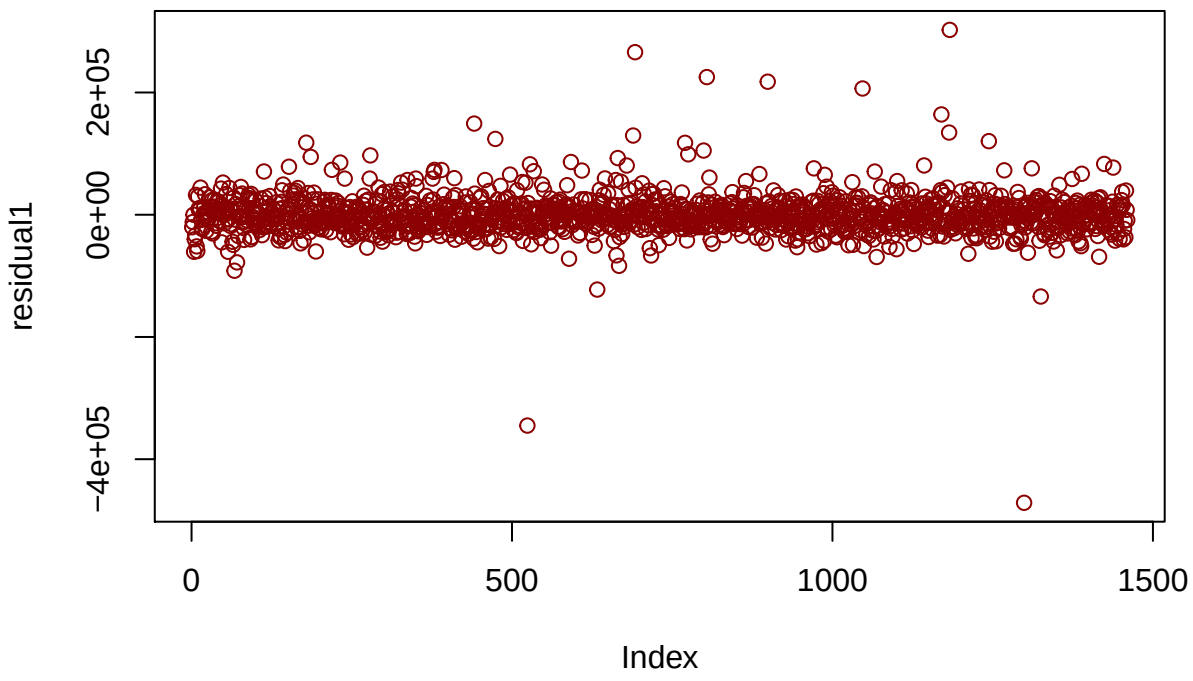





```r
residual1 <- resid(model1)
hist(residual1, col = "steelblue2")
```




```
plot(residual1, col = 'dark red')
```



