Linear Regression Analysis: Regression Case Study

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Part I: Explanatory Modelling

Task 0: Exploratory Data Analysis and Data Cleaning

```
# rawDF <-
# read.csv('/Users/booranium/usf/601_regression/project/housing.txt',
# stringsAsFactors = T)
rawDF <- read.csv("/Users/santhoshhari/Documents/Coursework/LinearRegression/IowaHousing/Data/housing.t
    stringsAsFactors = T)
# rawDF <- read.csv('housing.txt', stringsAsFactors = T)
```

The Iowa housing dataset contains 1460 rows and 81 variables, a glimpse of which is as follows:

```
str(rawDF)
```

```
## '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     : Factor w/ 5 levels "C (all)","FV",..: 4 4 4 4 4 4 4 4 5 4 ...
##  $ 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       : Factor w/ 2 levels "Grvl","Pave": 2 2 2 2 2 2 2 2 2 2 ...
##  $ Alley        : Factor w/ 2 levels "Grvl","Pave": NA NA NA NA NA NA NA NA NA NA ...
##  $ LotShape     : Factor w/ 4 levels "IR1","IR2","IR3",..: 4 4 1 1 1 1 4 1 4 4 ...
##  $ LandContour  : Factor w/ 4 levels "Bnk","HLS","Low",..: 4 4 4 4 4 4 4 4 4 4 ...
##  $ Utilities    : Factor w/ 2 levels "AllPub","NoSeWa": 1 1 1 1 1 1 1 1 1 1 ...
##  $ LotConfig    : Factor w/ 5 levels "Corner","CulDSac",..: 5 3 5 1 3 5 5 1 5 1 ...
##  $ LandSlope    : Factor w/ 3 levels "Gtl","Mod","Sev": 1 1 1 1 1 1 1 1 1 1 ...
##  $ Neighborhood : Factor w/ 25 levels "Blmngtn","Blueste",..: 6 25 6 7 14 12 21 17 18 4 ...
##  $ Condition1   : Factor w/ 9 levels "Artery","Feedr",..: 3 2 3 3 3 3 3 5 1 1 ...
##  $ Condition2   : Factor w/ 8 levels "Artery","Feedr",..: 3 3 3 3 3 3 3 3 3 1 ...
##  $ BldgType     : Factor w/ 5 levels "1Fam","2fmCon",..: 1 1 1 1 1 1 1 1 1 2 ...
##  $ HouseStyle   : Factor w/ 8 levels "1.5Fin","1.5Unf",..: 6 3 6 6 6 1 3 6 1 2 ...
##  $ 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    : Factor w/ 6 levels "Flat","Gable",..: 2 2 2 2 2 2 2 2 2 2 ...
##  $ RoofMatl     : Factor w/ 8 levels "ClyTile","CompShg",..: 2 2 2 2 2 2 2 2 2 2 ...
##  $ Exterior1st  : Factor w/ 15 levels "AsbShng","AsphShn",..: 13 9 13 14 13 13 13 7 4 9 ...
##  $ Exterior2nd  : Factor w/ 16 levels "AsbShng","AsphShn",..: 14 9 14 16 14 14 14 7 16 9 ...
##  $ MasVnrType   : Factor w/ 4 levels "BrkCmn","BrkFace",..: 2 3 2 3 2 3 4 4 3 3 ...
##  $ MasVnrArea   : int  196 0 162 0 350 0 186 240 0 0 ...
##  $ ExterQual    : Factor w/ 4 levels "Ex","Fa","Gd",..: 3 4 3 4 3 4 3 4 4 4 ...
##  $ ExterCond    : Factor w/ 5 levels "Ex","Fa","Gd",..: 5 5 5 5 5 5 5 5 5 5 ...
##  $ Foundation   : Factor w/ 6 levels "BrkTil","CBlock",..: 3 2 3 1 3 6 3 2 1 1 ...
##  $ BsmtQual     : Factor w/ 4 levels "Ex","Fa","Gd",..: 3 3 3 4 3 3 1 3 4 4 ...
##  $ BsmtCond     : Factor w/ 4 levels "Fa","Gd","Po",..: 4 4 4 2 4 4 4 4 4 4 ...
```

```
##  $ BsmtExposure : Factor w/ 4 levels "Av","Gd","Mn",..: 4 2 3 4 1 4 1 3 4 4 ...
##  $ BsmtFinType1 : Factor w/ 6 levels "ALQ","BLQ","GLQ",..: 3 1 3 1 3 3 3 1 6 3 ...
##  $ BsmtFinSF1   : int  706 978 486 216 655 732 1369 859 0 851 ...
##  $ BsmtFinType2 : Factor w/ 6 levels "ALQ","BLQ","GLQ",..: 6 6 6 6 6 6 6 2 6 6 ...
##  $ 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      : Factor w/ 6 levels "Floor","GasA",..: 2 2 2 2 2 2 2 2 2 2 ...
##  $ HeatingQC    : Factor w/ 5 levels "Ex","Fa","Gd",..: 1 1 1 3 1 1 1 1 3 1 ...
##  $ CentralAir   : Factor w/ 2 levels "N","Y": 2 2 2 2 2 2 2 2 2 2 ...
##  $ Electrical   : Factor w/ 5 levels "FuseA","FuseF",..: 5 5 5 5 5 5 5 5 2 5 ...
##  $ 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  : Factor w/ 4 levels "Ex","Fa","Gd",..: 3 4 3 3 3 4 3 4 4 4 ...
##  $ TotRmsAbvGrd : int  8 6 6 7 9 5 7 7 8 5 ...
##  $ Functional   : Factor w/ 7 levels "Maj1","Maj2",..: 7 7 7 7 7 7 7 7 3 7 ...
##  $ Fireplaces   : int  0 1 1 1 1 0 1 2 2 2 ...
##  $ FireplaceQu  : Factor w/ 5 levels "Ex","Fa","Gd",..: NA 5 5 3 5 NA 3 5 5 5 ...
##  $ GarageType   : Factor w/ 6 levels "2Types","Attchd",..: 2 2 2 6 2 2 2 2 6 2 ...
##  $ GarageYrBlt  : int  2003 1976 2001 1998 2000 1993 2004 1973 1931 1939 ...
##  $ GarageFinish : Factor w/ 3 levels "Fin","RFn","Unf": 2 2 2 3 2 3 2 2 3 2 ...
##  $ 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   : Factor w/ 5 levels "Ex","Fa","Gd",..: 5 5 5 5 5 5 5 5 2 3 ...
##  $ GarageCond   : Factor w/ 5 levels "Ex","Fa","Gd",..: 5 5 5 5 5 5 5 5 5 5 ...
##  $ PavedDrive   : Factor w/ 3 levels "N","P","Y": 3 3 3 3 3 3 3 3 3 3 ...
##  $ 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       : Factor w/ 3 levels "Ex","Fa","Gd": NA NA NA NA NA NA NA NA NA NA ...
##  $ Fence        : Factor w/ 4 levels "GdPrv","GdWo",..: NA NA NA NA NA 3 NA NA NA NA ...
##  $ MiscFeature  : Factor w/ 4 levels "Gar2","Othr",..: NA NA NA NA NA 3 NA 3 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     : Factor w/ 9 levels "COD","Con","ConLD",..: 9 9 9 9 9 9 9 9 9 9 ...
##  $ SaleCondition: Factor w/ 6 levels "Abnorml","AdjLand",..: 5 5 5 1 5 5 5 5 1 5 ...
##  $ SalePrice    : int  208500 181500 223500 140000 250000 143000 307000 200000 129900 118000 ...
```

At first glance, we see that most of the variables are categorical - both numeric and character types - and only a handful are continuous. The response variable for our analysis is `SalePrice`, and the remaining 79 variables (excluding the record `ID` column) are considered potential predictor variables. Checking the data dictionary, we found the following distribution for the predictor variables:

- 49 categorical
- 19 are continuous, e.g. area, price
- 11 are discrete, e.g. count, year

There are 0 duplicate rows in the dataset.

Handling NA Values

Below, we compute that number and percentage of `NA`s per variable in the dataset having at least 1 `NA`.

```
NA_columns <- colnames(rawDF)[unique(which(is.na(rawDF), arr.ind = T)[,
    2])]

NA_count <- rawDF %>% dplyr::select(NA_columns) %>% summarise_all(funs(sum(is.na(.)))) %>%
    gather(key = "Variable", value = "num_na", everything()) %>% arrange(desc(num_na))

NA_count %<>% mutate(perc_na = paste(round(num_na/nrow(rawDF), 4) *
    100, "%"))
colnames(NA_count) <- c("**Variable**", "**Number of NA**", "**Percentage of NA**")
row.names(NA_count) <- NULL
knitr::kable(NA_count, caption = "\\label{tab:NACount} Variable NA Count and Percentage",
    format.args = list(big.mark = ","))
```

Table 1: Variable NA Count and Percentage

Variable	**Number of NA**	**Percentage of NA**
PoolQC	1,453	99.52 %
MiscFeature	1,406	96.3 %
Alley	1,369	93.77 %
Fence	1,179	80.75 %
FireplaceQu	690	47.26 %
LotFrontage	259	17.74 %
GarageType	81	5.55 %
GarageYrBlt	81	5.55 %
GarageFinish	81	5.55 %
GarageQual	81	5.55 %
GarageCond	81	5.55 %
BsmtExposure	38	2.6 %
BsmtFinType2	38	2.6 %
BsmtQual	37	2.53 %
BsmtCond	37	2.53 %
BsmtFinType1	37	2.53 %
MasVnrType	8	0.55 %
MasVnrArea	8	0.55 %
Electrical	1	0.07 %

The data dictionary tells us that for most of the fields in Table 1, `NA` is actually meaningful, indicating non-applicability or a lack of the feature rather than missing data. After checking the data dictionary for the meaning of each field, we imputed - for every categorical variable for which `NA` was meaningful - `NA`s with `0`s.

```
# Create a copy of rawDF to be our working data frame
housingDF <- rawDF

# Update NAs with 0s for applicable fields
```

```r
levels(housingDF$PoolQC) <- c("0", levels(housingDF$PoolQC))
housingDF$PoolQC[is.na(housingDF$PoolQC)] <- "0"
levels(housingDF$MiscFeature) <- c("0", levels(housingDF$MiscFeature))
housingDF$MiscFeature[is.na(housingDF$MiscFeature)] <- "0"
levels(housingDF$Alley) <- c("0", levels(housingDF$Alley))
housingDF$Alley[is.na(housingDF$Alley)] <- "0"
levels(housingDF$Fence) <- c("0", levels(housingDF$Fence))
housingDF$Fence[is.na(housingDF$Fence)] <- "0"
levels(housingDF$FireplaceQu) <- c("0", levels(housingDF$FireplaceQu))
housingDF$FireplaceQu[is.na(housingDF$FireplaceQu)] <- "0"
levels(housingDF$GarageType) <- c("0", levels(housingDF$GarageType))
housingDF$GarageType[is.na(housingDF$GarageType)] <- "0"
levels(housingDF$GarageFinish) <- c("0", levels(housingDF$GarageFinish))
housingDF$GarageFinish[is.na(housingDF$GarageFinish)] <- "0"
levels(housingDF$GarageQual) <- c("0", levels(housingDF$GarageQual))
housingDF$GarageQual[is.na(housingDF$GarageQual)] <- "0"
levels(housingDF$GarageCond) <- c("0", levels(housingDF$GarageCond))
housingDF$GarageCond[is.na(housingDF$GarageCond)] <- "0"
levels(housingDF$BsmtExposure) <- c("0", levels(housingDF$BsmtExposure))
housingDF$BsmtExposure[is.na(housingDF$BsmtExposure)] <- "0"
levels(housingDF$BsmtFinType2) <- c("0", levels(housingDF$BsmtFinType2))
housingDF$BsmtFinType2[is.na(housingDF$BsmtFinType2)] <- "0"
levels(housingDF$BsmtQual) <- c("0", levels(housingDF$BsmtQual))
housingDF$BsmtQual[is.na(housingDF$BsmtQual)] <- "0"
levels(housingDF$BsmtCond) <- c("0", levels(housingDF$BsmtCond))
housingDF$BsmtCond[is.na(housingDF$BsmtCond)] <- "0"
levels(housingDF$BsmtFinType1) <- c("0", levels(housingDF$BsmtFinType1))
housingDF$BsmtFinType1[is.na(housingDF$BsmtFinType1)] <- "0"
```

We then re-check the count and percentage of `NA`s per variable left in the dataset.

```r
NA_columns <- colnames(housingDF)[unique(which(is.na(housingDF), arr.ind = T)[,
    2])]

NA_count <- housingDF %>% dplyr::select(NA_columns) %>% summarise_all(funs(sum(is.na(.)))) %>%
    gather(key = "Variable", value = "num_na", everything()) %>% arrange(desc(num_na))

NA_count %<>% mutate(perc_na = paste(round(num_na/nrow(housingDF),
    4) * 100, "%"))
colnames(NA_count) <- c("**Variable**", "**Number of NA**", "**Percentage of NA**")
row.names(NA_count) <- NULL
knitr::kable(NA_count, caption = "\\label{tab:NACount1} Variable NA Count and Percentage(after replacin
    format.args = list(big.mark = ","))
```

Table 2: Variable NA Count and Percentage(after replacing NAs with 0s, where appropriate)

