Final

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```r
library(tidyverse)
library(kableExtra)
```

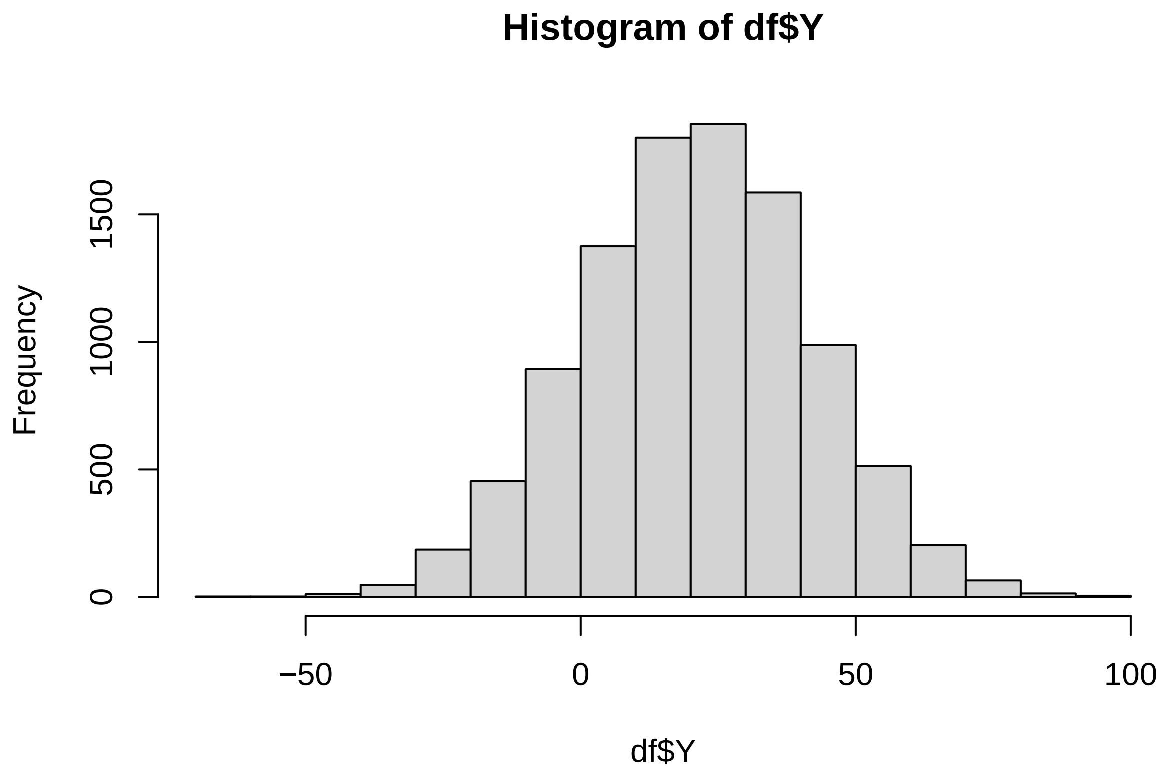
Problem 1

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 $\mu = \sigma = (N+1)/2$.

```r
set.seed(41)
N <- 41 # Random number greater than or equal to 6
n <- 10000 # Quantity of random normal numbers to generate
sigma <- (N + 1)/2 # Sigma
mu <- sigma # Mu = Sigma
# Generate random number
df <- data.frame(X = runif(n, min = 1, max = N),
                 Y = rnorm(n, mean = mu, sd = sigma))
# Display random numbers
head(df, 10)
```

```
##            X         Y
## 1   9.539620 21.708869
## 2  39.849134 17.692613
## 3  24.127480 24.785695
## 4   6.683199 21.316268
## 5  34.670271 -8.210459
## 6  39.481321 14.583845
## 7  37.050824 -1.709704
## 8  21.876923 36.841523
## 9  33.698672 30.865059
## 10 27.731654 41.466029
```

```r
hist(df$Y)
```



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.

$$A.\ P(X > x|X > y) \quad B.\ P(X > x, Y > y) \quad C.P(X < x|X > y)$$

If we assume the small letter x is estimated as the median of X variable, and the small letter y is estimated as the 1st quartile of the Y variable then we have the following values of x and y and can calculate the minimum as such:

```
x = median(df$X) # median of X
y = quantile(df$Y, 0.25) # 1st quartile of Y
# A. P(X>x | X>y)
PXxXy <- df %>%
  filter(X>x, X>y) %>%
  nrow() / n
PXy <- df %>%
  filter(X>y) %>%
  nrow() / n
A <- signif((PXxXy / PXy), 3)
# B. P(X>x, Y>y)
PXxXy <- df %>%
  filter(X>x, Y>y) %>%
  nrow() / n
B <- signif(PXxXy, 3)
# C. P(X<x | X>y)
```

```r
PXxXy <- df %>%
  filter(X < x,
         X > y) %>%
  nrow() / n
PXy <- df %>%
  filter(X > y) %>%
  nrow() / n
C <- PXxXy/PXy
print(paste("A.:",A,"B.:",B,"C.:",C))
```

```
## [1] "A.: 0.583 B.: 0.375 C.: 0.417045587035094"
```

We can interpret the meaning of $P(X > x|X > y)$ as approximately 0.583. That is to say (in words), the probability of X>x given X>y is 0.583. For B, where $P(X > x, Y > y)$ we have 0.375 and would state verbally that the probability X is greater than x and Y is greater than y is 0.375. Lastly, for C, where P(X>x | X>y), we have 0.4170456 and simply say that the probability of Xy is 0.4170456.

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

```r
# Joint P
JAB <- df %>%
  mutate(A = ifelse(X > x, "X > x", "X < x")) %>%
  mutate(B = ifelse(Y > y, " Y > y", " Y < y")) %>%
  group_by(A, B) %>%
  summarise(total = n()) %>%
  mutate(P = total / n)
# Marginal P
MA <- JAB %>%
  ungroup() %>%
  group_by(A) %>%
  summarise(sum = sum(total), P = sum(P))
MB <- JAB %>%
  ungroup() %>%
  group_by(B) %>%
  summarise(sum = sum(total), P = sum(P))
# build a table
tbl <- bind_rows(JAB, MA, MB) %>%
  select(-total) %>%
  spread(A, P)
colnames(tbl) <- c("Condition", "sum", "X<x", "X>x", "Total")
kable(tbl)
```

Condition	sum	X<x	X>x	Total
Y < y	2500	NA	NA	0.25
Y < y	NA	0.125	0.125	NA
Y > y	7500	NA	NA	0.75
Y > y	NA	0.375	0.375	NA
NA	5000	0.500	0.500	NA

They are the approximately the same. Close enough that we can state $P(X > xandY > y) = P(X > x)P(Y > y)$.

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?

```r
xy <- table(df$X>x, df$Y>y)
chisq.test(xy, correct=T)
```

```
##
##  Pearson's Chi-squared test
##
## data:  xy
## X-squared = 0, df = 1, p-value = 1
```

```r
fisher.test(xy,simulate.p.value=T)
```

```
##
##  Fisher's Exact Test for Count Data
##
## data:  xy
## p-value = 1
## alternative hypothesis: true odds ratio is not equal to 1
## 95 percent confidence interval:
##  0.9124854 1.0959080
## sample estimates:
## odds ratio
##          1
```

Chi-squared is most appropriate due to sample size and independence holds with large p-value.

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.

^{1}5 points. 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?

^{2}5 points. 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.

^{3}5 points. 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 for this distribution, and then take 1000 samples from this exponential distribution using this value (e.g., rexp(1000,)). 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.

^{4}10 points. 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.

```
# Packages
library(psych)
library(corrplot)
library(matrixcalc)
library(MASS)
theme_set(theme_minimal())
```

Section 1: Descriptive and Inferential Statistics

```
# Load the data
train <- read.csv("https://raw.githubusercontent.com/palmorezm/msds/main/605/train.csv")
test <- read.csv("https://raw.githubusercontent.com/palmorezm/msds/main/605/test.csv")
```