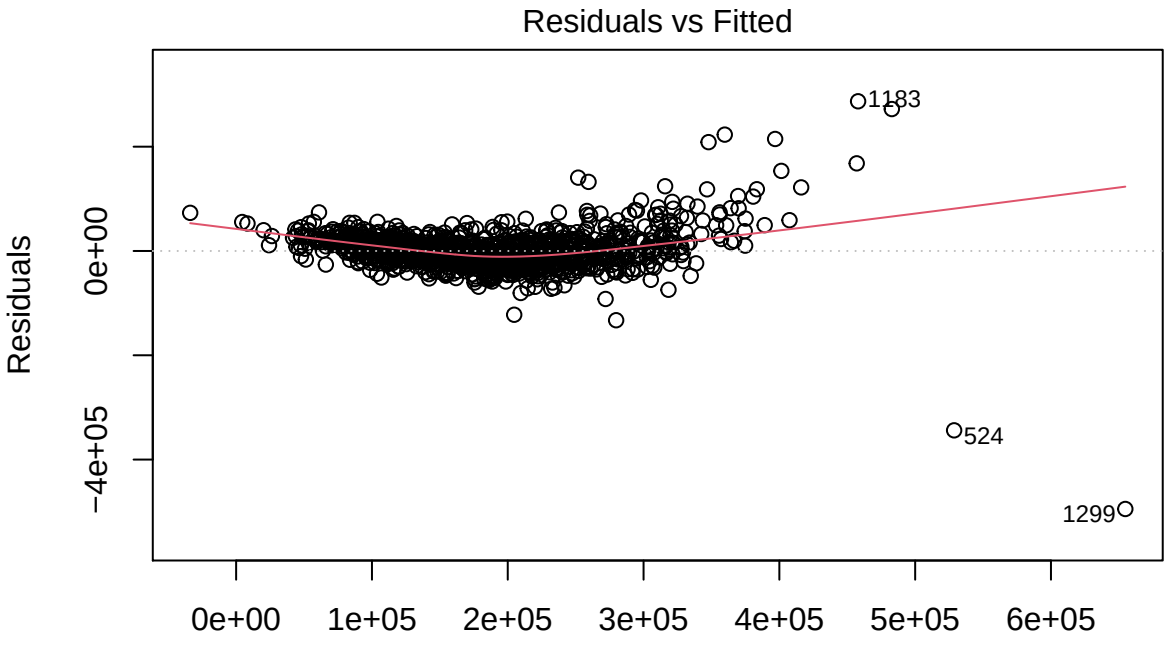
Model2 with significant variables

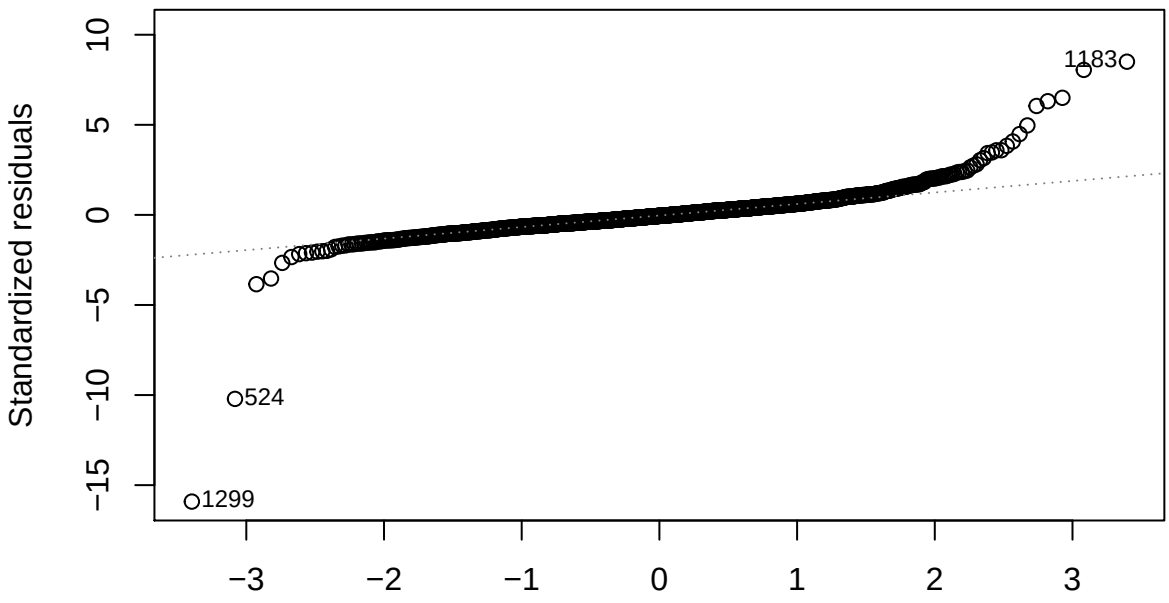
```
model2 <- lm(SalePrice ~ MSSubClass + LotArea + OverallQual + OverallCond +
               YearBuilt + YearRemodAdd + MasVnrArea + BsmtFinSF1 + BsmtUnfSF +
               X1stFlrSF + X2ndFlrSF + BsmtFullBath + BedroomAbvGr + KitchenAbvGr +
```