Variable	**Number of NA**	**Percentage of NA**
LotFrontage	259	17.74 %
GarageYrBlt	81	5.55 %
MasVnrType	8	0.55 %
MasVnrArea	8	0.55 %
Electrical	1	0.07 %

```r
colnames(housingDF)
```

```
##  [1] "Id"            "MSSubClass"    "MSZoning"      "LotFrontage"
##  [5] "LotArea"       "Street"        "Alley"         "LotShape"
##  [9] "LandContour"   "Utilities"     "LotConfig"     "LandSlope"
## [13] "Neighborhood"  "Condition1"    "Condition2"    "BldgType"
## [17] "HouseStyle"    "OverallQual"   "OverallCond"   "YearBuilt"
## [21] "YearRemodAdd"  "RoofStyle"     "RoofMatl"      "Exterior1st"
## [25] "Exterior2nd"   "MasVnrType"    "MasVnrArea"    "ExterQual"
## [29] "ExterCond"     "Foundation"    "BsmtQual"      "BsmtCond"
## [33] "BsmtExposure"  "BsmtFinType1"  "BsmtFinSF1"    "BsmtFinType2"
## [37] "BsmtFinSF2"    "BsmtUnfSF"     "TotalBsmtSF"   "Heating"
## [41] "HeatingQC"     "CentralAir"    "Electrical"    "X1stFlrSF"
## [45] "X2ndFlrSF"     "LowQualFinSF"  "GrLivArea"     "BsmtFullBath"
## [49] "BsmtHalfBath"  "FullBath"      "HalfBath"      "BedroomAbvGr"
## [53] "KitchenAbvGr"  "KitchenQual"   "TotRmsAbvGrd"  "Functional"
## [57] "Fireplaces"    "FireplaceQu"   "GarageType"    "GarageYrBlt"
## [61] "GarageFinish"  "GarageCars"    "GarageArea"    "GarageQual"
## [65] "GarageCond"    "PavedDrive"    "WoodDeckSF"    "OpenPorchSF"
## [69] "EnclosedPorch" "X3SsnPorch"    "ScreenPorch"   "PoolArea"
## [73] "PoolQC"        "Fence"         "MiscFeature"   "MiscVal"
## [77] "MoSold"        "YrSold"        "SaleType"      "SaleCondition"
## [81] "SalePrice"
```

Table 2 shows the list of remaining variables where `NA` indicates missing data. We impute `NA`s in these variables with

- mean of the data, for continuous variables (LotFrontage)
- median of the data, for discrete variables (GarageYrBlt)
- mode of the data, for categorical variables (MasVnrType, Electrical)

```r
# Function to get mode of data
getmode <- function(v) {
    uniqv <- unique(v)
    uniqv[which.max(tabulate(match(v, uniqv)))]
}

# Impute NAs
housingDF$LotFrontage[is.na(housingDF$LotFrontage)] <- mean(housingDF$LotFrontage,
    na.rm = T)
housingDF$GarageYrBlt[is.na(housingDF$GarageYrBlt)] <- median(housingDF$GarageYrBlt,
    na.rm = T)
housingDF$MasVnrType[is.na(housingDF$MasVnrType)] <- getmode(housingDF$MasVnrType)
housingDF$MasVnrArea[is.na(housingDF$MasVnrArea)] <- 0
housingDF$Electrical[is.na(housingDF$Electrical)] <- getmode(housingDF$Electrical)

# Convert MSSubClass to factor
housingDF$MSSubClass <- factor(housingDF$MSSubClass)
housingDF$MoSold <- factor(housingDF$MoSold)
```

Since Masonry veneer area (`MasVnrArea`) is directly related to `MasVnrType`, we impute for area based on the mode of `MasVnrType`, which is None. Our cleaned dataset is named `housingDF`.

Exploratory Data Visualization

With our clean dataset, we perform exploratory data visualization of the distribution of key measures such as volume and sale price of houses by what we hypothesize to be key predictor variables.

To begin with, we check the distribution of sale prices using a histogram and box-plot.

```
# hist(housingDF$SalePrice, main = 'Histogram of Sale Price')
# boxplot(housingDF$SalePricem, main = 'Boxplot of Sale Price')
summary(housingDF$SalePrice)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   34900  129975  163000  180921  214000  755000
```

Intuition suggests the neighborhood is a key determining factor in a house's sale price, hence below, we plot the distribution of sale price by neighborhood.

```
housingDF %>% dplyr::select(Neighborhood, SalePrice) %>% ggplot(aes(factor(Neighborhood),
    SalePrice)) + geom_boxplot() + theme(axis.text.x = element_text(angle = 90,
    hjust = 1)) + xlab("Neighborhoods")
```

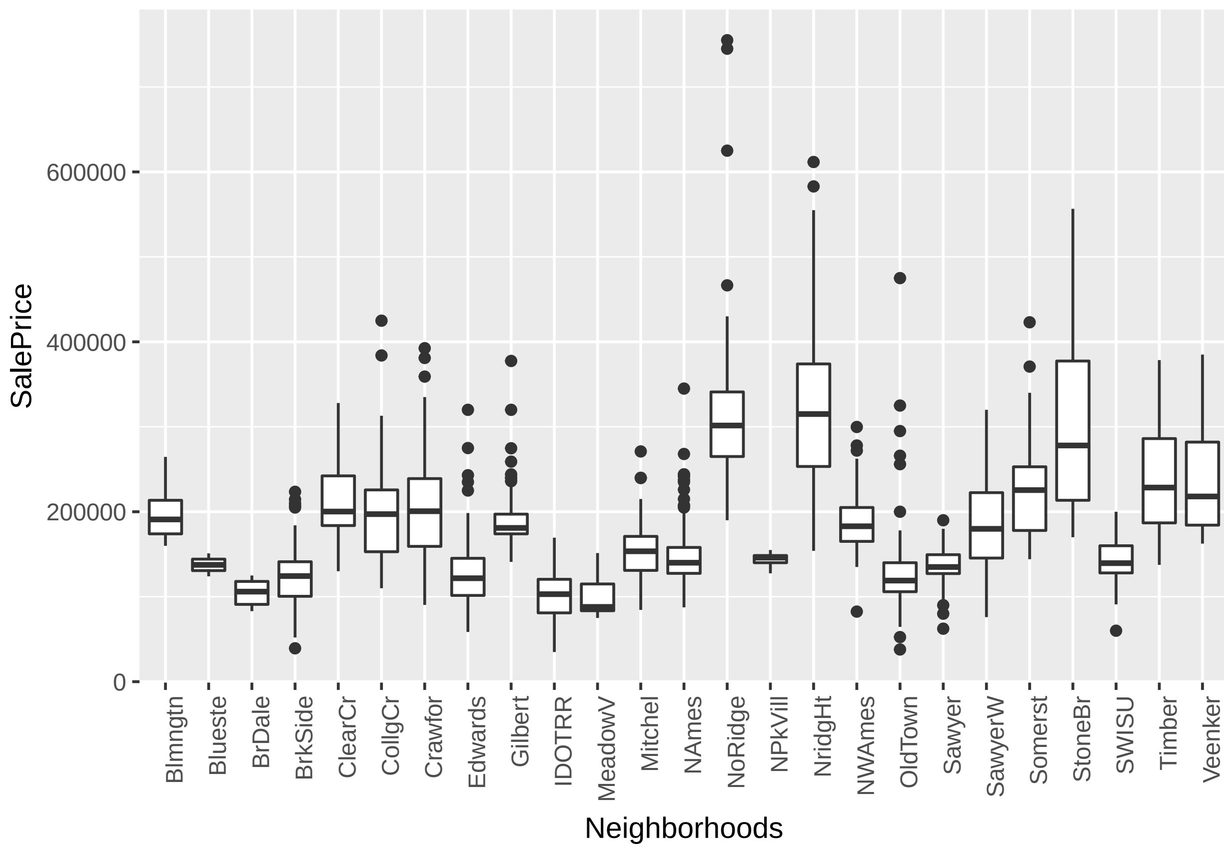


Figure 1: SalePrice distribution per neighborhood

From Figure 1, we can observe that Brookside and Meadow Vista have the lowest median house price while Northridge and Northridge Height have the heighest median house price as well as several outliers.

We then distribution of houses by a number of key features we hypothesize to be important in determining housing price: the property's zoning class (`MSZoning`), type of road access to the property (`Street`), type of alley access to the property (`Alley`), and type of utiles available (`Utilities`)

```
plotHist <- function(data_in, i) {
    data <- data.frame(x = data_in[[i]])
```

```r
    p <- ggplot(data = data, aes(x = factor(x))) + stat_count() +
        xlab(colnames(data_in)[i]) + theme_light() + theme(axis.text.x = element_text(angle = 90,
        hjust = 1))
    return(p)
}

doPlots <- function(data_in, fun, ii, ncol = 3) {
    pp <- list()
    for (i in ii) {
        p <- fun(data_in = data_in, i = i)
        pp <- c(pp, list(p))
    }
    do.call("grid.arrange", c(pp, ncol = ncol))
}

plotDen <- function(data_in, i) {
    data <- data.frame(x = data_in[[i]], SalePrice = data_in$SalePrice)
    p <- ggplot(data = data) + geom_line(aes(x = x), stat = "density",
        size = 1, alpha = 1) + xlab(paste0((colnames(data_in)[i]),
        "\n", "Skewness: ", round(skewness(data_in[[i]], na.rm = TRUE),
            2))) + theme_light()
    return(p)
}

plotCorr <- function(data_in, i) {
    data <- data.frame(x = data_in[[i]], SalePrice = data_in$SalePrice)
    p <- ggplot(data, aes(x = x, y = SalePrice)) + geom_point(na.rm = TRUE) +
        geom_smooth(method = lm) + xlab(paste0(colnames(data_in)[i],
        "\n", "R-Squared: ", round(cor(data_in[[i]], data$SalePrice,
            use = "complete.obs"), 2))) + theme_light()
    return(suppressWarnings(p))
}
```

```r
doPlots(housingDF, fun = plotHist, ii = c(3, 6, 7, 10), ncol = 2)
```

We also plot the distribution of houses against a number of features related to the physical geography of the property:

```r
doPlots(housingDF, fun = plotHist, ii = c(8, 9, 11, 12), ncol = 2)
```

Figure 2 suggests that most of the houses are located in `Medium/Low Density` residential areas. We can also observe that most of the houses have paved road access, do not have alleys and have all public utilities(E,G,W,& S). From Figure **??**{fig:hist2}, we can notice that most of the properties are regular or slightly irregular in share, built on level surfaces with gentle slope.

```r
housingDF %>% dplyr::select(LandSlope, Neighborhood) %>% arrange(Neighborhood) %>%
    group_by(Neighborhood, LandSlope) %>% summarize(Count = n()) %>%
    ggplot(aes(Neighborhood, Count)) + geom_bar(aes(fill = LandSlope),
    position = "dodge", stat = "identity") + theme(axis.text.x = element_text(angle = 90,
    hjust = 1))
```

From Figure **??**{fig:hist3}, we can see that houses with severe slope are located only in Clear Creek and Timberland while more than 10 neighborhoods have properties with moderate slope.

```r
num_var <- names(housingDF)[which(sapply(housingDF, is.numeric))]
housing_numeric <- housingDF[num_var]
```