```
# univariate descriptive statistics for training set
describe(train)
```

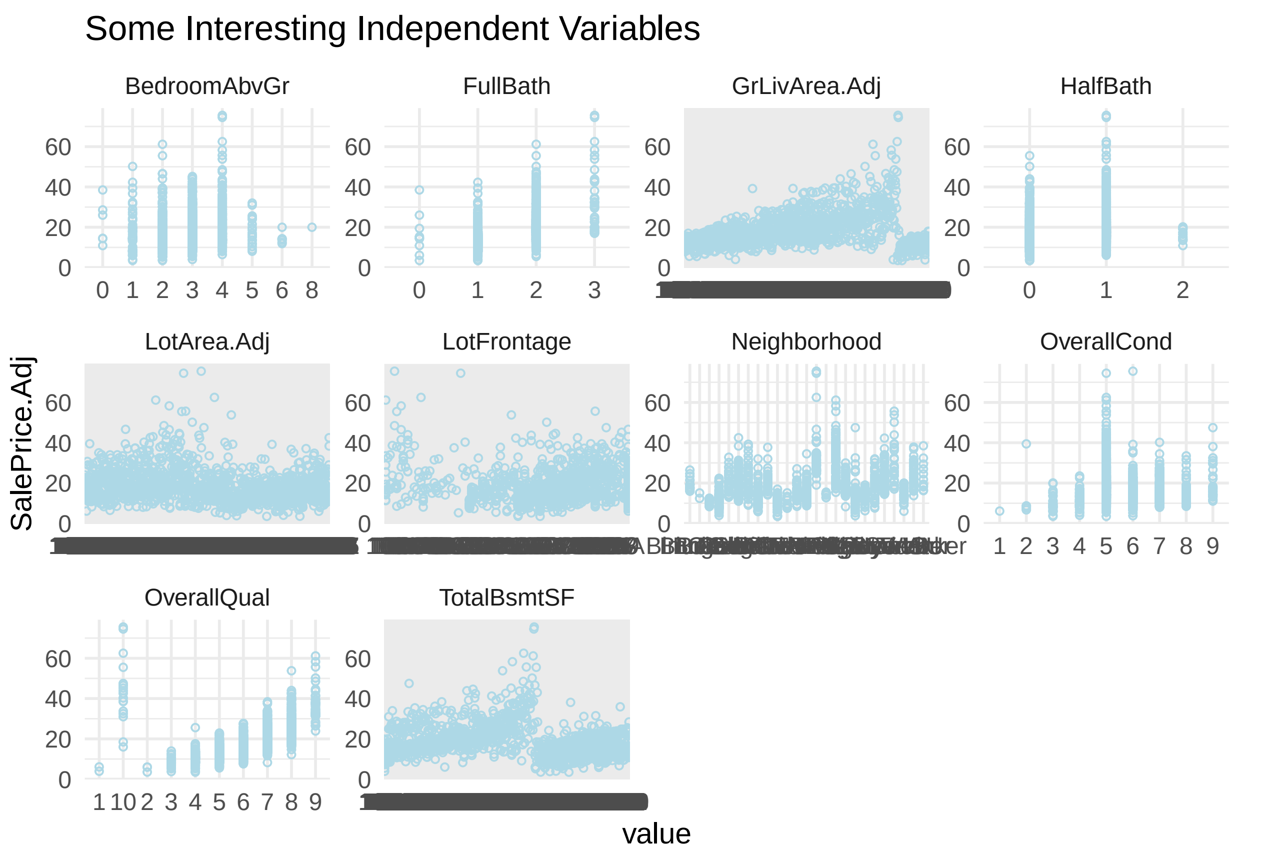
```
##                vars    n     mean      sd  median  trimmed     mad  min
## Id                1 1460   730.50  421.61   730.5   730.50  541.15    1
## MSSubClass        2 1460    56.90   42.30    50.0    49.15   44.48   20
## MSZoning*         3 1460     4.03    0.63     4.0     4.06    0.00    1
## LotFrontage       4 1201    70.05   24.28    69.0    68.94   16.31   21
## LotArea           5 1460 10516.83 9981.26  9478.5  9563.28 2962.23 1300
## Street*           6 1460     2.00    0.06     2.0     2.00    0.00    1
## Alley*            7   91     1.45    0.50     1.0     1.44    0.00    1
## LotShape*         8 1460     2.94    1.41     4.0     3.05    0.00    1
## LandContour*      9 1460     3.78    0.71     4.0     4.00    0.00    1
## Utilities*       10 1460     1.00    0.03     1.0     1.00    0.00    1
## LotConfig*       11 1460     4.02    1.62     5.0     4.27    0.00    1
## LandSlope*       12 1460     1.06    0.28     1.0     1.00    0.00    1
## Neighborhood*    13 1460    13.15    5.89    13.0    13.11    7.41    1
## Condition1*      14 1460     3.03    0.87     3.0     3.00    0.00    1
## Condition2*      15 1460     3.01    0.26     3.0     3.00    0.00    1
## BldgType*        16 1460     1.49    1.20     1.0     1.14    0.00    1
## HouseStyle*      17 1460     4.04    1.91     3.0     4.03    1.48    1
## OverallQual      18 1460     6.10    1.38     6.0     6.08    1.48    1
## OverallCond      19 1460     5.58    1.11     5.0     5.48    0.00    1
## YearBuilt        20 1460  1971.27   30.20  1973.0  1974.13   37.06 1872
## YearRemodAdd     21 1460  1984.87   20.65  1994.0  1986.37   19.27 1950
## RoofStyle*       22 1460     2.41    0.83     2.0     2.26    0.00    1
## RoofMatl*        23 1460     2.08    0.60     2.0     2.00    0.00    1
## Exterior1st*     24 1460    10.62    3.20    13.0    10.93    1.48    1
## Exterior2nd*     25 1460    11.34    3.54    14.0    11.65    2.97    1
## MasVnrType*      26 1452     2.76    0.62     3.0     2.73    0.00    1
## MasVnrArea       27 1452   103.69  181.07     0.0    63.15    0.00    0
## ExterQual*       28 1460     3.54    0.69     4.0     3.65    0.00    1
## ExterCond*       29 1460     4.73    0.73     5.0     4.95    0.00    1
## Foundation*      30 1460     2.40    0.72     2.0     2.46    1.48    1
```