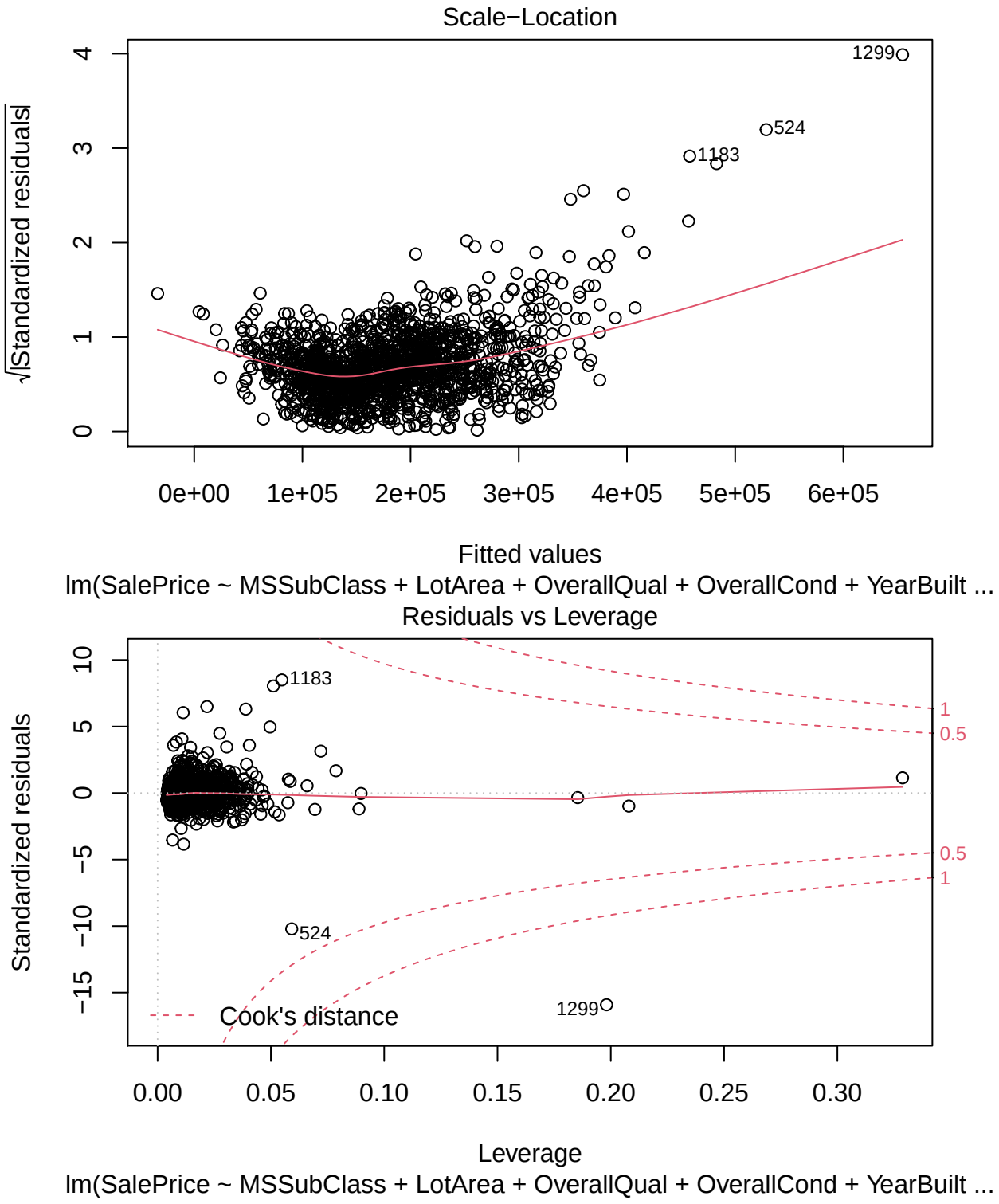
```
              TotRmsAbvGrd + Fireplaces + GarageYrBlt + GarageCars + WoodDeckSF +
              ScreenPorch, data = train_4)
summary(model2)
```

```
##
## Call:
## lm(formula = SalePrice ~ MSSubClass + LotArea + OverallQual +
##     OverallCond + YearBuilt + YearRemodAdd + MasVnrArea + BsmtFinSF1 +
##     BsmtUnfSF + X1stFlrSF + X2ndFlrSF + BsmtFullBath + BedroomAbvGr +
##     KitchenAbvGr + TotRmsAbvGrd + Fireplaces + GarageYrBlt +
##     GarageCars + WoodDeckSF + ScreenPorch, data = train_4)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -494744  -16147   -1821   13648  287029
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -1.121e+06  1.217e+05  -9.208  < 2e-16 ***
## MSSubClass   -1.648e+02  2.581e+01  -6.382 2.34e-10 ***
## LotArea       4.291e-01  9.987e-02   4.296 1.85e-05 ***
## OverallQual   1.774e+04  1.167e+03  15.195  < 2e-16 ***
## OverallCond   4.452e+03  1.014e+03   4.390 1.22e-05 ***
## YearBuilt     2.485e+02  5.874e+01   4.230 2.48e-05 ***
## YearRemodAdd  1.475e+02  6.746e+01   2.186 0.028980 *
## MasVnrArea    3.055e+01  5.868e+00   5.206 2.21e-07 ***
## BsmtFinSF1    1.571e+01  3.905e+00   4.024 6.02e-05 ***
## BsmtUnfSF     6.632e+00  3.630e+00   1.827 0.067874 .
## X1stFlrSF     5.147e+01  5.094e+00  10.104  < 2e-16 ***
## X2ndFlrSF     4.722e+01  4.089e+00  11.548  < 2e-16 ***
## BsmtFullBath  9.087e+03  2.399e+03   3.788 0.000158 ***
## BedroomAbvGr -9.634e+03  1.663e+03  -5.795 8.40e-09 ***
## KitchenAbvGr -1.298e+04  5.056e+03  -2.567 0.010365 *
## TotRmsAbvGrd  5.217e+03  1.211e+03   4.306 1.77e-05 ***
## Fireplaces    3.808e+03  1.758e+03   2.167 0.030428 *
## GarageYrBlt   1.419e+02  6.592e+01   2.152 0.031530 *
## GarageCars    1.030e+04  1.691e+03   6.088 1.46e-09 ***
## WoodDeckSF    2.389e+01  7.894e+00   3.027 0.002517 **
## ScreenPorch   5.369e+01  1.685e+01   3.186 0.001475 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 34720 on 1439 degrees of freedom
## Multiple R-squared:  0.8116, Adjusted R-squared:  0.809
## F-statistic:   310 on 20 and 1439 DF,  p-value: < 2.2e-16
```