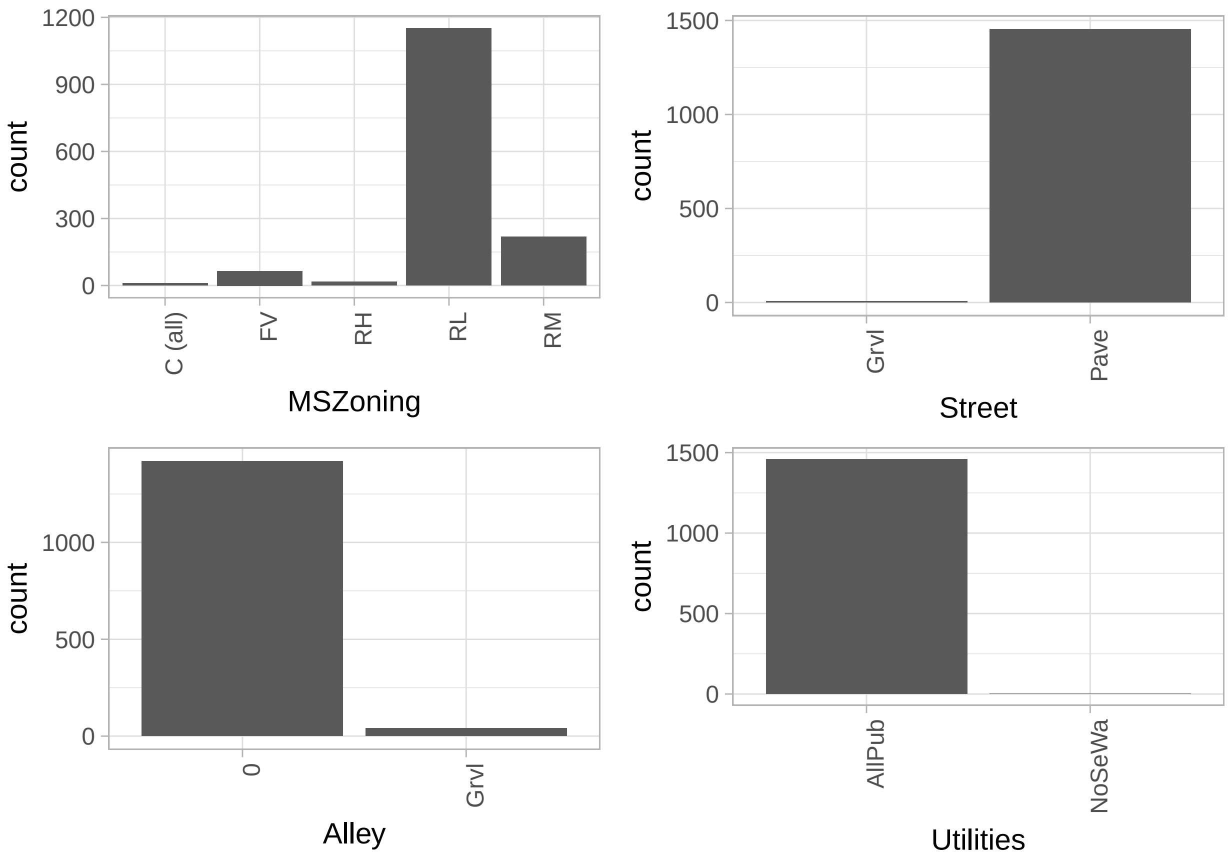


Figure 2: Locality, access, utility features distribution

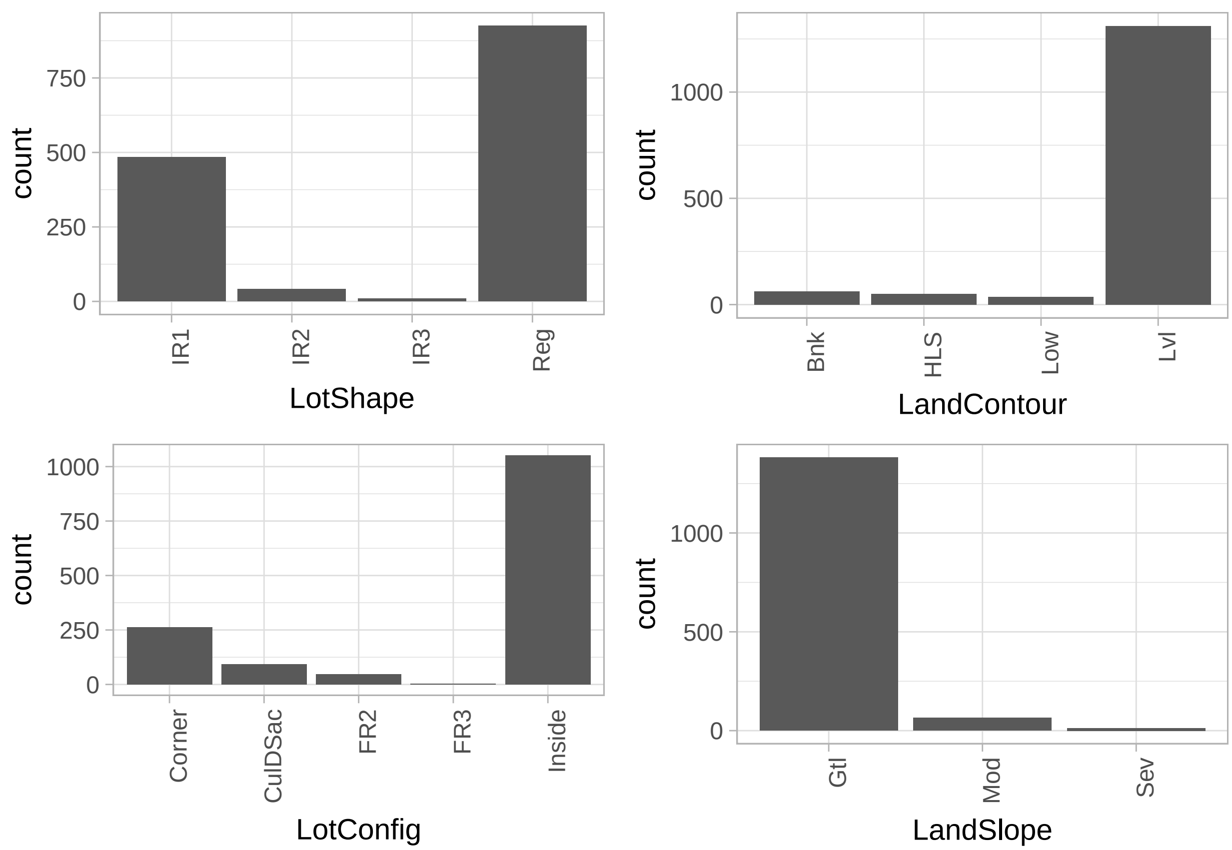


Figure 3: Lot/Land feature distribution

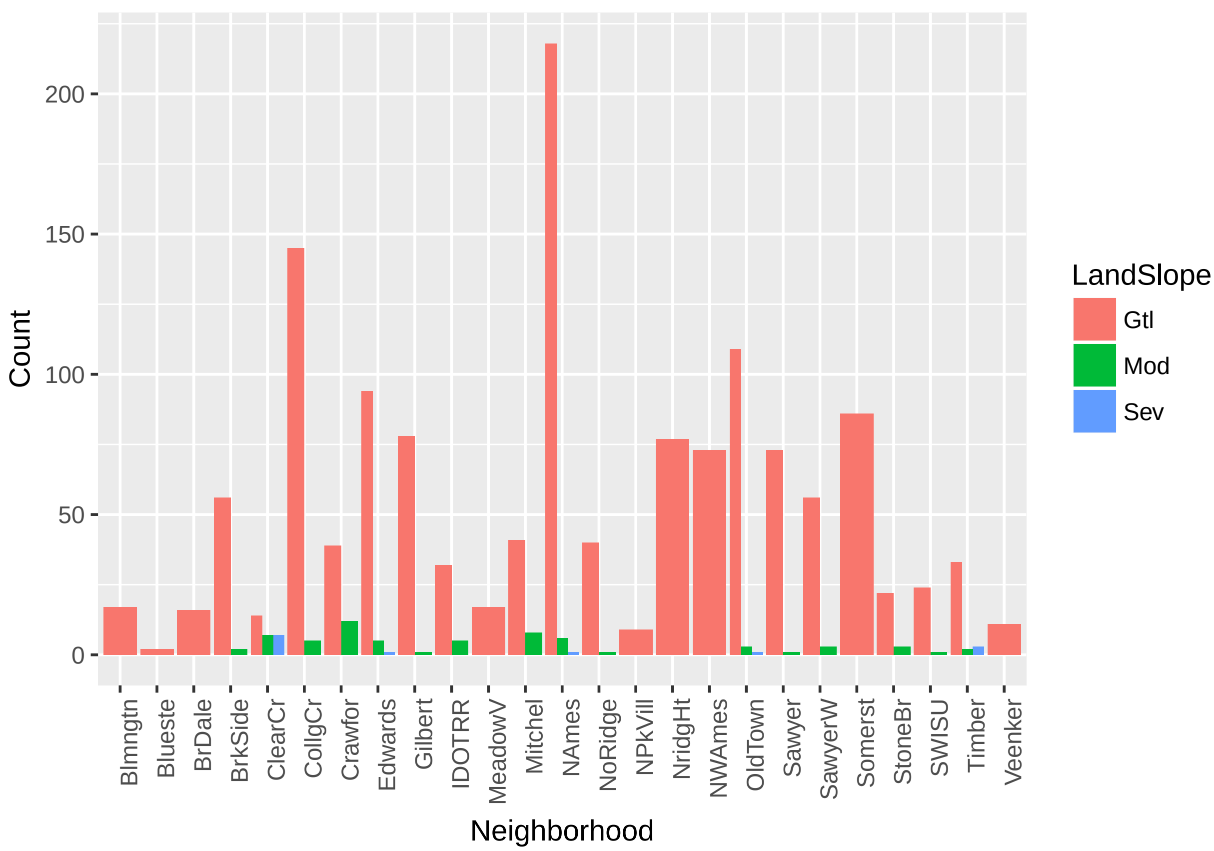


Figure 4: Neighborhood level slope distribution

```r
correlations <- cor(housing_numeric[, -1])
highcorr <- c(names(correlations[, "SalePrice"])[which(correlations[,
    "SalePrice"] > 0.5)], names(correlations[, "SalePrice"])[which(correlations[,
    "SalePrice"] < -0.2)])
data_corr <- housingDF[highcorr]
doPlots(data_corr, fun = plotCorr, ii = 1:10)
```

Task 1. Building the Explanatory Model

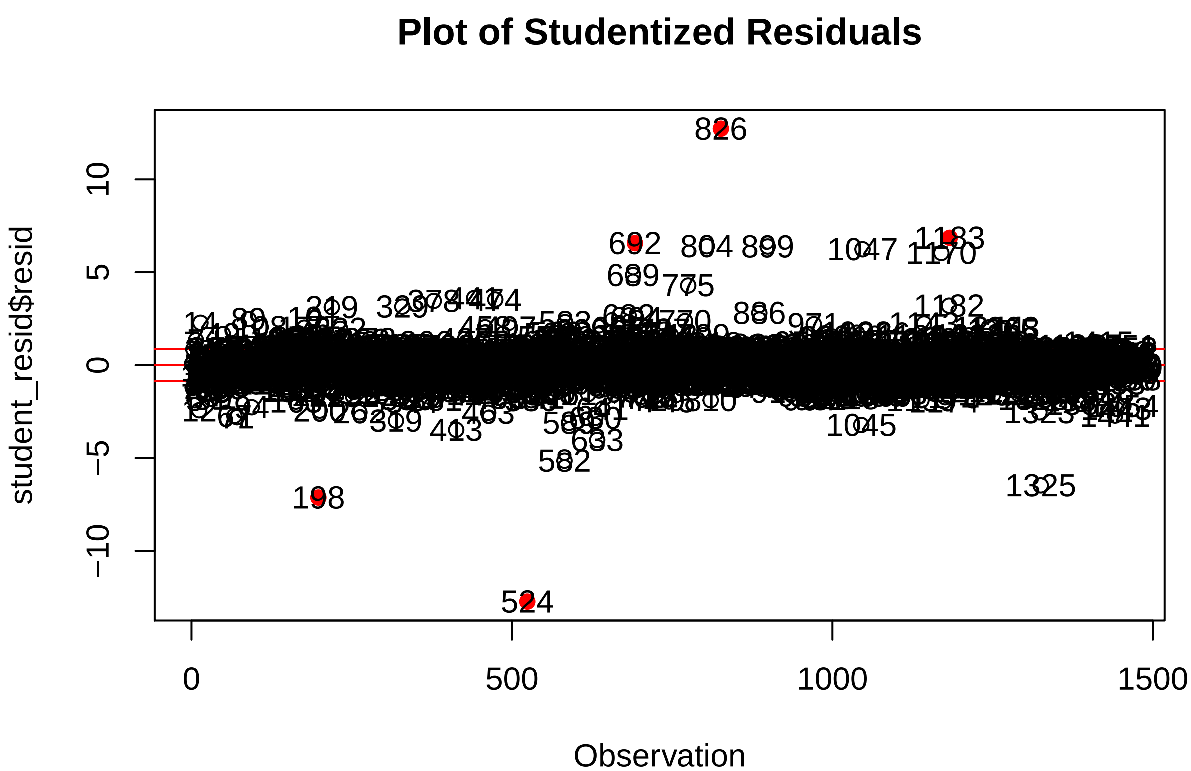
Testing for Influential Points

Having dealt with the NAs in our dataset, we use the `model.matrix()` function from the `glmnet` package to convert each categorical variable into an appropriate set of binary indicators: for a categorical variable that takes k levels, `model.matrix()` produces k-1 binary indicators. We then reappend our response vector `SalePrice` to the resulting wide design matrix `designDF` to create `workingDF`, which includes both the converted predictors and response variables.

```r
designDF <- model.matrix(SalePrice ~ ., data = housingDF)[, -1]
designDF <- as.data.frame(designDF)
workingDF <- cbind(designDF, SalePrice = housingDF$SalePrice)
```

In looking for influential points, we leverage the `OLSRR` package to test observations for influence according to the DFFITS diagnostic. We do this by first fitting a saturated model on `workingDF` and then calling `ols_dffits_plot()` on it.

```r
ols_model <- lm(SalePrice ~ ., data = workingDF)
ols_dffits_plot(ols_model)
```




```r
# identify threshold t for points of influence
n = nrow(workingDF)
```