```
## BsmtQual*         31 1423      3.26     0.87      3.0      3.43     1.48     1
## BsmtCond*         32 1423      3.81     0.66      4.0      4.00     0.00     1
## BsmtExposure*     33 1422      3.27     1.15      4.0      3.46     0.00     1
## BsmtFinType1*     34 1423      3.73     1.83      3.0      3.79     2.97     1
## BsmtFinSF1        35 1460    443.64   456.10    383.5    386.08   568.58     0
## BsmtFinType2*     36 1422      5.71     0.94      6.0      5.98     0.00     1
## BsmtFinSF2        37 1460     46.55   161.32      0.0      1.38     0.00     0
## BsmtUnfSF         38 1460    567.24   441.87    477.5    519.29   426.99     0
## TotalBsmtSF       39 1460   1057.43   438.71    991.5   1036.70   347.67     0
## Heating*          40 1460      2.04     0.30      2.0      2.00     0.00     1
## HeatingQC*        41 1460      2.54     1.74      1.0      2.42     0.00     1
## CentralAir*       42 1460      1.93     0.25      2.0      2.00     0.00     1
## Electrical*       43 1459      4.68     1.05      5.0      5.00     0.00     1
## X1stFlrSF         44 1460   1162.63   386.59   1087.0   1129.99   347.67   334
## X2ndFlrSF         45 1460    346.99   436.53      0.0    285.36     0.00     0
## LowQualFinSF      46 1460      5.84    48.62      0.0      0.00     0.00     0
## GrLivArea         47 1460   1515.46   525.48   1464.0   1467.67   483.33   334
## BsmtFullBath      48 1460      0.43     0.52      0.0      0.39     0.00     0
## BsmtHalfBath      49 1460      0.06     0.24      0.0      0.00     0.00     0
## FullBath          50 1460      1.57     0.55      2.0      1.56     0.00     0
## HalfBath          51 1460      0.38     0.50      0.0      0.34     0.00     0
## BedroomAbvGr      52 1460      2.87     0.82      3.0      2.85     0.00     0
## KitchenAbvGr      53 1460      1.05     0.22      1.0      1.00     0.00     0
## KitchenQual*      54 1460      3.34     0.83      4.0      3.50     0.00     1
## TotRmsAbvGrd      55 1460      6.52     1.63      6.0      6.41     1.48     2
## Functional*       56 1460      6.75     0.98      7.0      7.00     0.00     1
## Fireplaces        57 1460      0.61     0.64      1.0      0.53     1.48     0
## FireplaceQu*      58  770      3.73     1.13      3.0      3.80     1.48     1
## GarageType*       59 1379      3.28     1.79      2.0      3.11     0.00     1
## GarageYrBlt       60 1379   1978.51    24.69   1980.0   1981.07    31.13  1900
## GarageFinish*     61 1379      2.18     0.81      2.0      2.23     1.48     1
## GarageCars        62 1460      1.77     0.75      2.0      1.77     0.00     0
## GarageArea        63 1460    472.98   213.80    480.0    469.81   177.91     0
## GarageQual*       64 1379      4.86     0.61      5.0      5.00     0.00     1
## GarageCond*       65 1379      4.90     0.52      5.0      5.00     0.00     1
## PavedDrive*       66 1460      2.86     0.50      3.0      3.00     0.00     1
## WoodDeckSF        67 1460     94.24   125.34      0.0     71.76     0.00     0
## OpenPorchSF       68 1460     46.66    66.26     25.0     33.23    37.06     0
## EnclosedPorch     69 1460     21.95    61.12      0.0      3.87     0.00     0
## X3SsnPorch        70 1460      3.41    29.32      0.0      0.00     0.00     0
## ScreenPorch       71 1460     15.06    55.76      0.0      0.00     0.00     0
## PoolArea          72 1460      2.76    40.18      0.0      0.00     0.00     0
## PoolQC*           73    7      2.14     0.90      2.0      2.14     1.48     1
## Fence*            74  281      2.43     0.86      3.0      2.48     0.00     1
## MiscFeature*      75   54      2.91     0.45      3.0      3.00     0.00     1
## MiscVal           76 1460     43.49   496.12      0.0      0.00     0.00     0
## MoSold            77 1460      6.32     2.70      6.0      6.25     2.97     1
## YrSold            78 1460   2007.82     1.33   2008.0   2007.77     1.48  2006
## SaleType*         79 1460      8.51     1.56      9.0      8.92     0.00     1
## SaleCondition*    80 1460      4.77     1.10      5.0      5.00     0.00     1
## SalePrice         81 1460 180921.20 79442.50 163000.0 170783.29 56338.80 34900
##                    max  range   skew kurtosis      se
## Id                1460   1459   0.00    -1.20   11.03
## MSSubClass         190    170   1.40     1.56    1.11
```

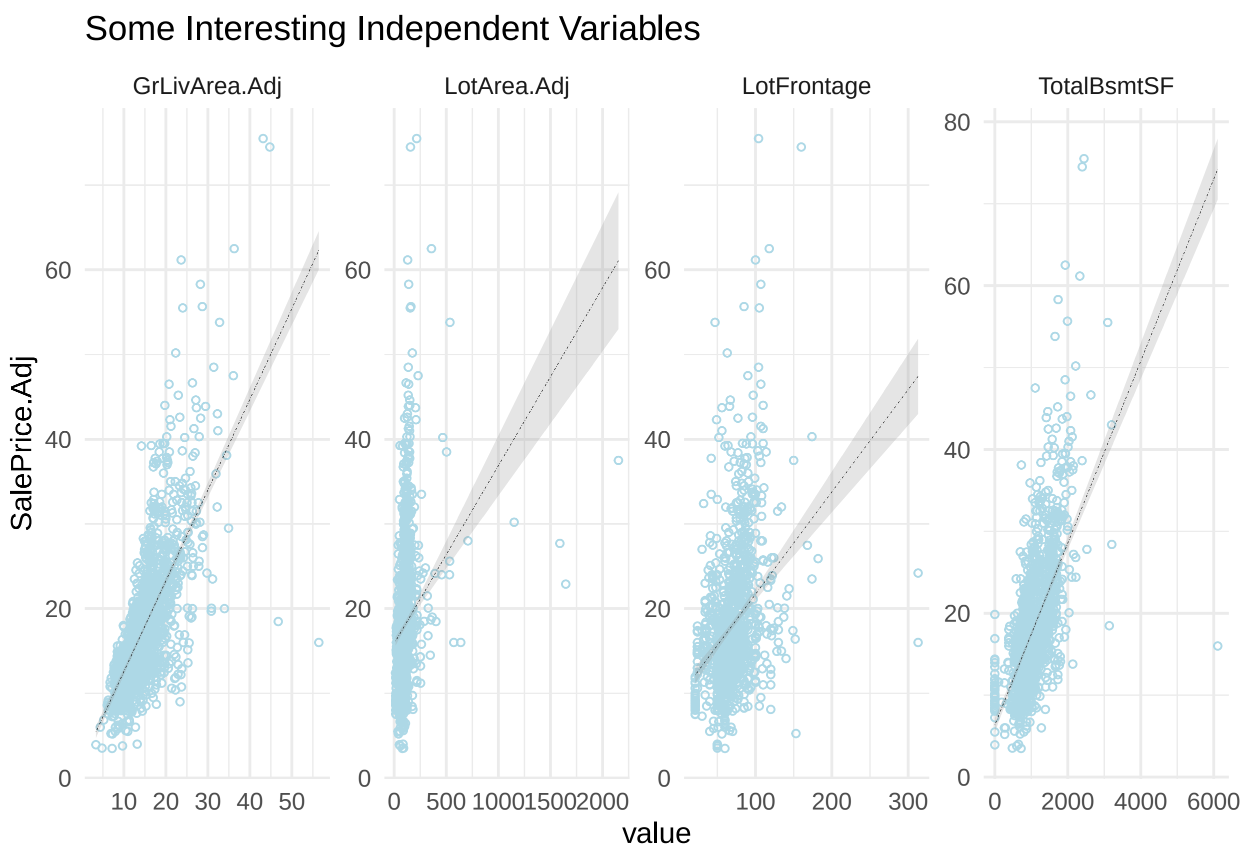
```
## MSZoning*          5      4  -1.73    6.25   0.02
## LotFrontage      313    292   2.16   17.34   0.70
## LotArea       215245 213945  12.18  202.26 261.22
## Street*            2      1 -15.49  238.01   0.00
## Alley*             2      1   0.20   -1.98   0.05
## LotShape*          4      3  -0.61   -1.60   0.04
## LandContour*       4      3  -3.16    8.65   0.02
## Utilities*         2      1  38.13 1453.00   0.00
## LotConfig*         5      4  -1.13   -0.59   0.04
## LandSlope*         3      2   4.80   24.47   0.01
## Neighborhood*     25     24   0.02   -1.06   0.15
## Condition1*        9      8   3.01   16.34   0.02
## Condition2*        8      7  13.14  247.54   0.01
## BldgType*          5      4   2.24    3.41   0.03
## HouseStyle*        8      7   0.31   -0.96   0.05
## OverallQual       10      9   0.22    0.09   0.04
## OverallCond        9      8   0.69    1.09   0.03
## YearBuilt       2010    138  -0.61   -0.45   0.79
## YearRemodAdd    2010     60  -0.50   -1.27   0.54
## RoofStyle*         6      5   1.47    0.61   0.02
## RoofMatl*          8      7   8.09   66.28   0.02
## Exterior1st*      15     14  -0.72   -0.37   0.08
## Exterior2nd*      16     15  -0.69   -0.52   0.09
## MasVnrType*        4      3  -0.07   -0.13   0.02
## MasVnrArea      1600   1600   2.66   10.03   4.75
## ExterQual*         4      3  -1.83    3.86   0.02
## ExterCond*         5      4  -2.56    5.29   0.02
## Foundation*        6      5   0.09    1.02   0.02
## BsmtQual*          4      3  -1.31    1.27   0.02
## BsmtCond*          4      3  -3.39   10.14   0.02
## BsmtExposure*      4      3  -1.15   -0.39   0.03
## BsmtFinType1*      6      5  -0.02   -1.39   0.05
## BsmtFinSF1      5644   5644   1.68   11.06  11.94
## BsmtFinType2*      6      5  -3.56   12.32   0.02
## BsmtFinSF2      1474   1474   4.25   20.01   4.22
## BsmtUnfSF       2336   2336   0.92    0.46  11.56
## TotalBsmtSF     6110   6110   1.52   13.18  11.48
## Heating*           6      5   9.83  110.98   0.01
## HeatingQC*         5      4   0.48   -1.51   0.05
## CentralAir*        2      1  -3.52   10.42   0.01
## Electrical*        5      4  -3.06    7.49   0.03
## X1stFlrSF       4692   4358   1.37    5.71  10.12
## X2ndFlrSF       2065   2065   0.81   -0.56  11.42
## LowQualFinSF     572    572   8.99   82.83   1.27
## GrLivArea       5642   5308   1.36    4.86  13.75
## BsmtFullBath       3      3   0.59   -0.84   0.01
## BsmtHalfBath       2      2   4.09   16.31   0.01
## FullBath           3      3   0.04   -0.86   0.01
## HalfBath           2      2   0.67   -1.08   0.01
## BedroomAbvGr       8      8   0.21    2.21   0.02
## KitchenAbvGr       3      3   4.48   21.42   0.01
## KitchenQual*       4      3  -1.42    1.72   0.02
## TotRmsAbvGrd      14     12   0.67    0.87   0.04
## Functional*        7      6  -4.08   16.37   0.03
```

```
## Fireplaces           3      3   0.65    -0.22    0.02
## FireplaceQu*         5      4  -0.16    -0.98    0.04
## GarageType*          6      5   0.76    -1.30    0.05
## GarageYrBlt       2010    110  -0.65    -0.42    0.66
## GarageFinish*        3      2  -0.35    -1.41    0.02
## GarageCars           4      4  -0.34     0.21    0.02
## GarageArea        1418   1418   0.18     0.90    5.60
## GarageQual*          5      4  -4.43    18.25    0.02
## GarageCond*          5      4  -5.28    26.77    0.01
## PavedDrive*          3      2  -3.30     9.22    0.01
## WoodDeckSF         857    857   1.54     2.97    3.28
## OpenPorchSF        547    547   2.36     8.44    1.73
## EnclosedPorch      552    552   3.08    10.37    1.60
## X3SsnPorch         508    508  10.28   123.06    0.77
## ScreenPorch        480    480   4.11    18.34    1.46
## PoolArea           738    738  14.80   222.19    1.05
## PoolQC*              3      2  -0.22    -1.90    0.34
## Fence*               4      3  -0.57    -0.88    0.05
## MiscFeature*         4      3  -2.93    10.71    0.06
## MiscVal          15500  15500  24.43   697.64   12.98
## MoSold              12     11   0.21    -0.41    0.07
## YrSold            2010      4   0.10    -1.19    0.03
## SaleType*            9      8  -3.83    14.57    0.04
## SaleCondition*       6      5  -2.74     6.82    0.03
## SalePrice       755000 720100   1.88     6.50 2079.11
```