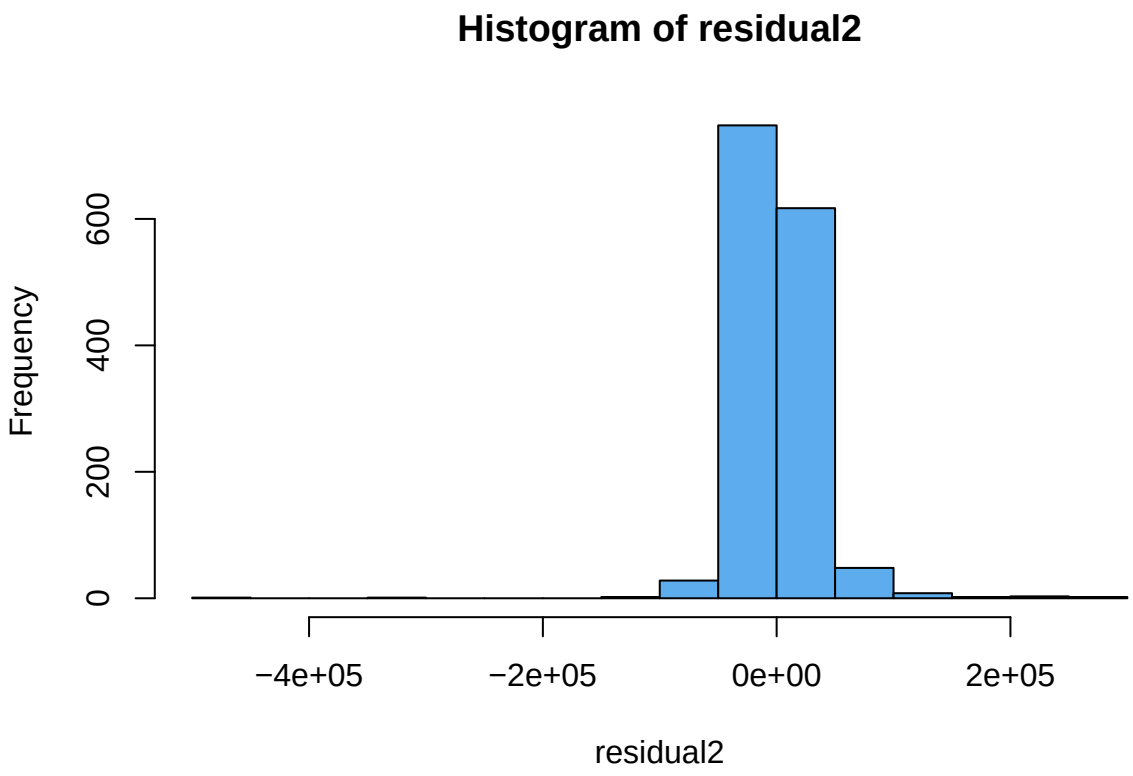
```
plot(model2)
```


Residuals vs Fitted
Residuals
0e+00
−4e+05
1183
524
1299
0e+00
1e+05
2e+05
3e+05
4e+05
5e+05
6e+05
Fitted values
lm(SalePrice ~ MSSubClass + LotArea + OverallQual + OverallCond + YearBuilt ...