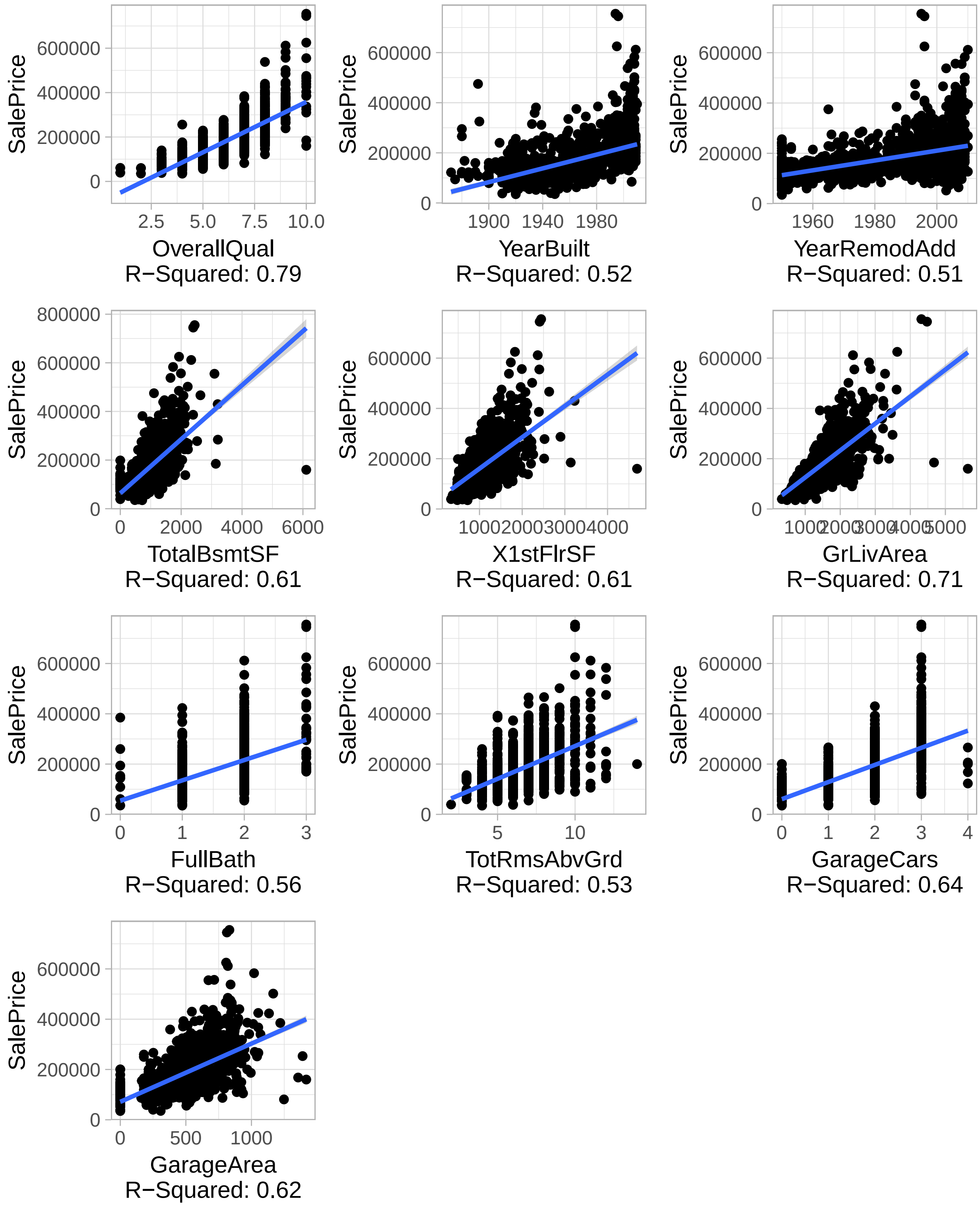
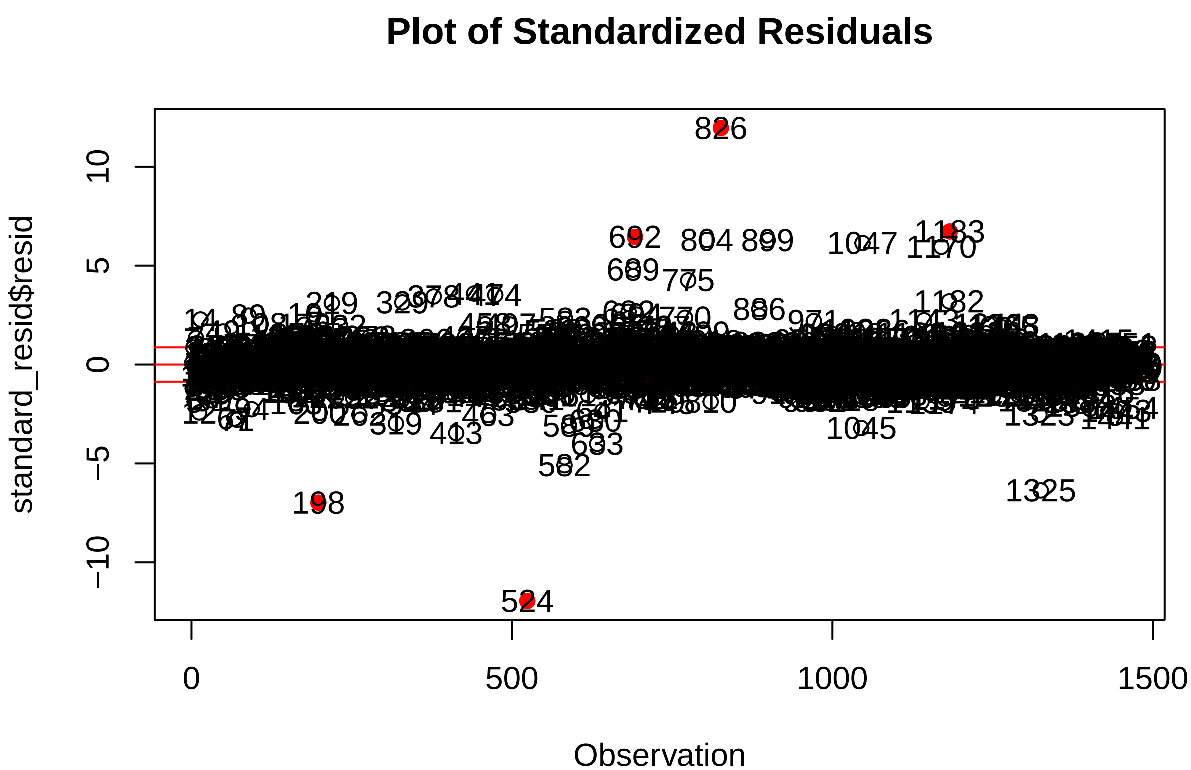


Figure 5: Scatter plot of variables showing high positive linear relationship with SalePrice

```r
p = ncol(workingDF - 1)  # remove response var
t = 2 * sqrt(p/n)
```

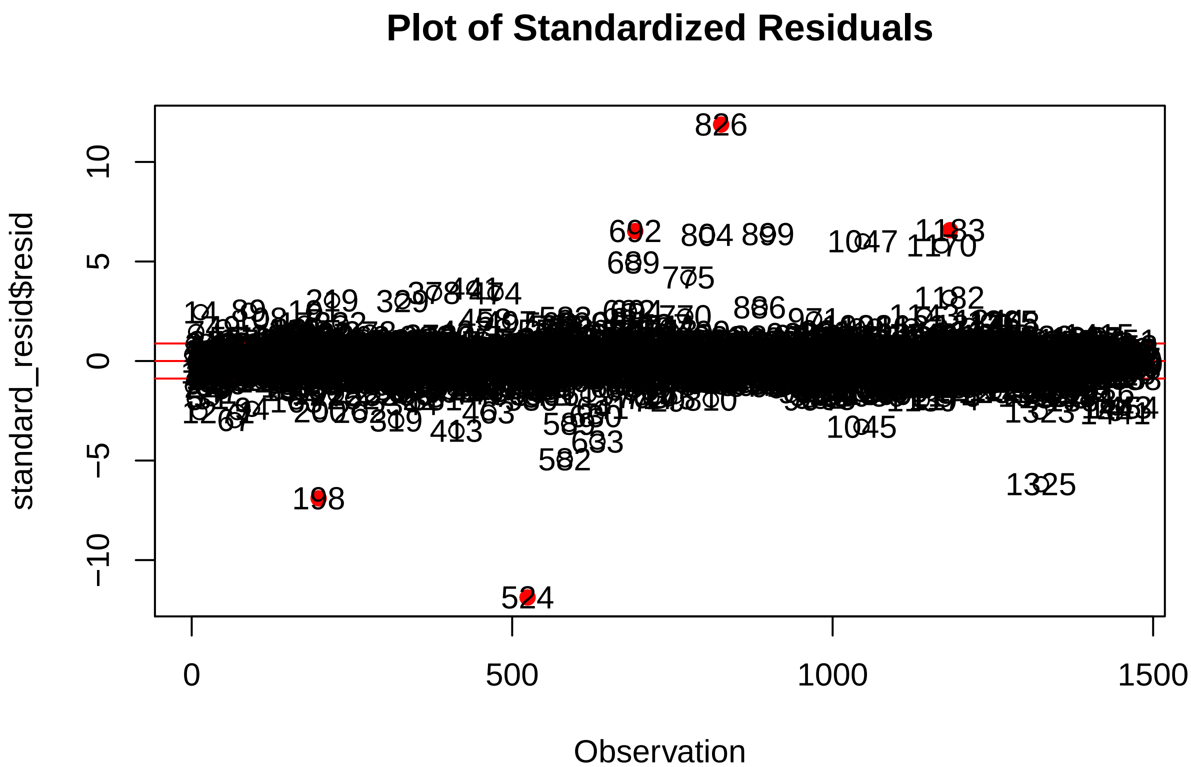
Note that according to the criterion of threshold t = 2*sqrt(n/p) = 0.85, the DFFITS plot shows a large number of influential observations. We look specifically at 6 points greater than threshold = abs(5): 198, 524, 692, 826 and 1183. Below we plot the standardized and studentized residuals to check these observations for being outliers and/or points of leverage respectively.

```r
# Creating from scratch because OLSRR ols_srsd_plot() function is
# not working.

# Create df of studentized residuals
student_resid <- as.data.frame(rstudent(ols_model))
student_resid <- setDT(student_resid, keep.rownames = TRUE)[]
colnames(student_resid) <- c("ix", "resid")

# Plot
plot(student_resid$ix, student_resid$resid, col = ifelse(workingDF$Id ==
    198 | workingDF$Id == 524 | workingDF$Id == 692 | workingDF$Id ==
    826 | workingDF$Id == 1183, "red", "black"), pch = ifelse(workingDF$Id ==
    198 | workingDF$Id == 524 | workingDF$Id == 692 | workingDF$Id ==
    826 | workingDF$Id == 1183, 19, 1), main = "Plot of Studentized Residuals",
    xlab = "Observation")
abline(h = t, col = "red")
abline(h = 0, col = "red")
abline(h = -t, col = "red")
text(student_resid$ix, student_resid$resid, labels = student_resid$ix)
```



Our plot of studentized resdiuals indicates that observations all 5 points are leverage points.

```
# Create df of standardized residuals
standard_resid <- as.data.frame(rstandard(ols_model))
standard_resid <- setDT(standard_resid, keep.rownames = TRUE)[]
colnames(standard_resid) <- c("ix", "resid")

# Plot
plot(standard_resid$ix, standard_resid$resid, col = ifelse(workingDF$Id ==
    198 | workingDF$Id == 524 | workingDF$Id == 692 | workingDF$Id ==
    826 | workingDF$Id == 1183, "red", "black"), pch = ifelse(workingDF$Id ==
    198 | workingDF$Id == 524 | workingDF$Id == 692 | workingDF$Id ==
    826 | workingDF$Id == 1183, 19, 1), main = "Plot of Standardized Residuals",
    xlab = "Observation")
abline(h = t, col = "red")
abline(h = 0, col = "red")
abline(h = -t, col = "red")
text(standard_resid$ix, standard_resid$resid, labels = standard_resid$ix)
```



Our plots of studentized and standardized resdiuals indicate that all 5 observations are both points of leverage and outliers. We remove them from our dataset and recreate the saturated OLS model below:

```
# remove influential points
workingDF <- filter(workingDF, !Id %in% c(198, 524, 692, 826, 1183))
# nrow(workingDF) #1455

# recreate model
ols_model <- lm(SalePrice ~ ., data = workingDF)
```

For the purposes of variable selection, we refer to the saturated OLS model created above and perform stepwise model selection according to both AIC and BIC criterions.

```r
# Code chunk not run; load saved model for expediency
model_aic <- step(ols_model, direction = "backward", trace = F)
model_bic <- step(ols_model, k = log(nrow(workingDF)), direction = "backward",
    trace = F)

## save the models
save(model_aic, file = "/Users/santhoshhari/Documents/Coursework/LinearRegression/IowaHousing/AIC_model
save(model_bic, file = "/Users/santhoshhari/Documents/Coursework/LinearRegression/IowaHousing/BIC_model
```

Per the AIC criterion, the following are the predictor variables signficant at the alpha = 0.05 level.

```r
# load('/Users/booranium/usf/601_regression/project/IowaHousing/AIC_model.rda')
# # model loaded as 'model_aic'
# load('/Users/santhoshhari/Documents/Coursework/LinearRegression/IowaHousing/AIC_model.rda')
# # model loaded as 'model_aic'
load("AIC_model.rda")

# Find coefficients significant at the alpha = 0.01 level
bool_aic <- summary(model_aic)$coeff[-1, 4] < 0.01
sig_var_aic <- names(bool_aic)[bool_aic == TRUE]
```

Per the BIC criterion, the following are the predictor variables signficant at the alpha = 0.05 level.

```r
# load('/Users/booranium/usf/601_regression/project/IowaHousing/BIC_model.rda')
# # model loaded as 'model_bic'
# load('/Users/santhoshhari/Documents/Coursework/LinearRegression/IowaHousing/BIC_model.rda')
# # model loaded as 'model_bic'
load("BIC_model.rda")
# find coefficients significant at the alpha = 0.01 level
bool_bic <- summary(model_bic)$coeff[-1, 4] < 0.01
sig_var_bic <- names(bool_bic)[bool_bic == TRUE]
```

Note that both criterions select the same set of variables.

```r
setdiff(sig_var_aic, sig_var_bic)
```

```
## character(0)
```

We can now perform OLS regression with our subset of 64 significant variables. The model summary is as follows:

```r
model_sig_formula <- as.formula(paste("SalePrice ~ ", paste(sig_var_bic,
    collapse = "+")))
model_sig <- lm(formula = model_sig_formula, data = workingDF)

# create a model with scaled Xs and Y for multicollinearity
# detection
model_sig_scaled <- lm(formula = model_sig_formula, data = as.data.frame(scale(workingDF)))
```

We check for multicollinearity in our model by checking for Variance Inflation Factors:

```r
vif(model_sig_scaled)[(sqrt(vif(model_sig_scaled)) > 10) == TRUE]
```

```
## GarageQualPo GarageCondPo
##     184.2926     171.8100
```

We see that there are two variables with VIF values > threshold = 10. This tells us there is multicollinearity present in the dataset. We verify this by checking the Singular Value Criteria for multicollinearity:

```r
coll_out = colldiag(model_sig, scale = TRUE, center = FALSE, add.intercept = TRUE)
coll_out$condindx[(coll_out$condindx > 30) == TRUE]
```

```
##  [1]   32.49461   36.98012   41.51708   50.60676   56.13318   71.42520
##  [7]   93.12395  271.11407  306.50195  915.64842 1232.96408
```

We see that there are several entries > threshold = 30, and hence we conclude that multicollinearity exists. In order to identify which variables are multicollinear:

```r
coll_out = colldiag(model_sig, scale = TRUE, center = FALSE, add.intercept = TRUE)
# unlist(coll_out[1], use.names = F) >30
# colnames(coll_out$pi)[unlist(coll_out[1], use.names = F) >30]
# dim(as.matrix(coll_out$pi[unlist(coll_out[1], use.names = F)
# >30, ]))
```

Based on results, we drop the Garage Condition variables since they are collinear with the Garage Quality variables.

```r
# Drop GarageCondition variables since they are correlated with
# Garage Quality variables
drop = c("GarageCondEx", "GarageCondFa", "GarageCondGd", "GarageCondPo")
new_sig_var_bic = sig_var_bic[!sig_var_bic %in% drop]
```