```
train  %>%
  mutate(SalePrice.Adj = SalePrice / 10000,
         GrLivArea.Adj = GrLivArea / 100,
         LotArea.Adj = LotArea / 100) %>%
  dplyr::select(SalePrice.Adj, OverallQual, OverallCond, Neighborhood, BedroomAbvGr, FullBath, HalfBath
         LotArea.Adj, LotFrontage, GrLivArea.Adj, TotalBsmtSF) %>%
  gather(variable, value, -SalePrice.Adj) %>%
  ggplot(., aes(value, SalePrice.Adj)) +
  ggtitle("Some Interesting Independent Variables") +
  geom_point(fill = "white",
             size=1,
             shape=1,
             color="light blue") +
  geom_smooth(formula = y~x,
              method = "lm",
              size=.1,
              se = TRUE,
              color = "black",
              linetype = "dotdash",
              alpha=0.25) +
  facet_wrap(~variable,
             scales ="free",
             ncol = 4)
```

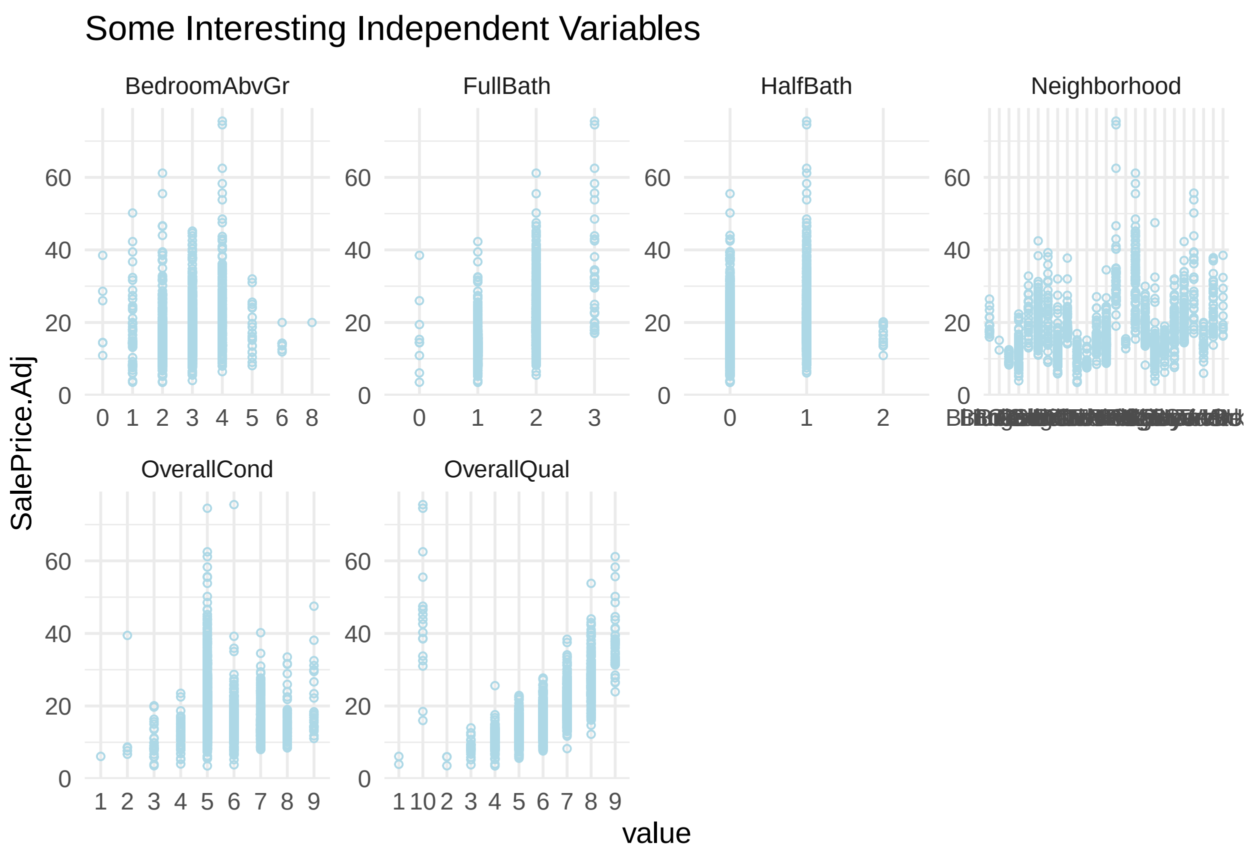



```r
# scatterplot matrix for at least two of the independent variables and the dependent variable
train  %>%
  mutate(SalePrice.Adj = SalePrice / 10000,
         GrLivArea.Adj = GrLivArea / 100,
         LotArea.Adj = LotArea / 100) %>%
  dplyr::select(SalePrice.Adj, LotArea.Adj, LotFrontage, GrLivArea.Adj, TotalBsmtSF) %>%
  gather(variable, value, -SalePrice.Adj) %>%
  ggplot(., aes(value, SalePrice.Adj)) +
  ggtitle("Some Interesting Independent Variables") +
  geom_point(fill = "white",
             size=1,
             shape=1,
             color="light blue") +
  geom_smooth(formula = y~x,
              method = "lm",
              size=.1,
              se = TRUE,
              color = "black",
              linetype = "dotdash",
              alpha=0.25) +
  facet_wrap(~variable,
             scales ="free",
             ncol = 4)
```

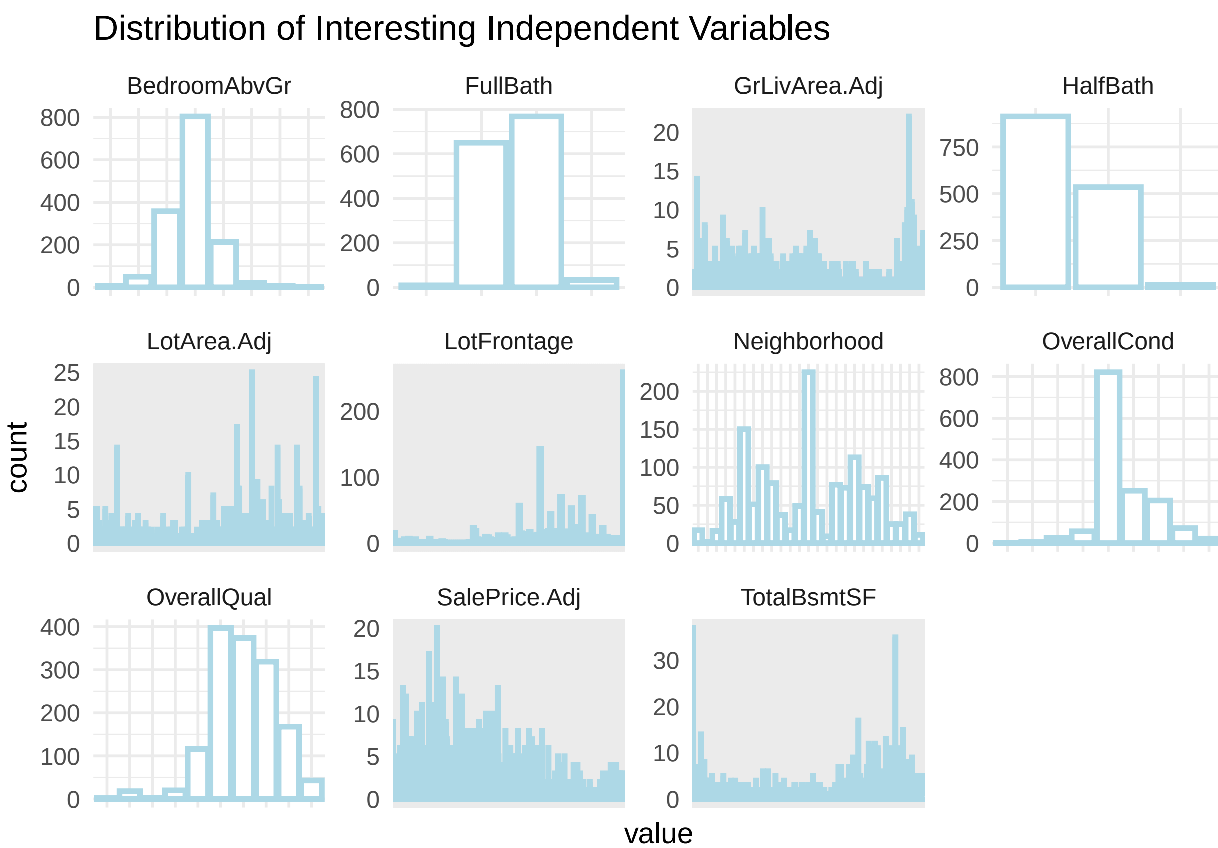



```
# theme(axis.text.x = element_blank(), axis.text.y = element_blank())
```

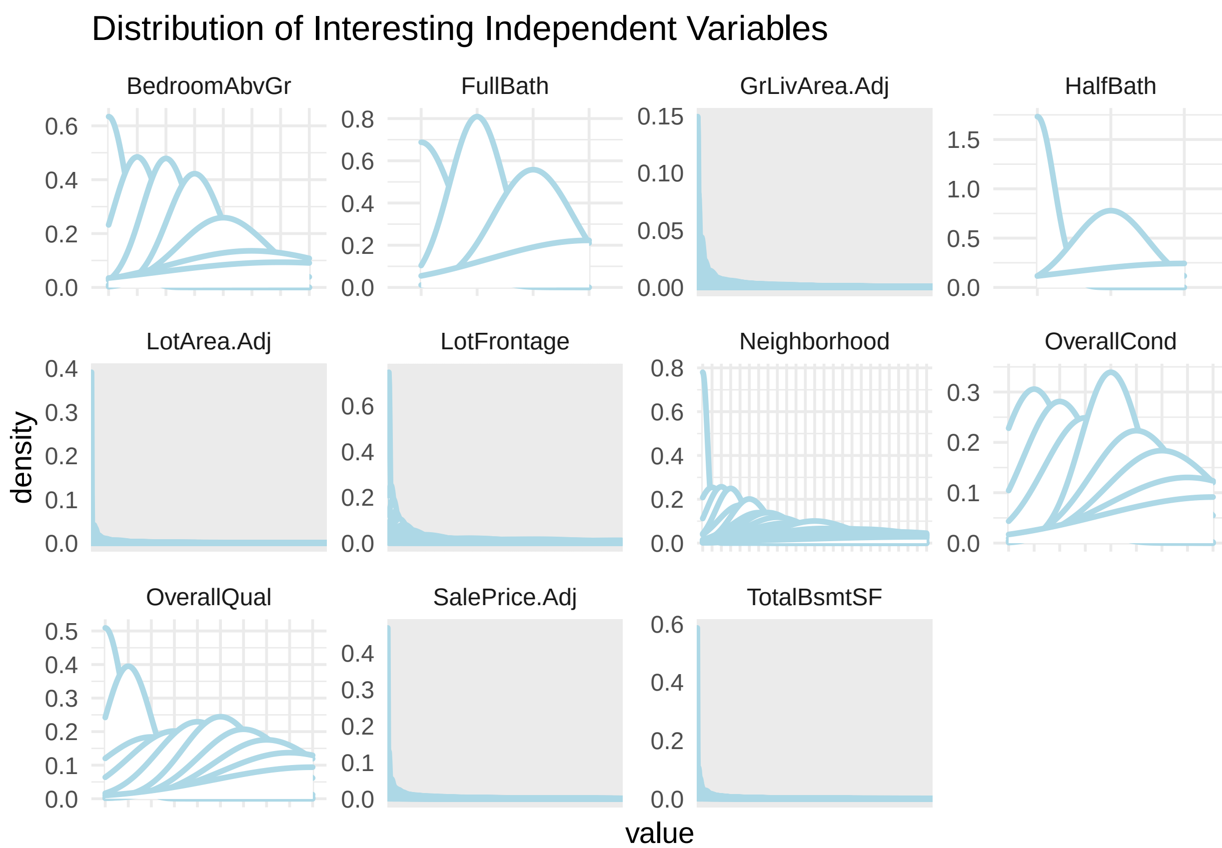
```
train  %>%
  mutate(SalePrice.Adj = SalePrice / 10000) %>%
  dplyr::select(SalePrice.Adj, OverallQual, OverallCond, Neighborhood, BedroomAbvGr, FullBath, HalfBath)
  gather(variable, value, -SalePrice.Adj) %>%
  ggplot(., aes(value, SalePrice.Adj)) +
  ggtitle("Some Interesting Independent Variables") +
  geom_point(fill = "white",
             size=1,
             shape=1,
             color="light blue") +
  geom_smooth(formula = y~x,
              method = "lm",
              size=.1,
              se = TRUE,
              color = "black",
              linetype = "dotdash",
              alpha=0.25) +
  facet_wrap(~variable,
             scales ="free",
             ncol = 4)
```