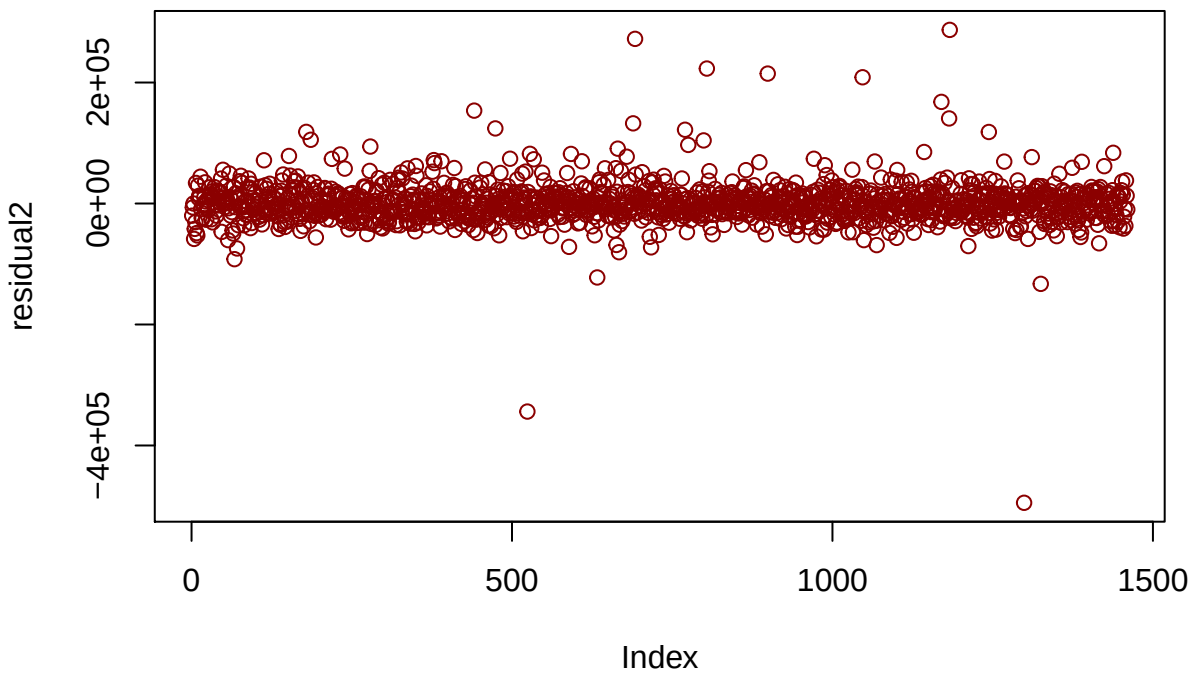

Normal Q−Q
Standardized residuals
10
5
0
−5
−10
−15
1183
524
1299
−3
−2
−1
0
1
2
3
Theoretical Quantiles
lm(SalePrice ~ MSSubClass + LotArea + OverallQual + OverallCond + YearBuilt ...




```r
residual2 <- resid(model2)
hist(residual2, col = "steelblue2")
```