We then rerun the model and recheck for multicollinearity using VIFS:

```r
new_model_formula <- as.formula(paste("SalePrice ~ ", paste(new_sig_var_bic,
    collapse = "+")))
new_model <- lm(formula = new_model_formula, data = workingDF)

# create a model with scaled Xs and Y for multicollinearity
# detection
new_model_scaled <- lm(formula = new_model_formula, data = as.data.frame(scale(workingDF)))

# check for MC
vif(new_model_scaled)[(sqrt(vif(new_model_scaled)) > 10) == TRUE]
```

```
## named numeric(0)
```

Using our rule of thumb, we conclude that there is no more multicollinearity in our model since there are no VIF values > 10. We print the summary of our model below:

```r
summary(new_model)
```

```
##
## Call:
## lm(formula = new_model_formula, data = workingDF)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -131485  -10264       0   10154  141543
##
## Coefficients:
##                         Estimate     Std. Error t value
## (Intercept)          -1501264.91302   112244.24739 -13.375
## MSSubClass120          -16220.08951     2850.38356  -5.690
## MSSubClass160          -22075.21962     3347.75394  -6.594
## MSZoningFV              38156.25052     8036.88635   4.748
## MSZoningRH              19652.20647     8926.62798   2.202
```

```
## MSZoningRL                23371.47826     7386.62559   3.164
## MSZoningRM                19051.08011     7420.13904   2.567
## LotArea                       0.75227        0.08234   9.137
## StreetPave                38663.50280     9376.39492   4.123
## LandContourLow           -10195.83610     4254.25975  -2.397
## LotConfigCulDSac           8779.72336     2388.54431   3.676
## LandSlopeSev             -41595.28359     8804.48586  -4.724
## NeighborhoodCollgCr         258.49691     2358.95728   0.110
## NeighborhoodCrawfor       19613.85511     3417.66256   5.739
## NeighborhoodEdwards       -8495.28154     2511.56384  -3.382
## NeighborhoodGilbert       -2895.07052     3018.05498  -0.959
## NeighborhoodMitchel      -13388.23766     3378.24743  -3.963
## NeighborhoodNAmes         -8194.95954     2039.33105  -4.018
## NeighborhoodNoRidge       27488.21640     4167.77030   6.595
## NeighborhoodNridgHt       19051.93042     3380.96462   5.635
## NeighborhoodNWAmes       -12512.36145     2915.34823  -4.292
## NeighborhoodOldTown       -5529.93302     2983.95330  -1.853
## NeighborhoodStoneBr       40921.72927     4719.78982   8.670
## Condition1Norm             6622.88542     1762.88860   3.757
## Condition1RRAe           -17398.07438     6705.93805  -2.594
## Condition2RRAe           -95060.05239    33065.48249  -2.875
## OverallQual                6688.31950      804.96840   8.309
## OverallCond                5355.15268      668.09521   8.016
## YearBuilt                   312.30718       46.27090   6.750
## YearRemodAdd                108.54151       44.41420   2.444
## RoofStyleShed             64239.54318    25119.21237   2.557
## RoofMatlCompShg          647160.04869    26054.58228  24.839
## RoofMatlMembran          721671.17292    35301.90723  20.443
## RoofMatlMetal            690777.89068    35169.27755  19.642
## RoofMatlRoll             634745.46777    33587.18762  18.898
## `RoofMatlTar&Grv`        637476.78963    26681.46875  23.892
## RoofMatlWdShake          641591.64489    28100.88317  22.832
## RoofMatlWdShngl          683006.14049    27586.87806  24.758
## Exterior1stBrkFace        16337.84226     3365.15389   4.855
## `Exterior1stWd Sdng`      -7630.98849     3370.11676  -2.264
## `Exterior2ndWd Sdng`       7733.43621     3344.56420   2.312
## MasVnrTypeStone            7204.58508     2323.17645   3.101
## MasVnrArea                   12.07108        3.97553   3.036
## ExterQualGd              -20087.06918     3524.14146  -5.700
## ExterQualTA              -22829.76580     3712.79583  -6.149
## BsmtQualEx               -12273.92721     4728.68724  -2.596
## BsmtQualFa               -20428.76983     2476.52955  -8.249
## BsmtQualGd               -16048.79772     2840.07243  -5.651
## BsmtExposureAv            19595.59377     2273.19595   8.620
## BsmtFinType1BLQ            4137.92986     1750.48172   2.364
## BsmtFinSF1                   37.75769        3.05222  12.371
## BsmtFinSF2                   25.80156        4.40669   5.855
## BsmtUnfSF                    22.51566        2.93701   7.666
## X1stFlrSF                    52.28720        3.81987  13.688
## X2ndFlrSF                    56.91686        2.79574  20.358
## BedroomAbvGr              -6118.75256     1094.29142  -5.592
## KitchenAbvGr             -25400.14493     3016.82367  -8.419
## KitchenQualFa            -19644.45816     4918.27287  -3.994
## KitchenQualGd            -22306.88810     2943.12682  -7.579
```

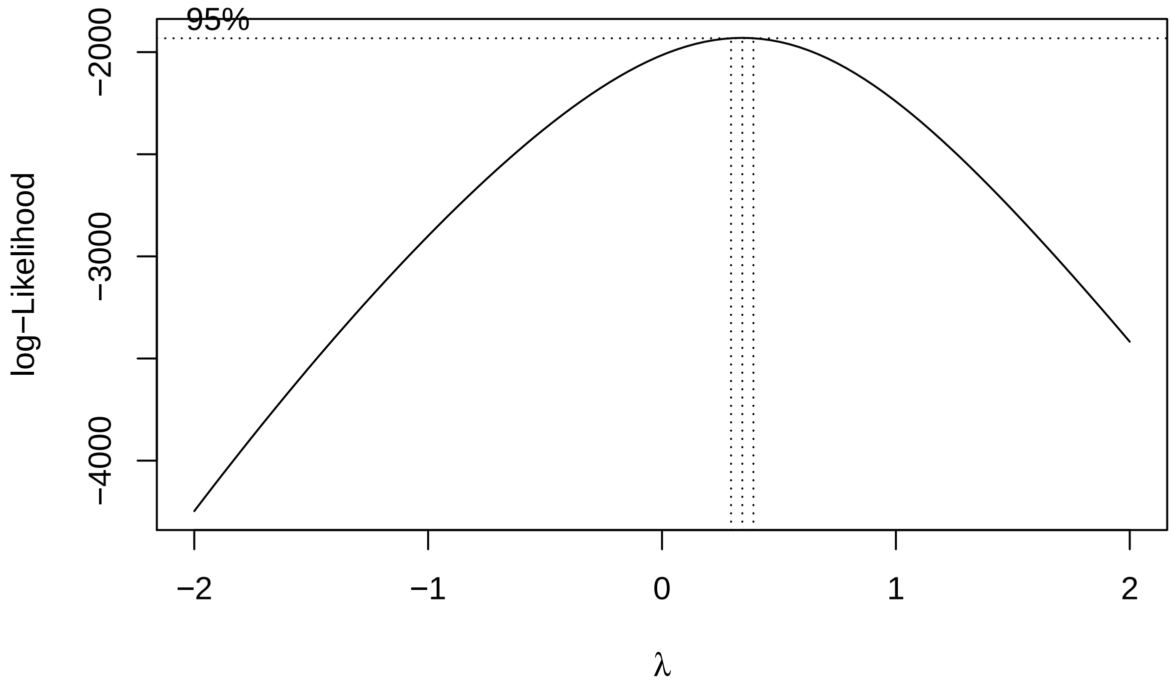
```
## KitchenQualTA          -22836.34400     3323.75948  -6.871
## TotRmsAbvGrd             2483.27537      782.09095   3.175
## FunctionalTyp           14814.79638     2469.94324   5.998
## GarageCars               9240.14566     1288.45962   7.171
## GarageQualEx           -15039.17858     4315.98810  -3.485
## GarageQualFa            -1456.50341     6588.04379  -0.221
## GarageQualGd           -16857.98707    12738.07414  -1.323
## GarageQualPo           -10156.77637     3230.28881  -3.144
## WoodDeckSF                 15.11486        4.93408   3.063
## ScreenPorch                41.82895       10.38260   4.029
## PoolArea                   46.54277       17.56247   2.650
## SaleTypeNew             22639.33785     3056.75435   7.406
## SaleConditionNormal      6635.61415     1988.58730   3.337
##                                    Pr(>|t|)
## (Intercept)          < 0.0000000000000002 ***
## MSSubClass120        0.000000015441952884 ***
## MSSubClass160        0.000000000060744262 ***
## MSZoningFV           0.000002271756534403 ***
## MSZoningRH                       0.027863 *
## MSZoningRL                       0.001590 **
## MSZoningRM                       0.010348 *
## LotArea              < 0.0000000000000002 ***
## StreetPave           0.000039538361591505 ***
## LandContourLow                   0.016679 *
## LotConfigCulDSac                 0.000246 ***
## LandSlopeSev         0.000002543849781085 ***
## NeighborhoodCollgCr              0.912758
## NeighborhoodCrawfor  0.000000011688777608 ***
## NeighborhoodEdwards              0.000738 ***
## NeighborhoodGilbert              0.337600
## NeighborhoodMitchel  0.000077768287814754 ***
## NeighborhoodNAmes    0.000061736078775388 ***
## NeighborhoodNoRidge  0.000000000060196556 ***
## NeighborhoodNridgHt  0.000000021177336753 ***
## NeighborhoodNWAmes   0.000018948718917523 ***
## NeighborhoodOldTown              0.064063 .
## NeighborhoodStoneBr  < 0.0000000000000002 ***
## Condition1Norm                   0.000179 ***
## Condition1RRAe                   0.009575 **
## Condition2RRAe                   0.004103 **
## OverallQual          0.000000000000000228 ***
## OverallCond          0.000000000000002313 ***
## YearBuilt            0.000000000021756978 ***
## YearRemodAdd                     0.014656 *
## RoofStyleShed                    0.010652 *
## RoofMatlCompShg      < 0.0000000000000002 ***
## RoofMatlMembran      < 0.0000000000000002 ***
## RoofMatlMetal        < 0.0000000000000002 ***
## RoofMatlRoll         < 0.0000000000000002 ***
## `RoofMatlTar&Grv`    < 0.0000000000000002 ***
## RoofMatlWdShake      < 0.0000000000000002 ***
## RoofMatlWdShngl      < 0.0000000000000002 ***
## Exterior1stBrkFace   0.000001340618306495 ***
## `Exterior1stWd Sdng`             0.023709 *
```

```
## `Exterior2ndWd Sdng`             0.020911 *
## MasVnrTypeStone                  0.001966 **
## MasVnrArea                       0.002439 **
## ExterQualGd          0.000000014636523040 ***
## ExterQualTA          0.000000001018871882 ***
## BsmtQualEx                       0.009542 **
## BsmtQualFa           0.000000000000000368 ***
## BsmtQualGd           0.000000019361569651 ***
## BsmtExposureAv       < 0.0000000000000002 ***
## BsmtFinType1BLQ                  0.018222 *
## BsmtFinSF1           < 0.0000000000000002 ***
## BsmtFinSF2           0.000000005947144042 ***
## BsmtUnfSF            0.000000000000033196 ***
## X1stFlrSF            < 0.0000000000000002 ***
## X2ndFlrSF            < 0.0000000000000002 ***
## BedroomAbvGr         0.000000027086389464 ***
## KitchenAbvGr         < 0.0000000000000002 ***
## KitchenQualFa        0.000068334389684203 ***
## KitchenQualGd        0.000000000000063342 ***
## KitchenQualTA        0.000000000009635832 ***
## TotRmsAbvGrd                     0.001530 **
## FunctionalTyp        0.000000002545803481 ***
## GarageCars           0.000000000001204751 ***
## GarageQualEx                     0.000508 ***
## GarageQualFa                     0.825061
## GarageQualGd                     0.185910
## GarageQualPo                     0.001701 **
## WoodDeckSF                       0.002231 **
## ScreenPorch          0.000059123036763314 ***
## PoolArea                         0.008138 **
## SaleTypeNew          0.000000000000224875 ***
## SaleConditionNormal              0.000870 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 20860 on 1383 degrees of freedom
## Multiple R-squared:  0.9293, Adjusted R-squared:  0.9257
## F-statistic: 256.1 on 71 and 1383 DF,  p-value: < 0.00000000000000022
```

At first glance, the multiple R-squared value of 0.9293 indicates that 92.93% of the variability in SalePrice around its mean is explained by the mode, i.e. by the predictor variables that have been included. This suggests a high-performing explanatory model.