```r
train  %>%
  mutate(SalePrice.Adj = SalePrice / 10000,
         GrLivArea.Adj = GrLivArea / 100,
         LotArea.Adj = LotArea / 100) %>%
  dplyr::select(SalePrice.Adj, OverallQual, OverallCond, Neighborhood, BedroomAbvGr, FullBath, HalfBath
         LotArea.Adj, LotFrontage, GrLivArea.Adj, TotalBsmtSF) %>%
  gather(variable, value) %>%
  ggplot(., aes(value)) +
  ggtitle("Distribution of Interesting Independent Variables") +
  geom_histogram(fill = "white",
              size=1,
              shape=1,
              color="light blue",
              stat = "count") +
  theme(axis.text.x = element_blank()) +
  facet_wrap(~variable,
              scales ="free",
              ncol = 4)
```




```r
train  %>%
  mutate(SalePrice.Adj = SalePrice / 10000,
         GrLivArea.Adj = GrLivArea / 100,
         LotArea.Adj = LotArea / 100) %>%
  dplyr::select(SalePrice.Adj, OverallQual, OverallCond, Neighborhood, BedroomAbvGr, FullBath, HalfBath
         LotArea.Adj, LotFrontage, GrLivArea.Adj, TotalBsmtSF) %>%
  gather(variable, value) %>%
  ggplot(., aes(value)) +
  ggtitle("Distribution of Interesting Independent Variables") +
  geom_density(fill = "white",
            size=1,
            shape=1,
            color="light blue") +
  theme(axis.text.x = element_blank()) +
  facet_wrap(~variable,
            scales ="free",
            ncol = 4)
```




```r
# Derive a correlation matrix for any three quantitative variables
train %>%
  dplyr::select(SalePrice, LotArea, OverallQual, OverallCond) %>%
  cor() %>%
  as.matrix()
```

```
##               SalePrice     LotArea OverallQual OverallCond
## SalePrice    1.00000000  0.26384335  0.79098160 -0.07785589
## LotArea      0.26384335  1.00000000  0.10580574 -0.00563627
## OverallQual  0.79098160  0.10580574  1.00000000 -0.09193234
## OverallCond -0.07785589 -0.00563627 -0.09193234  1.00000000
```

```r
cor.test(train$SalePrice, train$OverallCond, conf.level = 0.80)
```

```
##
##  Pearson's product-moment correlation
##
## data:  train$SalePrice and train$OverallCond
## t = -2.9819, df = 1458, p-value = 0.002912
## alternative hypothesis: true correlation is not equal to 0
## 80 percent confidence interval:
##  -0.1111272 -0.0444103
## sample estimates:
##         cor
## -0.07785589
```

```r
cor.test(train$SalePrice, train$OverallQual, conf.level = 0.80)
```

```
##
##  Pearson's product-moment correlation
##
## data:  train$SalePrice and train$OverallQual
## t = 49.364, df = 1458, p-value < 2.2e-16
## alternative hypothesis: true correlation is not equal to 0
## 80 percent confidence interval:
##  0.7780752 0.8032204
## sample estimates:
##       cor
## 0.7909816
```

```r
cor.test(train$SalePrice, train$LotArea, conf.level = 0.80)
```

```
##
##  Pearson's product-moment correlation
##
## data:  train$SalePrice and train$LotArea
## t = 10.445, df = 1458, p-value < 2.2e-16
## alternative hypothesis: true correlation is not equal to 0
## 80 percent confidence interval:
##  0.2323391 0.2947946
## sample estimates:
##       cor
## 0.2638434
```

There should be no worries about familywise errors which is the probability of making a false discovery (in other words, type 1 errors) because the values are relatively intuitive and easily interpreted as right or wrong. For example, a false rejection of the null hypothesis in the case of LotArea would likely mean that we conclude that greater lot sizes did not have an effect on sale price when we know this to be false. We should expect that for almost any of these variables an increase in something considered good or valuable by most people would result in an increase in sales price.

Meanwhile our variables could use some help and it is doubtful that many are beneficial to use in predicting sales price. In some of the most interesting variables that we thought would have the most influence over sales price, many are right skewed heavily. This will cause the model to predict higher than observed values if not accounted for.

The three variables we expect to perform best are LotArea, OverallQual, and OverallCond. Their correlations are completely different. OverallQual had the strongest correlation with SalePrice at about 0.79 which makes sense given that most people would consider it important to think about the overall quality of the home before agreeing to purchase it. However, there is still plenty of room for misinterpretation in any of these variables.

Section 2: Linear Algebra and Correlation

```r
cor.mtx <- train %>%
  dplyr::select(SalePrice, LotArea, OverallQual, OverallCond) %>%
  cor() %>%
```

```
  as.matrix()
pcn.mtx <- solve(cor.mtx)
rdu.mtx <- cor.mtx %*% pcn.mtx
lud.mtx <- lu.decomposition(rdu.mtx)
cor.mtx
```

```
##               SalePrice     LotArea OverallQual OverallCond
## SalePrice    1.00000000  0.26384335  0.79098160 -0.07785589
## LotArea      0.26384335  1.00000000  0.10580574 -0.00563627
## OverallQual  0.79098160  0.10580574  1.00000000 -0.09193234
## OverallCond -0.07785589 -0.00563627 -0.09193234  1.00000000
```

```
pcn.mtx
```

```
##               SalePrice      LotArea OverallQual  OverallCond
## SalePrice    2.92833783 -0.533593316  -2.2582064  0.017378675
## LotArea     -0.53359332  1.108568702   0.3040949 -0.007339038
## OverallQual -2.25820645  0.304094866   2.7613570  0.079757301
## OverallCond  0.01737868 -0.007339038   0.0797573  1.008643943
```

```
rdu.mtx
```

```
##                 SalePrice       LotArea   OverallQual   OverallCond
## SalePrice    1.000000e+00  2.287667e-17  8.673617e-19  0.000000e+00
## LotArea     -2.535678e-17  1.000000e+00 -6.342583e-18 -8.673617e-19
## OverallQual -1.084202e-16  1.821460e-17  1.000000e+00  0.000000e+00
## OverallCond -1.734723e-17 -6.938894e-18  4.163336e-17  1.000000e+00
```

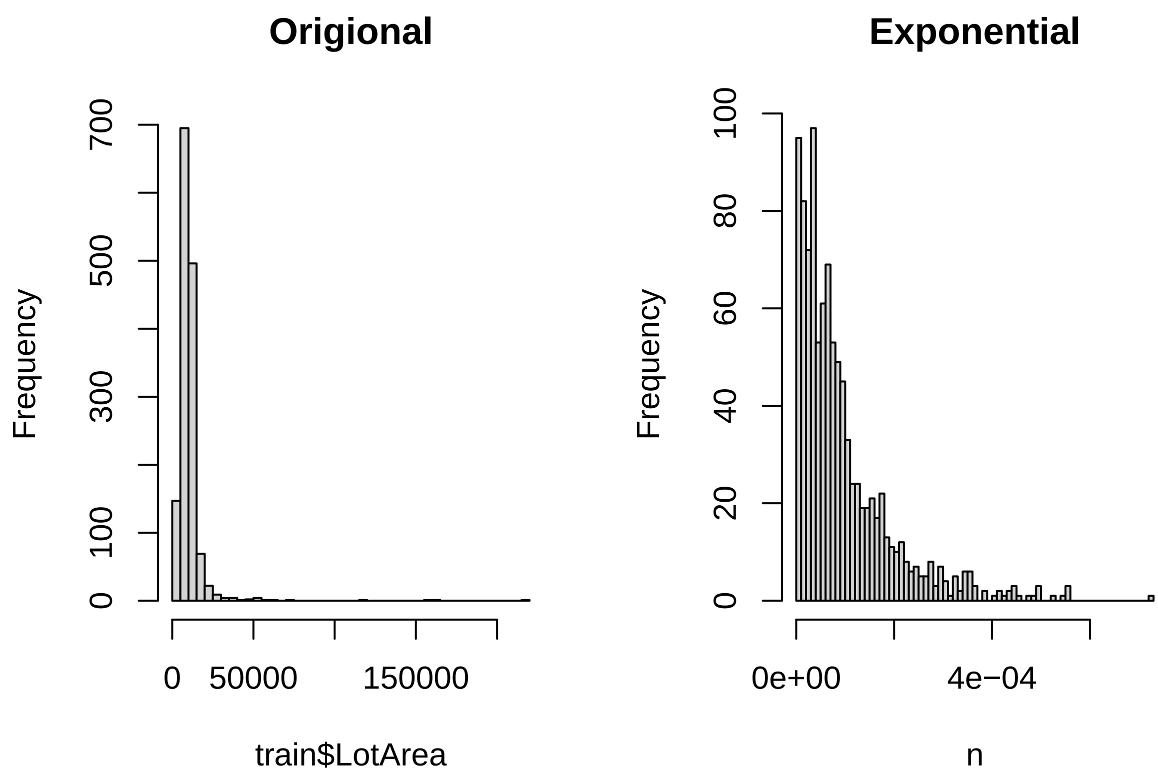
```
lud.mtx
```