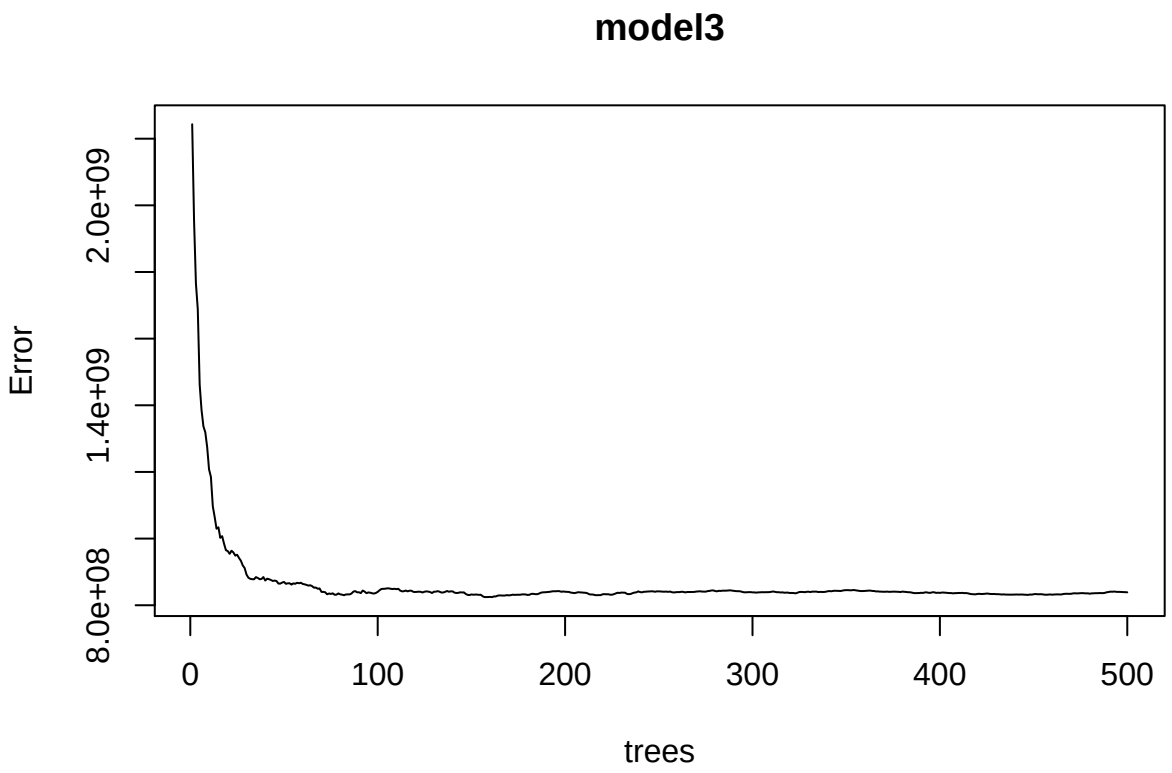

```
plot(residual2, col = 'dark red')
```



Model3 Random Forest

Select best model to predict salesprice on test dataset

```
library(randomForest)
#pull out Y variable and store into seperate var.
y_train <- train_4$SalePrice
#select all but y variable.
x_train <- subset(train_4, select = -SalePrice)

#run the randomForest model
model3 <- randomForest(x_train, y = y_train, ntree = 500, importance = T)
plot(model3)
```



Select model1 and Model3 to predict the salesPrice on testdata.

```
pred1<-predict(model1, test_4)
#export data for Kaggle
train_5 <- as.data.frame(cbind(test$Id, pred1))
colnames(train_5) <- c("Id", "SalePrice")
write.csv(train_5, file = "Kaggle_Submission1.csv", quote=FALSE, row.names=FALSE)
```

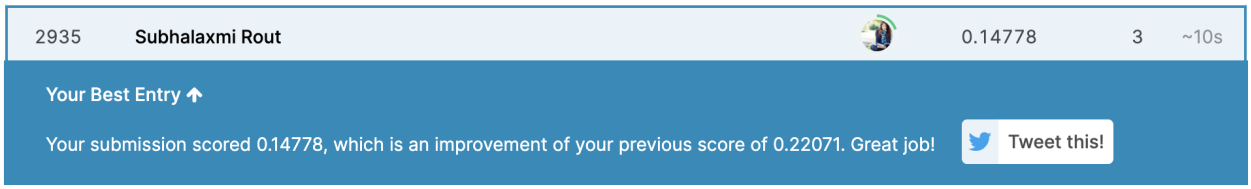
```
pred3<-predict(model3, test_4)
#export data for Kaggle
train_7 <- as.data.frame(cbind(test$Id, pred3))
colnames(train_7) <- c("Id", "SalePrice")
write.csv(train_7, file = "Kaggle_Submission3.csv", quote=FALSE, row.names=FALSE)
```

Prediction Submission Scores Model1 : Linear Regression

Kaggle username: Subhalaxmi Rout

Model3 : Random Forest

Kaggle username: Subhalaxmi Rout



Future work Model can be improved using KNN, Decision Tree, XGBoost algorithms or combination of other algorithms. In future I will work more data cleaning and model building to get optimal prediction.

Reference

https://www.kaggle.com/c/house-prices-advanced-regression-techniques/data?select=sample_submission.csv