Let Before welcoming this conclusion, we validate the linearity and normality assumptions of our model by checking our residuals as follows:

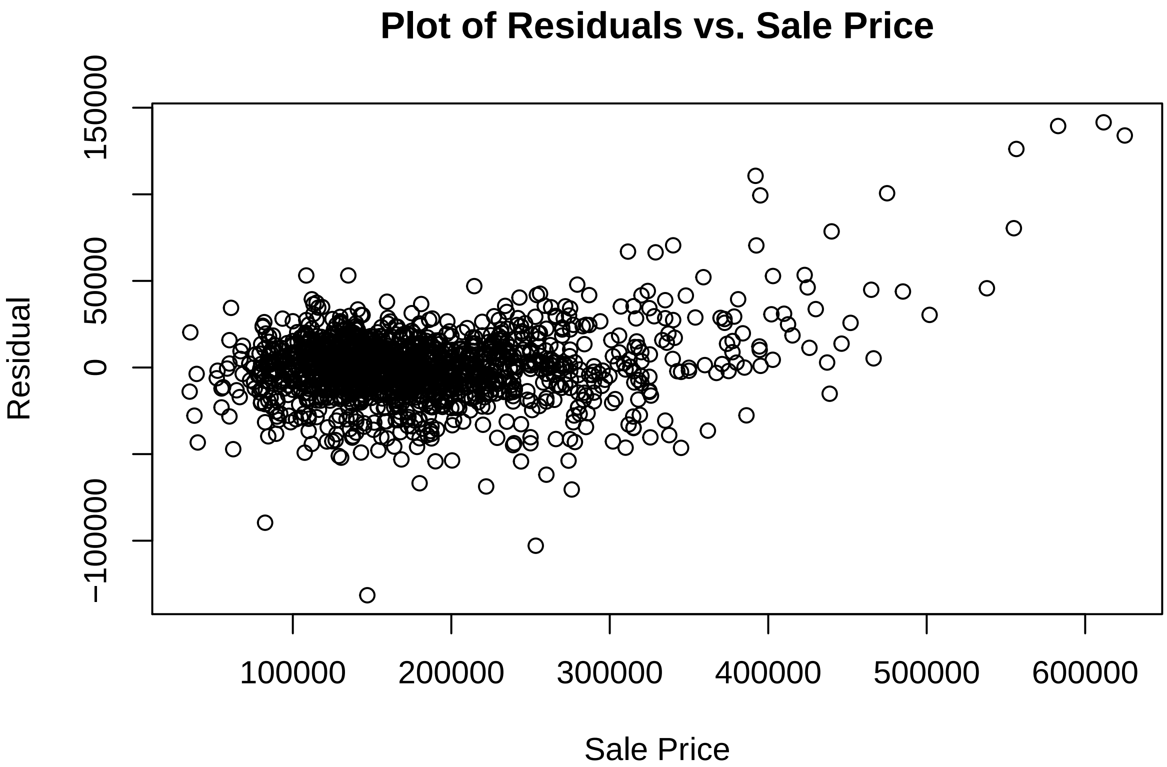
```r
# Residual plots

res = resid(new_model)  # residuals
stdres = rstandard(new_model)  # standardized residuals

# QQ Plot of Residuals - for normality
qqnorm(stdres, main = "QQ Plot of Standardized Residuals", xlab = "Normal Scores",
    ylab = "Standardized Residual")
qqline(stdres)
```




```
# Shapiro-Wilks test for normality
shapiro.test(res)
```

```
##
##  Shapiro-Wilk normality test
##
## data:  res
## W = 0.91064, p-value < 0.00000000000000022
```

```
# Plot of residuals vs. fitted values - for linearity
plot(workingDF$SalePrice, res, main = "Plot of Residuals vs. Sale Price",
    xlab = "Sale Price", ylab = "Residual")
```

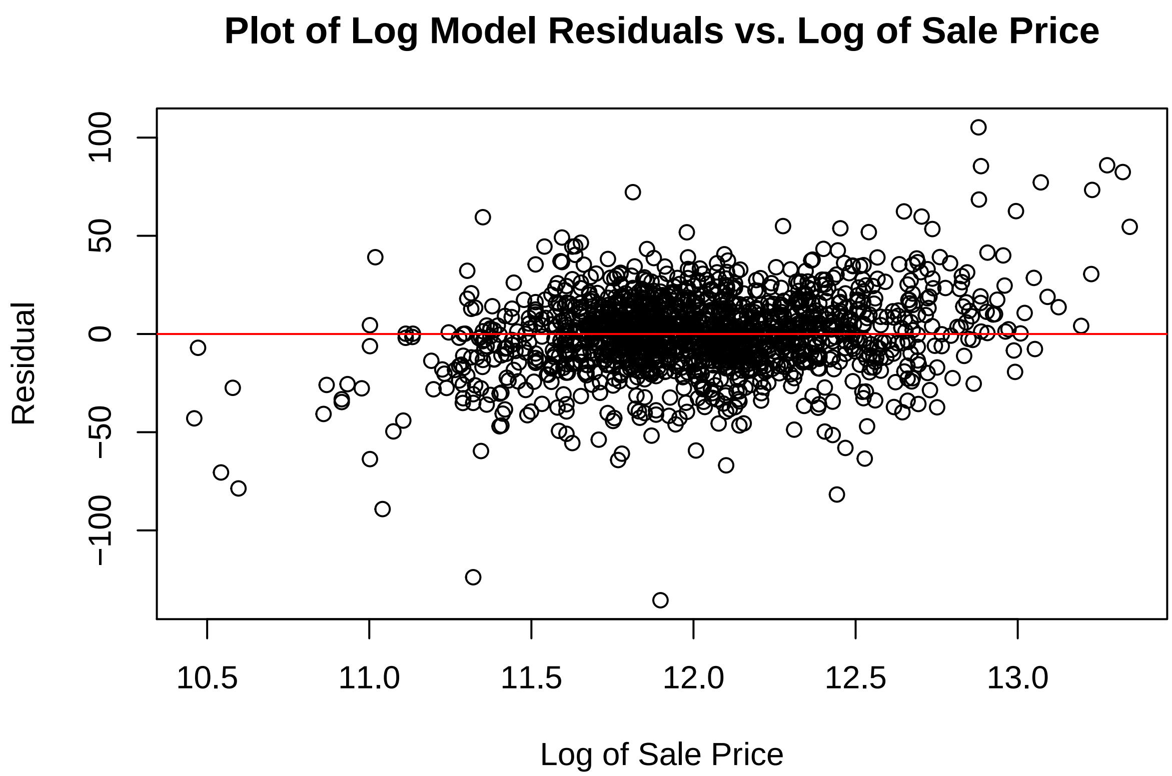



```
# abline(h=c(0,0), col = 'red') abline(v=350000, col = 'blue')
```

The plot of residuals against fitted values shows that for the most part, the residuals are evenly distributed across the y = 0 line. However, we see that as Sale Price increases, the residuals start to deviate homoscedasticity. More specifically, we see this deviation happen at approximately Sale Price = $350K, which our earlier summary showed to be between the variable's 3rd quartile and maximum. This suggets that for the last quartile of high-priced houses, the fitted regression model is not as adequate as it is for the reset of the population. The normal probability (QQ) plot corroborates this finding: it shows deviance from linearity at both tail ends of the residual rang, which suggests a heavy tailed distribution. This occurs at both ends of the distribution, i.e. both extremely low-priced houses and extremely high-priced houses are pulling the distribution away from normality. Indeed, the formal Shapiro-Wilks test for normality produces a p-value of ~0, which leads us to reject the null hypothesis, at the alpha = 0.05 level, that the residuals are normally distributed.

As a remedial measure, we consider performing a transformation on Sale Price. We use the `boxcox()` function to determine the transformation under which the maximum likelihood [of ?] is attained.

```
boxcox(new_model)
```

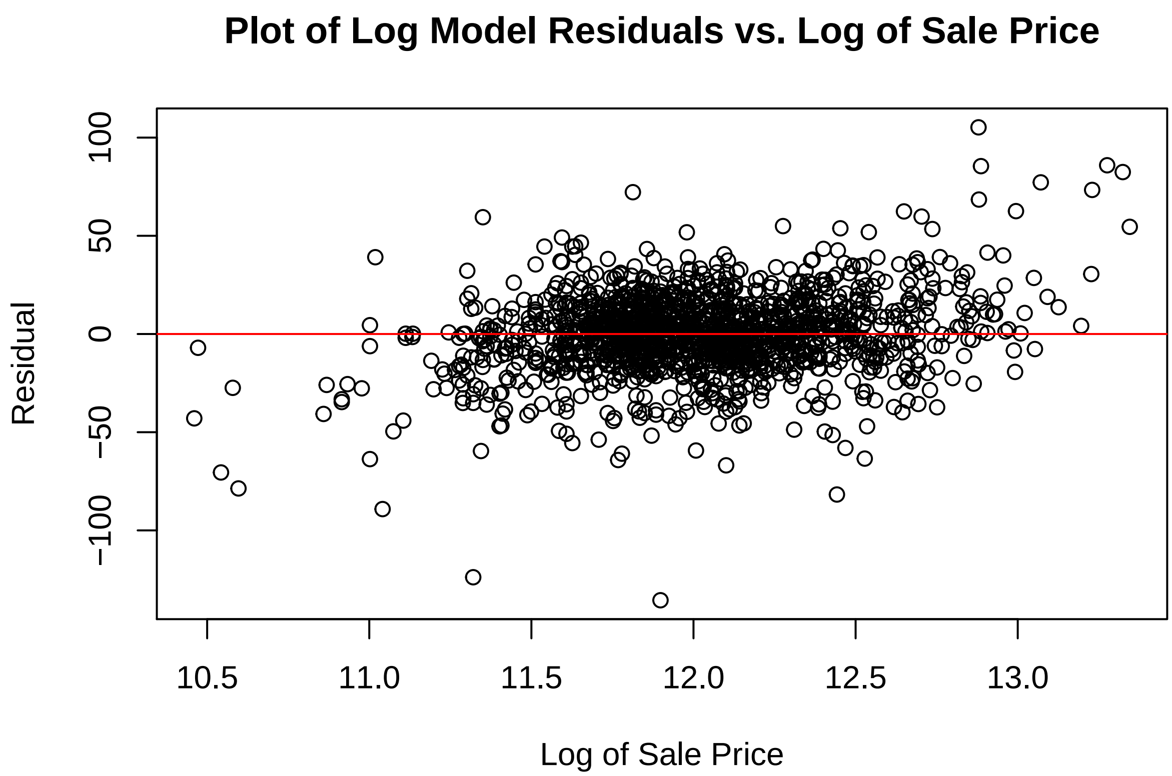


We see that lambda = 1 is not captured in the 95% CI of lambdas, indicated by the three vertical dashed lines. This means a transformation is necessary. We choose lambda = ~ 0.5 since this is an interpretable transformation value. Below, we apply a square root transformation to Sale Price, refit the model, and revalidate our model assumptions with residual plots as above.

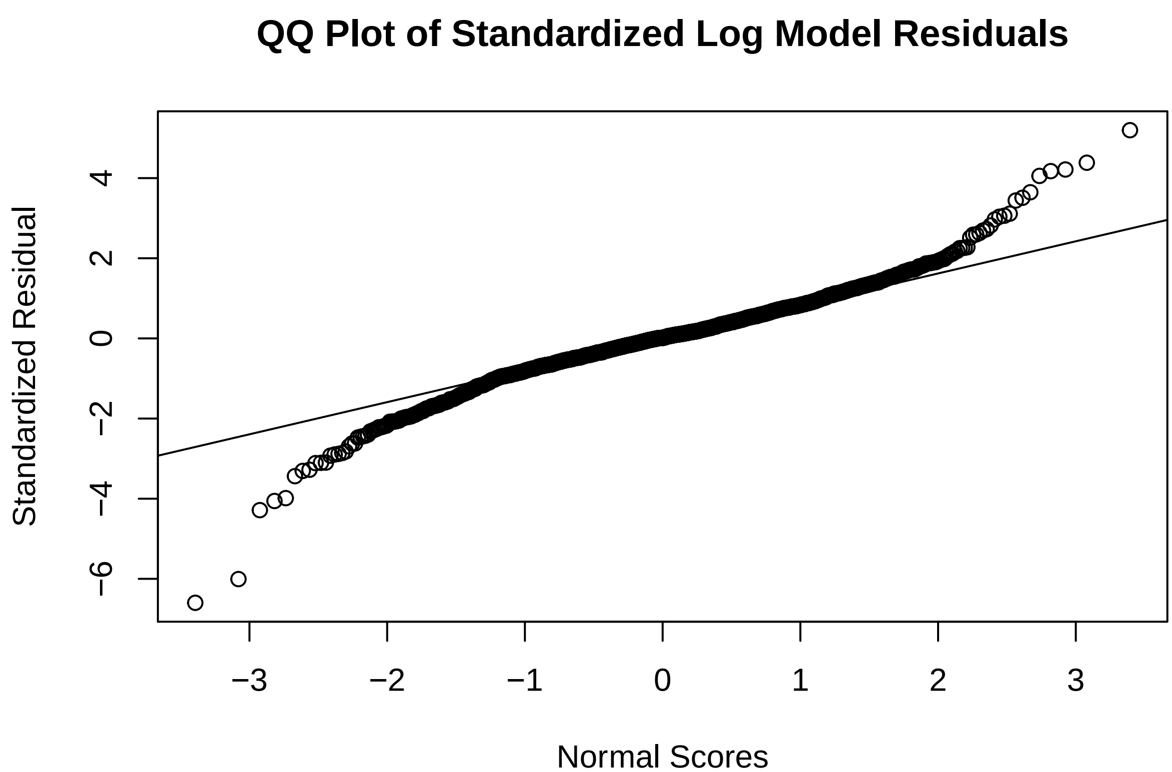
```
# Log Transformation
log_model_formula <- as.formula(paste("sqrt(SalePrice) ~ ", paste(new_sig_var_bic,
    collapse = "+")))
log_model <- lm(formula = log_model_formula, data = workingDF)

res_log = resid(log_model)  # residuals
stdres_log = rstandard(log_model)  # standardized residuals

shapiro.test(res_log)
```

```
##
##  Shapiro-Wilk normality test
##
## data:  res_log
## W = 0.95909, p-value < 0.00000000000000022
```

```
# Plot of Residuals from Log Model vs. Fitted Values
plot(log(workingDF$SalePrice), res_log, main = "Plot of Log Model Residuals vs. Log of Sale Price",
    xlab = "Log of Sale Price", ylab = "Residual")
abline(h = c(0, 0), col = "red")
abline(v = 350000, col = "blue")
```




```r
# Normal Probability Plot of Residuals from Log Model
qqnorm(stdres_log, main = "QQ Plot of Standardized Log Model Residuals",
    xlab = "Normal Scores", ylab = "Standardized Residual")
qqline(stdres_log)
```



Our new model produces an R-squared value of 0.9411, indicating that 94.11% of the variance in Sale Price is captured by the model. Our residuals vs. fitted values plot shows a better pattern of homoscedasticity, which suggests that our linear regression model adequately captures the trend in the log-transformed data. The normal probability plot of the standardized residuals also shows better adherence to a linear pattern, which suggests that our assumption of normality is better.