```
## $L
##               [,1]          [,2]         [,3] [,4]
## [1,]  1.000000e+00  0.000000e+00 0.000000e+00    0
## [2,] -2.535678e-17  1.000000e+00 0.000000e+00    0
## [3,] -1.084202e-16  1.821460e-17 1.000000e+00    0
## [4,] -1.734723e-17 -6.938894e-18 4.163336e-17    1
##
## $U
##      [,1]         [,2]          [,3]          [,4]
## [1,]    1 2.287667e-17  8.673617e-19  0.000000e+00
## [2,]    0 1.000000e+00 -6.342583e-18 -8.673617e-19
## [3,]    0 0.000000e+00  1.000000e+00  1.579864e-35
## [4,]    0 0.000000e+00  0.000000e+00  1.000000e+00
```

Section 3: Calculus-Based Probability & Statistics

```
fd.exp <- fitdistr(train$LotArea, densfun = "exponential")
y <- fd.exp$estimate
rate <- 1/y
```

```r
n <- rexp(1000, rate)
par(mfrow = c(1,2))
hist(train$LotArea, breaks = 75, main = "Origional")
hist(n, breaks = 75, main = "Exponential")
```




```r
# 5th and 95th Percentiles
print(paste("CDF Percentile =", signif(qexp(c(0.05, 0.95), rate = rate), 3)))
```

```
## [1] "CDF Percentile = 4.88e-06" "CDF Percentile = 0.000285"
```

```r
# 95% confidence interval
print(paste("95% Confidence =",round((qnorm(c(0.025, 0.975),
      mean=mean(train$LotArea), sd=sd(train$LotArea))), 3)))
```

```
## [1] "95% Confidence = -9046.092" "95% Confidence = 30079.748"
```

```r
print(paste("Empirical =", round(quantile(train$LotArea, c(0.05, 0.95)), 3)))
```

```
## [1] "Empirical = 3311.7"    "Empirical = 17401.15"
```

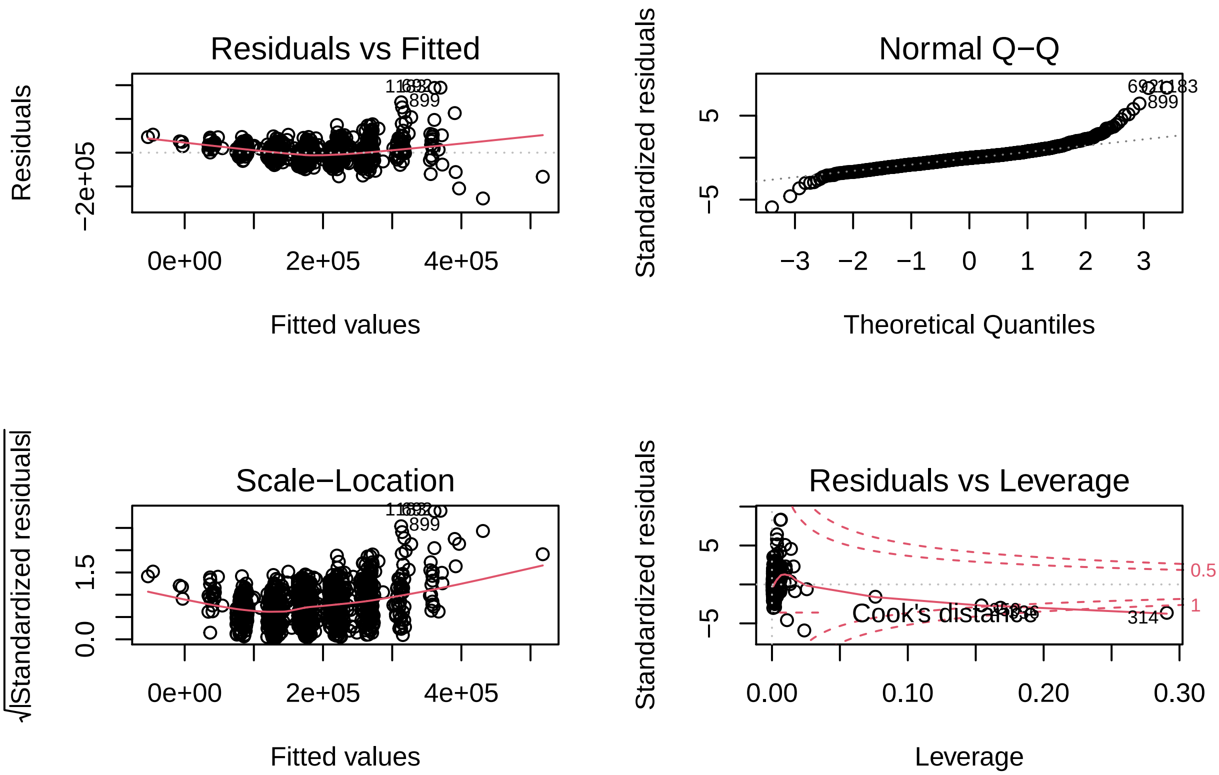
The 5th and 95th percentiles differ from CDF to Empirical. Our histogram shows the exponential distribution spreads itself more normally than the original. From the 95% confidence calculation we have the range -9046.092 to 30079.748. This is completely unrealistic of the variable given that lot area is not normally distributed and is also always positive (otherwise you have nothing to sell). Alternatively we have the empirically calculated range 3311.7 to 17401.15 which is larger but more realistic.

Section 4: Modeling

```
mod1 <- lm(SalePrice~LotArea + OverallQual, train)
summary(mod1)
```

```
##
## Call:
## lm(formula = SalePrice ~ LotArea + OverallQual, data = train)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -271225  -26819   -1459   20172  385190
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -1.047e+05  5.547e+03  -18.88   <2e-16 ***
## LotArea      1.450e+00  1.225e-01   11.83   <2e-16 ***
## OverallQual  4.433e+04  8.844e+02   50.12   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 46460 on 1457 degrees of freedom
## Multiple R-squared:  0.6585, Adjusted R-squared:  0.658
## F-statistic:  1405 on 2 and 1457 DF,  p-value: < 2.2e-16
```

```
par(mfrow = c(2,2))
plot(mod1)
```



This model was meant to elucidate the behavior of two of the most likely variables thought to influence sales price. Of course, this could be improved since we have plenty of room to do so. Ignoring the problem outliers in our Residuals vs Leverage plot as well as the sinking Scale-Location plot, we have close enough to normal set to build on (though declaring it normal is a stretch here too given the tails). Interestingly, our R^2 is moderately strong at about 0.659.

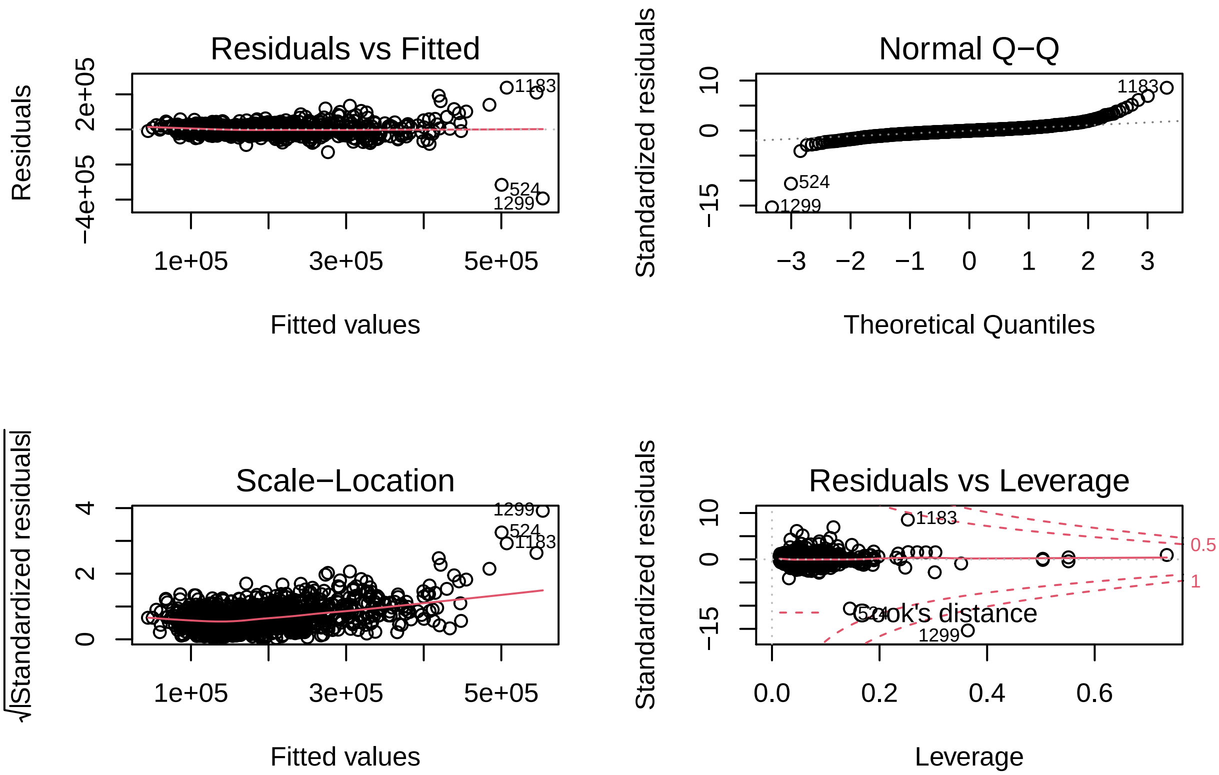
```
mod2.lm <- lm(SalePrice ~ LotArea +
                Neighborhood +
                LotFrontage +
                OverallQual +
                OverallCond +
                GrLivArea +
                HalfBath +
                FullBath +
                TotRmsAbvGrd +
                TotalBsmtSF +
                YearRemodAdd +
                YearBuilt +
                Fireplaces +
                GarageFinish +
                PavedDrive +
                GarageArea +
                GarageYrBlt +
                GarageCars +
                PoolArea +
                KitchenAbvGr +
```