Accepting our new model, we provide its summary as follows:

```r
summary(log_model)
```

```
##
## Call:
## lm(formula = log_model_formula, data = workingDF)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -135.567  -10.635    0.261   11.306  105.225
##
## Coefficients:
##                          Estimate     Std. Error t value
## (Intercept)          -1671.18357282   112.58872806 -14.843
## MSSubClass120          -10.64752125     2.85913147  -3.724
## MSSubClass160          -26.18081164     3.35802829  -7.796
## MSZoningFV              65.46041153     8.06155177   8.120
## MSZoningRH              42.89043937     8.95402404   4.790
## MSZoningRL              48.03525028     7.40929535   6.483
## MSZoningRM              38.45017202     7.44291165   5.166
## LotArea                  0.00073517     0.00008259   8.902
## StreetPave              31.53534731     9.40517134   3.353
## LandContourLow          -7.17666556     4.26731619  -1.682
## LotConfigCulDSac         8.15820547     2.39587482   3.405
## LandSlopeSev           -39.91544398     8.83150706  -4.520
## NeighborhoodCollgCr     -0.01011682     2.36619698  -0.004
## NeighborhoodCrawfor     24.00687376     3.42815146   7.003
## NeighborhoodEdwards    -10.53432796     2.51927190  -4.181
## NeighborhoodGilbert     -1.28573035     3.02731747  -0.425
## NeighborhoodMitchel    -12.26751912     3.38861536  -3.620
## NeighborhoodNAmes       -7.48489934     2.04558981  -3.659
## NeighborhoodNoRidge     17.29709181     4.18056130   4.138
## NeighborhoodNridgHt     15.42677210     3.39134089   4.549
## NeighborhoodNWAmes     -11.21336222     2.92429552  -3.835
## NeighborhoodOldTown     -5.14713279     2.99311114  -1.720
## NeighborhoodStoneBr     32.00644840     4.73427499   6.761
## Condition1Norm           7.48316286     1.76829895   4.232
## Condition1RRAe         -20.11004958     6.72651876  -2.990
## Condition2RRAe        -102.75611865    33.16696136  -3.098
## OverallQual              8.93921706     0.80743887  11.071
## OverallCond              7.15741893     0.67014561  10.680
## YearBuilt                0.40385545     0.04641291   8.701
## YearRemodAdd             0.16358008     0.04455051   3.672
## RoofStyleShed           72.49869955    25.19630392   2.877
## RoofMatlCompShg        674.45031929    26.13454451  25.807
## RoofMatlMembran        755.12050273    35.41024975  21.325
## RoofMatlMetal          730.65450605    35.27721303  20.712
## RoofMatlRoll           663.16972068    33.69026761  19.684
```

```
## `RoofMatlTar&Grv`      668.08268748    26.76335491  24.963
## RoofMatlWdShake        666.66645567    28.18712555  23.651
## RoofMatlWdShngl        703.17079135    27.67154294  25.411
## Exterior1stBrkFace      16.54367684     3.37548164   4.901
## `Exterior1stWd Sdng`    -8.22155502     3.38045974  -2.432
## `Exterior2ndWd Sdng`     7.74299867     3.35482876   2.308
## MasVnrTypeStone          7.35971115     2.33030634   3.158
## MasVnrArea               0.00715501     0.00398773   1.794
## ExterQualGd            -10.85790351     3.53495715  -3.072
## ExterQualTA            -14.04465027     3.72419051  -3.771
## BsmtQualEx              -7.65520773     4.74319971  -1.614
## BsmtQualFa             -13.91804704     2.48413009  -5.603
## BsmtQualGd             -10.71663639     2.84878869  -3.762
## BsmtExposureAv          16.72368119     2.28017245   7.334
## BsmtFinType1BLQ          4.29191348     1.75585399   2.444
## BsmtFinSF1               0.04088735     0.00306158  13.355
## BsmtFinSF2               0.02891711     0.00442021   6.542
## BsmtUnfSF                0.02397144     0.00294602   8.137
## X1stFlrSF                0.06000525     0.00383159  15.661
## X2ndFlrSF                0.06310356     0.00280432  22.502
## BedroomAbvGr            -3.90758206     1.09764983  -3.560
## KitchenAbvGr           -24.61391838     3.02608238  -8.134
## KitchenQualFa          -18.19947694     4.93336719  -3.689
## KitchenQualGd          -18.59497607     2.95215936  -6.299
## KitchenQualTA          -19.88106371     3.33396019  -5.963
## TotRmsAbvGrd             2.06333085     0.78449120   2.630
## FunctionalTyp           16.21671425     2.47752357   6.546
## GarageCars              10.52823232     1.29241394   8.146
## GarageQualEx           -10.17295582     4.32923399  -2.350
## GarageQualFa             8.48332330     6.60826268   1.284
## GarageQualGd           -16.49507217    12.77716764  -1.291
## GarageQualPo            -2.39845798     3.24020265  -0.740
## WoodDeckSF               0.01810918     0.00494922   3.659
## ScreenPorch              0.05080009     0.01041447   4.878
## PoolArea                 0.04605799     0.01761637   2.614
## SaleTypeNew             23.80567847     3.06613561   7.764
## SaleConditionNormal      9.87327013     1.99469032   4.950
##                                    Pr(>|t|)
## (Intercept)          < 0.0000000000000002 ***
## MSSubClass120                    0.000204 ***
## MSSubClass160        0.000000000000012444 ***
## MSZoningFV           0.000000000000001021 ***
## MSZoningRH           0.000001846634598217 ***
## MSZoningRL           0.000000000124711745 ***
## MSZoningRM           0.000000274125859981 ***
## LotArea              < 0.0000000000000002 ***
## StreetPave                       0.000821 ***
## LandContourLow                   0.092838 .
## LotConfigCulDSac                 0.000680 ***
## LandSlopeSev         0.000006722390861845 ***
## NeighborhoodCollgCr              0.996589
## NeighborhoodCrawfor  0.000000000003901696 ***
## NeighborhoodEdwards  0.000030779955347722 ***
## NeighborhoodGilbert              0.671115
```

```
## NeighborhoodMitchel               0.000305 ***
## NeighborhoodNAmes                 0.000263 ***
## NeighborhoodNoRidge  0.000037228199946703 ***
## NeighborhoodNridgHt  0.000005865667023773 ***
## NeighborhoodNWAmes                0.000131 ***
## NeighborhoodOldTown               0.085718 .
## NeighborhoodStoneBr  0.000000000020210524 ***
## Condition1Norm       0.000024705134413399 ***
## Condition1RRAe                    0.002842 **
## Condition2RRAe                    0.001987 **
## OverallQual          < 0.0000000000000002 ***
## OverallCond          < 0.0000000000000002 ***
## YearBuilt            < 0.0000000000000002 ***
## YearRemodAdd                      0.000250 ***
## RoofStyleShed                     0.004072 **
## RoofMatlCompShg      < 0.0000000000000002 ***
## RoofMatlMembran      < 0.0000000000000002 ***
## RoofMatlMetal        < 0.0000000000000002 ***
## RoofMatlRoll         < 0.0000000000000002 ***
## `RoofMatlTar&Grv`    < 0.0000000000000002 ***
## RoofMatlWdShake      < 0.0000000000000002 ***
## RoofMatlWdShngl      < 0.0000000000000002 ***
## Exterior1stBrkFace   0.000001065352965006 ***
## `Exterior1stWd Sdng`              0.015139 *
## `Exterior2ndWd Sdng`              0.021145 *
## MasVnrTypeStone                   0.001621 **
## MasVnrArea                        0.072991 .
## ExterQualGd                       0.002171 **
## ExterQualTA                       0.000169 ***
## BsmtQualEx                        0.106770
## BsmtQualFa           0.000000025419586296 ***
## BsmtQualGd                        0.000176 ***
## BsmtExposureAv       0.000000000000377958 ***
## BsmtFinType1BLQ                   0.014636 *
## BsmtFinSF1           < 0.0000000000000002 ***
## BsmtFinSF2           0.000000000085228977 ***
## BsmtUnfSF            0.000000000000000895 ***
## X1stFlrSF            < 0.0000000000000002 ***
## X2ndFlrSF            < 0.0000000000000002 ***
## BedroomAbvGr                      0.000383 ***
## KitchenAbvGr         0.000000000000000916 ***
## KitchenQualFa                     0.000234 ***
## KitchenQualGd        0.000000000402233982 ***
## KitchenQualTA        0.000000003135879653 ***
## TotRmsAbvGrd                      0.008629 **
## FunctionalTyp        0.000000000083308288 ***
## GarageCars           0.000000000000000832 ***
## GarageQualEx                      0.018922 *
## GarageQualFa                      0.199446
## GarageQualGd                      0.196926
## GarageQualPo                      0.459293
## WoodDeckSF                        0.000263 ***
## ScreenPorch          0.000001196738264173 ***
## PoolArea                          0.009033 **
```

```
## SaleTypeNew           0.000000000000015906 ***
## SaleConditionNormal  0.000000834280350583 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 20.93 on 1383 degrees of freedom
## Multiple R-squared:  0.9411, Adjusted R-squared:  0.9381
## F-statistic: 311.2 on 71 and 1383 DF,  p-value: < 0.00000000000000022
```

We conclude that the variables included above are most relevant in determining a house's sale price. In particular, those variables that are significant at the 0.01 level, i.e., are most significant.

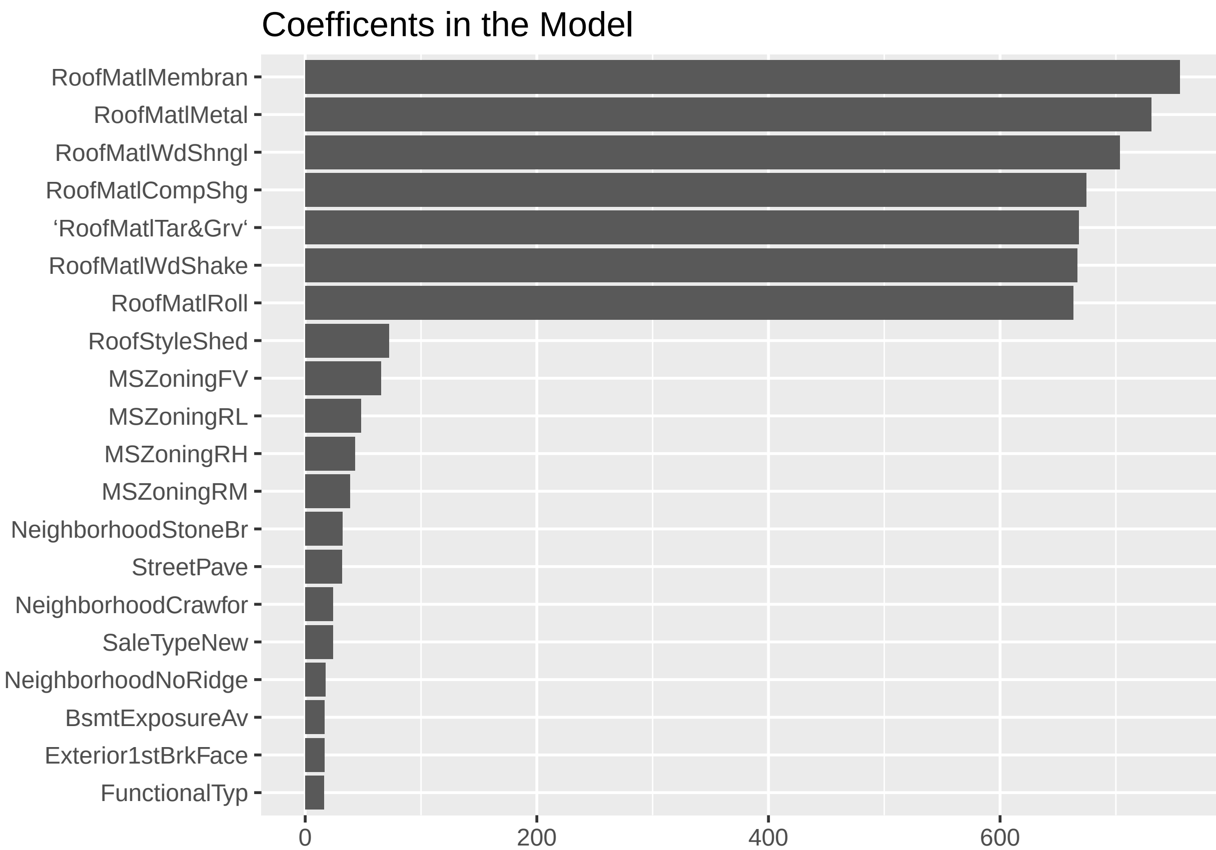
Task 2: Making recommendations

```r
# morty <-
# read.csv('/Users/booranium/usf/601_regression/project/Morty.txt',
# stringsAsFactors = T)
morty <- read.csv("/Users/santhoshhari/Documents/Coursework/LinearRegression/IowaHousing/Data/Morty.txt
    stringsAsFactors = T)
morty <- morty[, -1]
new_data <- rbind(housingDF, morty)
new_data <- model.matrix(SalePrice ~ ., data = new_data)[, -1]
x_morty <- as.data.frame(tail(new_data, 1))
new_sig_var_bic[which(new_sig_var_bic == "`RoofMatlTar&Grv`")] <- "RoofMatlTar&Grv"
new_sig_var_bic[which(new_sig_var_bic == "`Exterior1stWd Sdng`")] <- "Exterior1stWd Sdng"
new_sig_var_bic[which(new_sig_var_bic == "`Exterior2ndWd Sdng`")] <- "Exterior2ndWd Sdng"
sig_var_morty <- x_morty[, new_sig_var_bic]
```

The estimated sale price of Morty's property is $ 154314. To make a recommendation to Morty regarding the selling price of his house, we leverage the model built above to make a prediction of Sale Price based on select attributes as determined above.