```r
                 KitchenQual +
                 SaleCondition +
                 SaleType +
                 factor(OverallQual) +
                 LandSlope +
                 rexp(LotArea) +
                 rexp(LotFrontage) +
                 rexp(GrLivArea) +
                 rexp(TotRmsAbvGrd) +
                 rexp(TotalBsmtSF) +
                 rexp(GarageArea)
               , train)
mod2.both <- stepAIC(mod2.lm, trace = F, direction = "both")
mod2.call <- summary(mod2.both)$call
mod2 <- lm(mod2.call[2], train)
summary(mod2)
```

```
##
## Call:
## lm(formula = mod2.call[2], data = train)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -393429  -12267    -636   10598  238004
##
## Coefficients:
##                         Estimate Std. Error t value Pr(>|t|)
## (Intercept)           -4.709e+05  2.225e+05  -2.117 0.034530 *
## LotArea                7.709e-01  1.585e-01   4.864 1.32e-06 ***
## NeighborhoodBlueste   -1.355e+04  2.492e+04  -0.544 0.586707
## NeighborhoodBrDale    -7.978e+02  1.323e+04  -0.060 0.951921
## NeighborhoodBrkSide    1.483e+04  1.171e+04   1.267 0.205491
## NeighborhoodClearCr    2.964e+04  1.372e+04   2.160 0.031006 *
## NeighborhoodCollgCr    2.517e+04  9.649e+03   2.609 0.009221 **
## NeighborhoodCrawfor    3.690e+04  1.150e+04   3.210 0.001366 **
## NeighborhoodEdwards   -5.310e+03  1.059e+04  -0.502 0.615997
## NeighborhoodGilbert    1.195e+04  1.033e+04   1.157 0.247640
## NeighborhoodIDOTRR     1.430e+03  1.253e+04   0.114 0.909138
## NeighborhoodMeadowV   -8.362e+03  1.429e+04  -0.585 0.558630
## NeighborhoodMitchel    1.885e+04  1.116e+04   1.690 0.091391 .
## NeighborhoodNAmes      1.583e+04  1.026e+04   1.542 0.123390
## NeighborhoodNoRidge    7.785e+04  1.127e+04   6.909 8.44e-12 ***
## NeighborhoodNPkVill    8.952e+02  1.581e+04   0.057 0.954861
## NeighborhoodNridgHt    4.630e+04  1.019e+04   4.543 6.17e-06 ***
## NeighborhoodNWAmes     1.240e+04  1.077e+04   1.151 0.249932
## NeighborhoodOldTown    4.527e+03  1.129e+04   0.401 0.688593
## NeighborhoodSawyer     1.382e+04  1.096e+04   1.261 0.207736
## NeighborhoodSawyerW    2.367e+04  1.051e+04   2.252 0.024505 *
## NeighborhoodSomerst    2.739e+04  9.918e+03   2.762 0.005848 **
## NeighborhoodStoneBr    6.889e+04  1.181e+04   5.834 7.19e-09 ***
## NeighborhoodSWISU      4.196e+03  1.320e+04   0.318 0.750622
## NeighborhoodTimber     2.584e+04  1.098e+04   2.354 0.018740 *
## NeighborhoodVeenker    4.400e+04  1.564e+04   2.814 0.004985 **
```

```
## LotFrontage          -1.206e+02  5.472e+01  -2.204 0.027729 *
## OverallCond           7.554e+03  1.241e+03   6.085 1.63e-09 ***
## GrLivArea             3.687e+01  5.250e+00   7.023 3.87e-12 ***
## HalfBath              1.307e+02  2.759e+03   0.047 0.962237
## FullBath              3.918e+03  3.243e+03   1.208 0.227192
## TotRmsAbvGrd          2.368e+03  1.234e+03   1.918 0.055333 .
## TotalBsmtSF           1.368e+01  3.421e+00   3.998 6.84e-05 ***
## YearRemodAdd          5.593e+01  8.245e+01   0.678 0.497701
## YearBuilt             2.956e+02  9.604e+01   3.077 0.002143 **
## Fireplaces            7.827e+03  1.983e+03   3.947 8.42e-05 ***
## GarageFinishRFn      -3.869e+03  3.001e+03  -1.289 0.197550
## GarageFinishUnf      -9.218e+03  3.443e+03  -2.677 0.007535 **
## PavedDriveP          -3.176e+03  8.484e+03  -0.374 0.708224
## PavedDriveY           4.211e+03  5.390e+03   0.781 0.434887
## GarageArea           -7.639e-01  1.127e+01  -0.068 0.945959
## GarageYrBlt          -9.415e+01  8.146e+01  -1.156 0.248014
## GarageCars            1.460e+04  3.203e+03   4.559 5.73e-06 ***
## PoolArea             -3.694e+01  2.608e+01  -1.417 0.156917
## KitchenAbvGr         -2.944e+04  5.827e+03  -5.053 5.12e-07 ***
## KitchenQualFa        -2.673e+04  9.319e+03  -2.869 0.004204 **
## KitchenQualGd        -2.104e+04  4.995e+03  -4.213 2.74e-05 ***
## KitchenQualTA        -2.412e+04  5.709e+03  -4.224 2.60e-05 ***
## SaleConditionAdjLand  4.215e+04  3.364e+04   1.253 0.210525
## SaleConditionAlloca   3.930e+03  1.242e+04   0.316 0.751776
## SaleConditionFamily  -4.294e+03  8.764e+03  -0.490 0.624290
## SaleConditionNormal   5.163e+03  4.154e+03   1.243 0.214179
## SaleConditionPartial  1.988e+04  5.468e+03   3.636 0.000290 ***
## factor(OverallQual)3 -4.118e+02  2.573e+04  -0.016 0.987235
## factor(OverallQual)4 -3.055e+03  2.405e+04  -0.127 0.898929
## factor(OverallQual)5 -2.315e+03  2.401e+04  -0.096 0.923197
## factor(OverallQual)6 -1.447e+03  2.411e+04  -0.060 0.952159
## factor(OverallQual)7  8.881e+03  2.436e+04   0.365 0.715461
## factor(OverallQual)8  3.192e+04  2.471e+04   1.292 0.196624
## factor(OverallQual)9  8.513e+04  2.552e+04   3.335 0.000882 ***
## factor(OverallQual)10 1.077e+05  2.681e+04   4.018 6.28e-05 ***
## LandSlopeMod          1.320e+04  5.332e+03   2.476 0.013447 *
## LandSlopeSev         -2.185e+04  1.712e+04  -1.277 0.202047
## rexp(LotArea)        -6.386e+02  9.900e+02  -0.645 0.519025
## rexp(LotFrontage)     1.267e+02  1.066e+03   0.119 0.905379
## rexp(GrLivArea)       7.868e+02  9.221e+02   0.853 0.393733
## rexp(TotRmsAbvGrd)   -3.576e+02  1.025e+03  -0.349 0.727288
## rexp(TotalBsmtSF)     2.712e+02  9.621e+02   0.282 0.778076
## rexp(GarageArea)     -8.183e+02  9.876e+02  -0.829 0.407503
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 32160 on 1058 degrees of freedom
##   (333 observations deleted due to missingness)
## Multiple R-squared:  0.8597, Adjusted R-squared:  0.8507
## F-statistic: 95.32 on 68 and 1058 DF,  p-value: < 2.2e-16
```

```r
par(mfrow=c(2,2))
plot(mod2)
```



The goal in this model was to add any variables to the plot we thought might influence the sales price at then see if there any new trends we to be noticed and there are. Our initial expectation is at least partially wrong. We missed out on several beneficial variables (and may have missed more than what is listed here). Many of these predictors are not significant or particularly useful in predicting sales price. We select those that are significant and clean them up a bit before creating our third model.

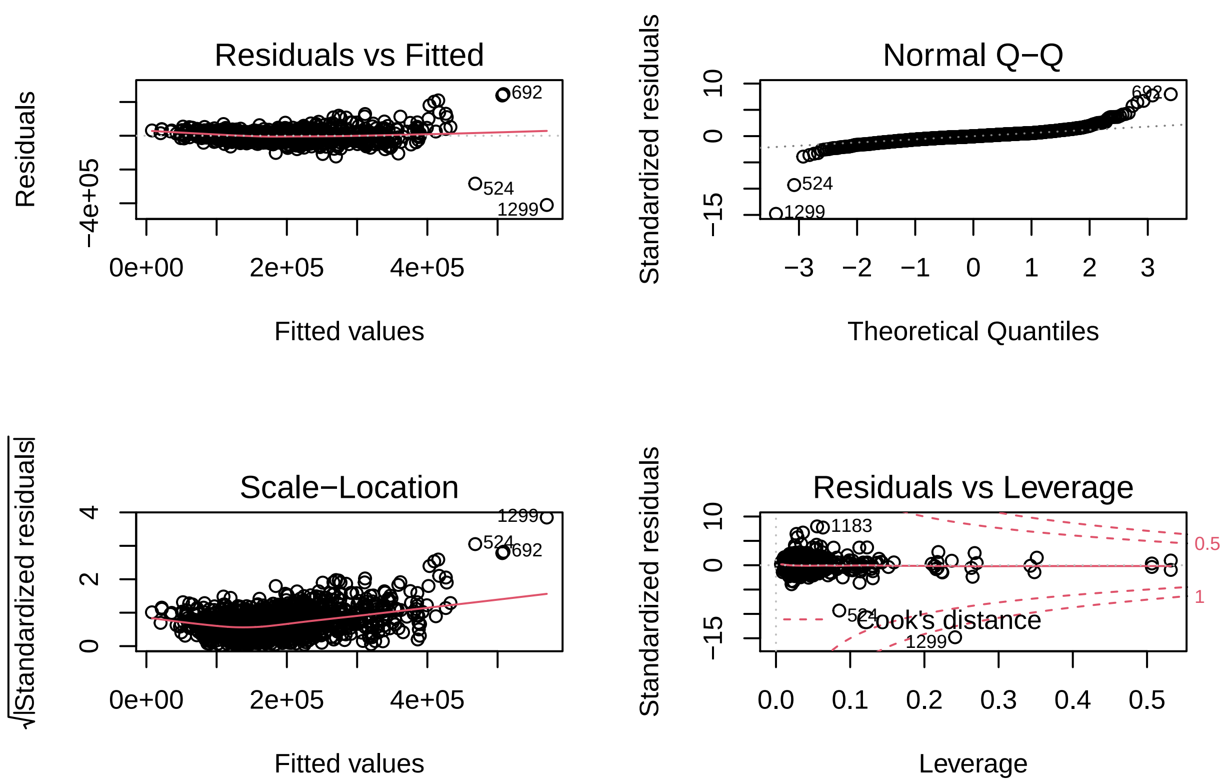
```
train$LotFrontage[is.na(train$LotFrontage)] <- median(train$LotFrontage, na.rm = T)
train$GarageCars[is.na(train$GarageCars)] <- median(train$GarageCars, na.rm = T)
train$TotalBsmtSF[is.na(train$TotalBsmtSF)] <- median(train$TotalBsmtSF, na.rm = T)
train$SaleType[is.na(train$SaleType)] <- "WD"
train$KitchenQual[is.na(train$KitchenQual)] <- "TA"
train$GarageFinish[is.na(train$GarageFinish)] <- "Unf"
mod3 <- lm(SalePrice ~
             LandSlope +
             OverallQual +
             KitchenQual +
             KitchenAbvGr +
             GarageCars +
             GarageFinish +
             Fireplaces +
             YearBuilt +
             TotalBsmtSF +
             TotRmsAbvGrd +
             SaleType +
             GrLivArea +
             OverallCond +
```

```r
             LotFrontage +
             Neighborhood
             , train)
summary(mod3)
```

```
##
## Call:
## lm(formula = SalePrice ~ LandSlope + OverallQual + KitchenQual +
##     KitchenAbvGr + GarageCars + GarageFinish + Fireplaces + YearBuilt +
##     TotalBsmtSF + TotRmsAbvGrd + SaleType + GrLivArea + OverallCond +
##     LotFrontage + Neighborhood, data = train)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -409980  -13199    -946   12369  246545
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)         -5.372e+05  1.380e+05  -3.892 0.000104 ***
## LandSlopeMod         1.626e+04  4.290e+03   3.791 0.000156 ***
## LandSlopeSev         1.931e+04  9.839e+03   1.962 0.049901 *
## OverallQual          9.877e+03  1.172e+03   8.427  < 2e-16 ***
## KitchenQualFa       -3.897e+04  7.299e+03  -5.339 1.09e-07 ***
## KitchenQualGd       -4.035e+04  4.084e+03  -9.882  < 2e-16 ***
## KitchenQualTA       -4.194e+04  4.629e+03  -9.061  < 2e-16 ***
## KitchenAbvGr        -1.904e+04  4.372e+03  -4.355 1.43e-05 ***
## GarageCars           1.180e+04  1.610e+03   7.331 3.84e-13 ***
## GarageFinishRFn     -8.140e+03  2.536e+03  -3.210 0.001357 **
## GarageFinishUnf     -8.356e+03  2.900e+03  -2.881 0.004025 **
## Fireplaces           7.057e+03  1.639e+03   4.305 1.79e-05 ***
## YearBuilt            2.679e+02  6.868e+01   3.901 0.000100 ***
## TotalBsmtSF          2.026e+01  2.630e+00   7.705 2.45e-14 ***
## TotRmsAbvGrd         2.260e+03  1.017e+03   2.223 0.026395 *
## SaleTypeCon          5.040e+04  2.374e+04   2.123 0.033925 *
## SaleTypeConLD        1.334e+04  1.183e+04   1.127 0.259838
## SaleTypeConLI        1.377e+04  1.522e+04   0.905 0.365826
## SaleTypeConLw        7.228e+03  1.526e+04   0.474 0.635804
## SaleTypeCWD          2.118e+04  1.683e+04   1.258 0.208436
## SaleTypeNew          2.487e+04  6.137e+03   4.052 5.35e-05 ***
## SaleTypeOth          3.214e+04  1.929e+04   1.666 0.095950 .
## SaleTypeWD           7.640e+03  5.080e+03   1.504 0.132830
## GrLivArea            4.078e+01  3.708e+00  10.998  < 2e-16 ***
## OverallCond          7.086e+03  8.971e+02   7.899 5.64e-15 ***
## LotFrontage         -1.423e+01  4.676e+01  -0.304 0.761018
## NeighborhoodBlueste -1.293e+04  2.418e+04  -0.535 0.592839
## NeighborhoodBrDale  -3.566e+03  1.172e+04  -0.304 0.760942
## NeighborhoodBrkSide  1.762e+04  1.004e+04   1.755 0.079493 .
## NeighborhoodClearCr  2.979e+04  1.061e+04   2.807 0.005070 **
## NeighborhoodCollgCr  2.740e+04  8.468e+03   3.235 0.001243 **
## NeighborhoodCrawfor  3.594e+04  9.930e+03   3.619 0.000306 ***
## NeighborhoodEdwards  7.767e+03  9.210e+03   0.843 0.399202
## NeighborhoodGilbert  1.468e+04  8.802e+03   1.668 0.095514 .
## NeighborhoodIDOTRR   6.444e+03  1.064e+04   0.606 0.544721
```

```
## NeighborhoodMeadowV  1.608e+03  1.157e+04   0.139 0.889464
## NeighborhoodMitchel  1.660e+04  9.464e+03   1.754 0.079720 .
## NeighborhoodNAmes    1.571e+04  8.818e+03   1.782 0.075007 .
## NeighborhoodNoRidge  8.530e+04  9.729e+03   8.768  < 2e-16 ***
## NeighborhoodNPkVill  2.368e+03  1.350e+04   0.175 0.860753
## NeighborhoodNridgHt  6.189e+04  8.933e+03   6.928 6.46e-12 ***
## NeighborhoodNWAmes   1.181e+04  9.124e+03   1.294 0.195952
## NeighborhoodOldTown  4.089e+03  9.821e+03   0.416 0.677250
## NeighborhoodSawyer   1.678e+04  9.319e+03   1.800 0.072040 .
## NeighborhoodSawyerW  2.466e+04  9.134e+03   2.700 0.007023 **
## NeighborhoodSomerst  3.103e+04  8.715e+03   3.561 0.000382 ***
## NeighborhoodStoneBr  7.270e+04  1.023e+04   7.109 1.85e-12 ***
## NeighborhoodSWISU    6.797e+03  1.131e+04   0.601 0.548045
## NeighborhoodTimber   3.456e+04  9.495e+03   3.640 0.000282 ***
## NeighborhoodVeenker  4.499e+04  1.280e+04   3.516 0.000452 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 31820 on 1410 degrees of freedom
## Multiple R-squared:  0.845,  Adjusted R-squared:  0.8396
## F-statistic: 156.8 on 49 and 1410 DF,  p-value: < 2.2e-16
```

```
par(mfrow = c(2,2))
plot(mod3)
```



Though is it rudamentary at best, it performs rather well without needing all of the variables (or further cleaning). Our R^2 value is hovering around 0.84 and this is with a substantial amount of leverage and highly unorganized residuals and data. Several of the variables remain in their original data type when others would be better suited to modeling. It would also be interesting to include other variables in this model because again, we simply pulled from the previous one to scrap together a third model. We finish by making predictions based on this third model, even though the second one performed better in some respects such as their coefficients, R^2 and F-statistics.

```
# Make predictions
df <- test %>%
  dplyr::select(
            LandSlope,
             OverallQual,
             KitchenQual,
             KitchenAbvGr,
             GarageCars,
             GarageFinish,
             Fireplaces,
             YearBuilt,
             TotalBsmtSF,
             TotRmsAbvGrd,
             SaleType,
             GrLivArea,
             OverallCond,
             LotFrontage,
             Neighborhood)
# impute missing values
df$LotFrontage[is.na(df$LotFrontage)] <- median(df$LotFrontage, na.rm = T)
df$GarageCars[is.na(df$GarageCars)] <- median(df$GarageCars, na.rm = T)
df$TotalBsmtSF[is.na(df$TotalBsmtSF)] <- median(df$TotalBsmtSF, na.rm = T)
df[df=='NA'] <- NA
df$SaleType[is.na(df$SaleType)] <- "WD"
df$KitchenQual[is.na(df$KitchenQual)] <- "TA"
df$GarageFinish[is.na(df$GarageFinish)] <- "Unf"
predictions <- data.frame(test$Id, predict(mod3, df))
colnames(predictions) <- c("Id","SalePrice")
```

```
# Export to csv for kaggle submission
write.csv(predictions, "C:/data/predictions.csv")
```

My Kaggle username is “zacharypalmore” and my score is 0.17215. This could have been greatly improved if I had imputed with realistic values removed missing values prior to each model, considered other variables beyond these initial thoughts, and much more. Honestly, I am surprised it turned out as well as it did given the circumstances.