We see that the 95% CI for the predicted Sale Price of Morty's house, based on selected attributes, is … As such, we recommend that Morty sell his house at a maximum of …, which is more/less than the other firm's recommendation of $143K.

```r
coef <- data.frame(coef.name = names(coef(log_model)), coef.value = matrix(coef(log_model)))

# exclude the (Intercept) term
coef <- coef[-1, ]
coef <- arrange(coef, -coef.value)
imp_coef <- head(coef, 20)
ggplot(imp_coef) + geom_bar(aes(x = reorder(coef.name, coef.value),
    y = coef.value), stat = "identity") + coord_flip() + ggtitle("Coefficents in the Model") +
    theme(axis.title = element_blank())
```



Part II: Predictive Modelling

For comparing the prediction accuracy, we use 4 models - 1. Ridge Regression 2. Lasso Regression 3. Elastic Net

Transformations done on the data before building models - 1. Imputing NAs 2. Creating dummy variables 3. Removing influential points

Train and test sets: 75% of the data forms the train set 25% of the data forms the test set

```
x <- workingDF[, -1]
x$SalePrice <- log(workingDF[, ncol(workingDF)])
# y_log = log(y) train/test
set.seed(121)
train <- sample(1:nrow(x), 3 * nrow(x)/4)
test <- (-train)
```

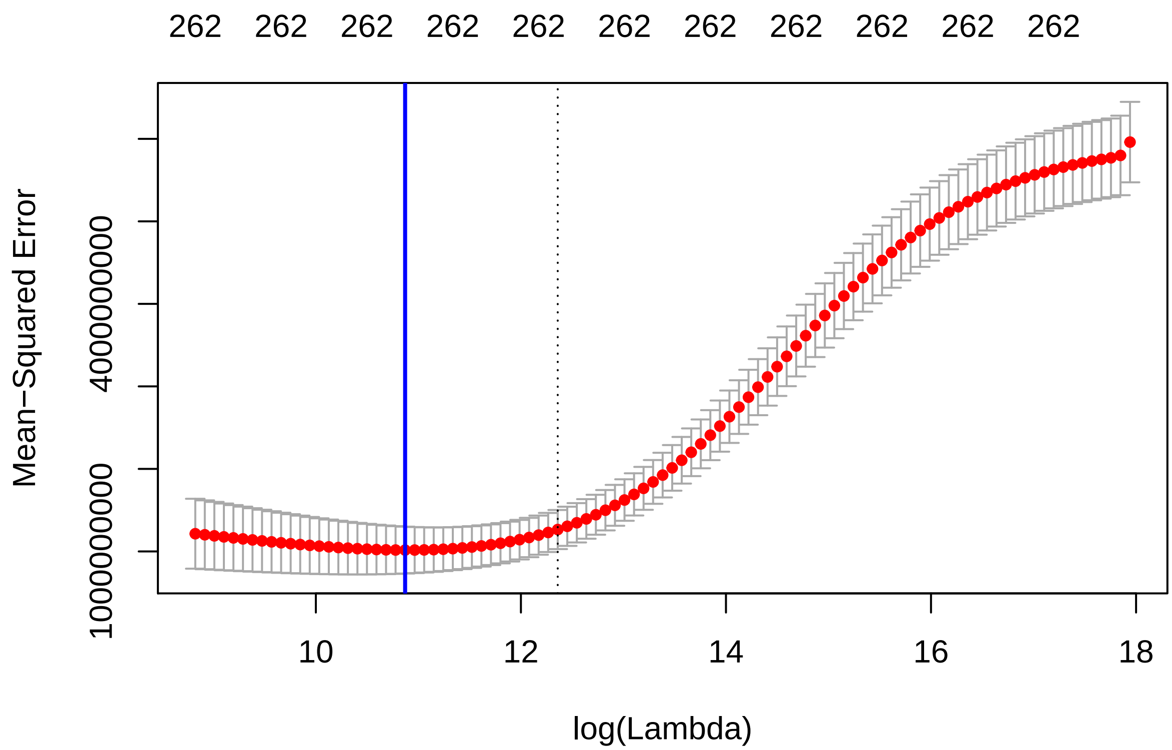
Ridge:

```
set.seed(121)

x <- workingDF[, 2:ncol(workingDF) - 1]
y <- workingDF$SalePrice

# train/test
y.train <- y[train]
y.test <- y[test]
```

```r
ridge <- cv.glmnet(as.matrix(x[train, ]), y.train, alpha = 0)
plot(ridge)
best.lambda <- ridge$lambda.min
best.lambda
```

```
## [1] 52607.68
```

```r
abline(v = log(best.lambda), col = "blue", lwd = 2)
```




```r
ridge.model.train <- glmnet(as.matrix(x[train, ]), y.train, alpha = 0,
    lambda = best.lambda)


ridge.pred <- predict(ridge.model.train, s = best.lambda, newx = as.matrix(x[test,
    ]))
mspe.ridge <- mean((ridge.pred - y.test)^2)

coef_ridge <- coef(ridge.model.train)
length(coef_ridge[coef_ridge != 0])
```

```
## <sparse>[ <logic> ] : .M.sub.i.logical() maybe inefficient
```

```
## [1] 263
```

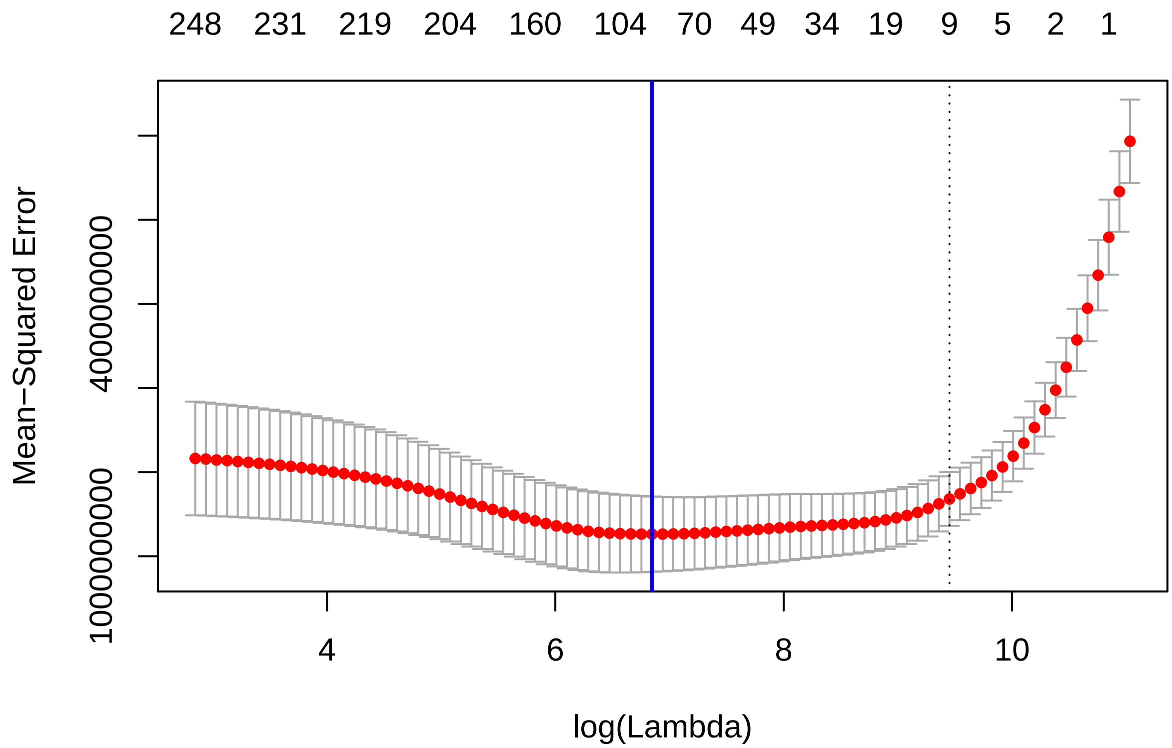
Lasso:

```r
set.seed(121)

x <- workingDF[, 2:ncol(workingDF) - 1]
y <- workingDF$SalePrice

lasso <- cv.glmnet(as.matrix(x[train, ]), y.train, alpha = 1)
```

```r
plot(lasso)
best.lambda <- lasso$lambda.min
best.lambda
```

```
## [1] 940.967
```

```r
abline(v = log(best.lambda), col = "blue", lwd = 2)
```




```r
lasso.model.train <- glmnet(as.matrix(x[train, ]), y.train, alpha = 1,
    lambda = best.lambda)


lasso.pred <- predict(lasso.model.train, s = best.lambda, newx = as.matrix(x[test,
    ]))
mspe.lasso <- mean((lasso.pred - y.test)^2)
mspe.lasso
```

```
## [1] 893359489
```

```r
# coef(lasso)
coef_lasso <- coef(lasso.model.train)
length(coef_lasso[coef_lasso != 0])
```

```
## <sparse>[ <logic> ] : .M.sub.i.logical() maybe inefficient
```

```
## [1] 94
```

Elastic Net:

```r
set.seed(121)
x <- workingDF[, 2:ncol(workingDF) - 1]
y <- workingDF$SalePrice
# find best alpha
```

```r
alphalist <- seq(0, 1, by = 0.1)
elasticnet <- lapply(alphalist, function(a) {
    cv.glmnet(as.matrix(x[train, ]), y.train, alpha = a)
})
mse <- list()
for (i in 1:11) {
    mse <- c(mse, min(elasticnet[[i]]$cvm))
    print(min(elasticnet[[i]]$cvm))
    print(i)
}
```

```
## [1] 1016142017
## [1] 1
## [1] 1117640754
## [1] 2
## [1] 939947706
## [1] 3
## [1] 1224250184
## [1] 4
## [1] 1230118261
## [1] 5
## [1] 1263783454
## [1] 6
## [1] 928585211
## [1] 7
## [1] 1272709084
## [1] 8
## [1] 1253079900
## [1] 9
## [1] 1254532583
## [1] 10
## [1] 1264612530
## [1] 11
```

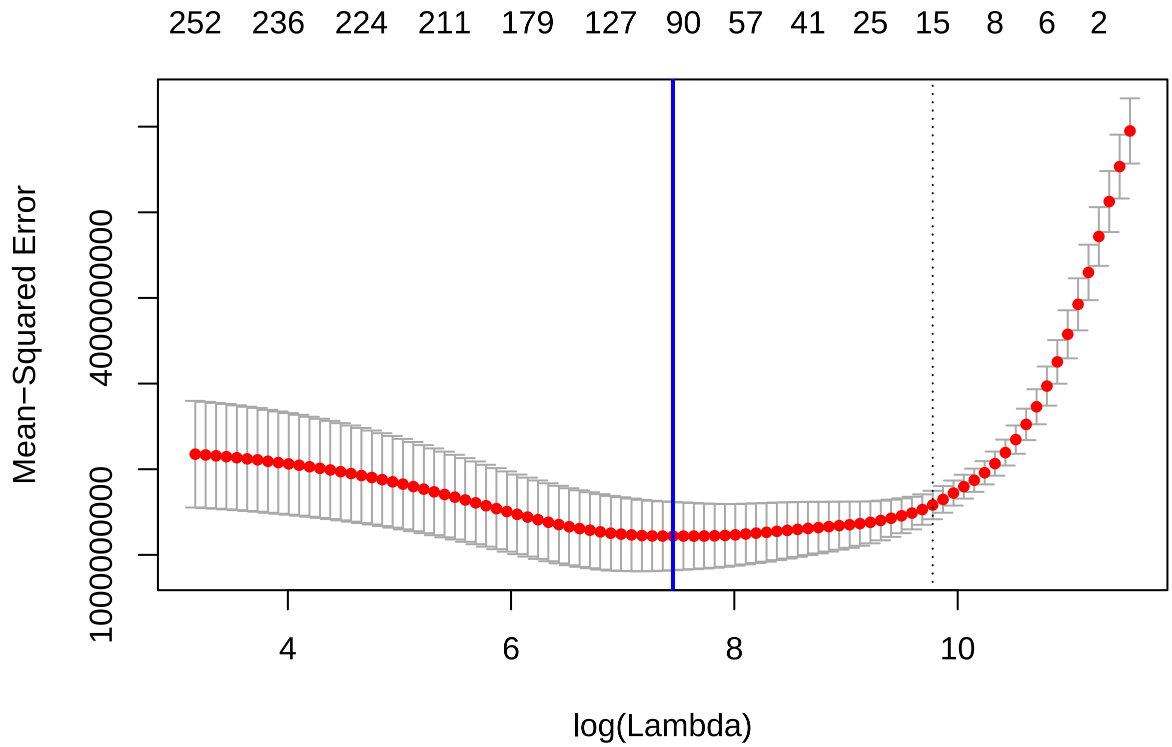
```r
which.min(unlist(mse))
```

```
## [1] 7
```

```r
alpha_min = alphalist[which.min(unlist(mse))]

# find best lambda for best alpha
cv.out <- cv.glmnet(as.matrix(x[train, ]), y.train, alpha = alpha_min)

plot(cv.out)
best.lambda <- cv.out$lambda.min
best.lambda
```

```
## [1] 1721.184
```

```r
abline(v = log(best.lambda), col = "blue", lwd = 2)
```




```
# train EN
EN.model.train <- glmnet(as.matrix(x[train, ]), y.train, alpha = alpha_min,
    lambda = best.lambda)

EN.pred <- predict(EN.model.train, newx = as.matrix(x[test, ]))
mspe.EN <- mean((EN.pred - y.test)^2)
coef_elastic <- coef(EN.model.train)
length(coef_elastic[coef_elastic != 0])
```

```
## <sparse>[ <logic> ] : .M.sub.i.logical() maybe inefficient
```

```
## [1] 95
```

```
MSPE <- data.frame(Ridge = mspe.ridge, Lasso = mspe.lasso, EN = mspe.EN)
```