HOUSING PRICE: USING ADVANCED REGRESSION TECHNIQUES

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INTRODUCTION:

Housing has always been seen as one of the major stepping stones in adulthood; people graduate college, get a job, start a family, and save enough money to buy a house. The question though has always been how much does it cost to buy a house and what factors into the price of a house. In this project, we looked into data set from 1460 houses bought in Ames Iowa to create a regression model that best predicts the price of a house in Ames, Iowa. The variable of interest that we study is Sales Price and in our data set we have eighty predictor variables that are utilized to predict the cost of a house. Of the eighty predictors, we have 23 nominal, 23 ordinal, 14 discrete, and 20 continuous and these range from everything from Total Plot Area to Fire Place and Pool. Our interest in this project is to select the most important variables to study and create a model that best predicts the Sales Price of a house. In evaluating our model, we will look into the bias of our model to the actual sales price, the maximal deviation, mean absolute deviation, and mean square error to conclude how accurately we created a model to predict the Sales Price. We will use 1060 observations in our training data set and compare our model to the 400 observations in the test data set to see how our modeled Sales Price compares to the actual Sales Price of the 400 observations.

From our data set, we will look into normalizing the Sales Price by using the log function, and we will convert some of our predictors into dummy variables. From the list of variables, we will focus on several that we believe are highly correlated with SalePrice, and then variable selection techniques also to see the maximum number of variables for predicting a highly accurate model without overfitting the data. The purpose is to create a model that can best predict the Sales Price from our validation data set, but also that could be used on other data sets and still get a good prediction.

DATA PREPROCESSING

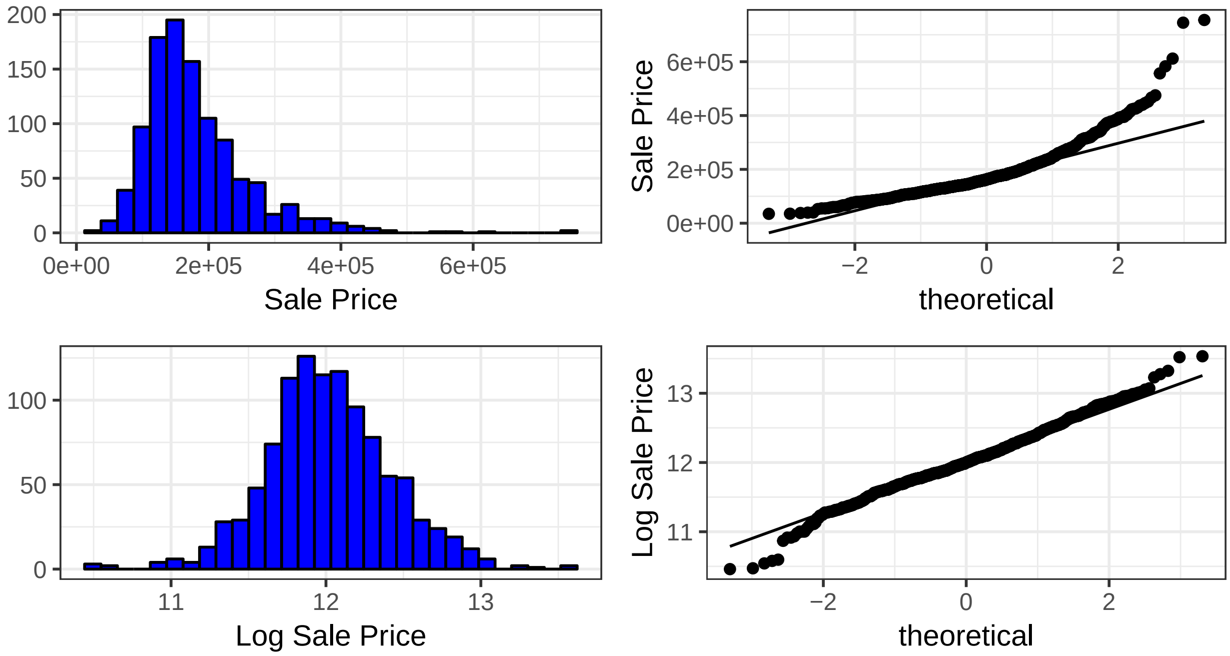
Before we start to apply our regression model to the data set, it is essential for us to have a clean and tide training data, the better training data we can get, the better performance of our regression model could behave. In data pre-processing we are mostly detecting and dealing with missing values, handling outliers and replacing the values with the median or most frequent value Treatment given to each variable is described below.

- Missing values in variables like PoolQC, MiscFeature, Alley, Fence, FireplaceQu, GarageType, GarageFinish, GarageQual, GarageCond, BsmtQual, BsmtCond, BsmtExposure, BsmtFinType1, BsmtFinType2, MasVnrType, MSSubClass are replaced by None based on data description.
- Missing values in LotFrontage is replace by the median LotFrontage of the neighborhood.
- Missing values in GarageYrBlt, GarageArea, GarageCars, BsmtFinSF1, BsmtFinSF2, BsmtUnfSF, To-talBsmtSF, BsmtFullBath, BsmtHalfBath, MasVnrArea are replaced with zero.
- Electrical which denotes type of electrical sytem is replace by “SBrkr” because it was most frequent data value in that series.

DATA EXPLORATION

After data cleaning and transformation we began with some exploratory analysis. A histogram plot shows the distribution of the target variable “SalePrice” as being was right-skewed. So we decided to take log of sale price in a way to obtain normal distribution for sale price.

Transformation of Sale Price



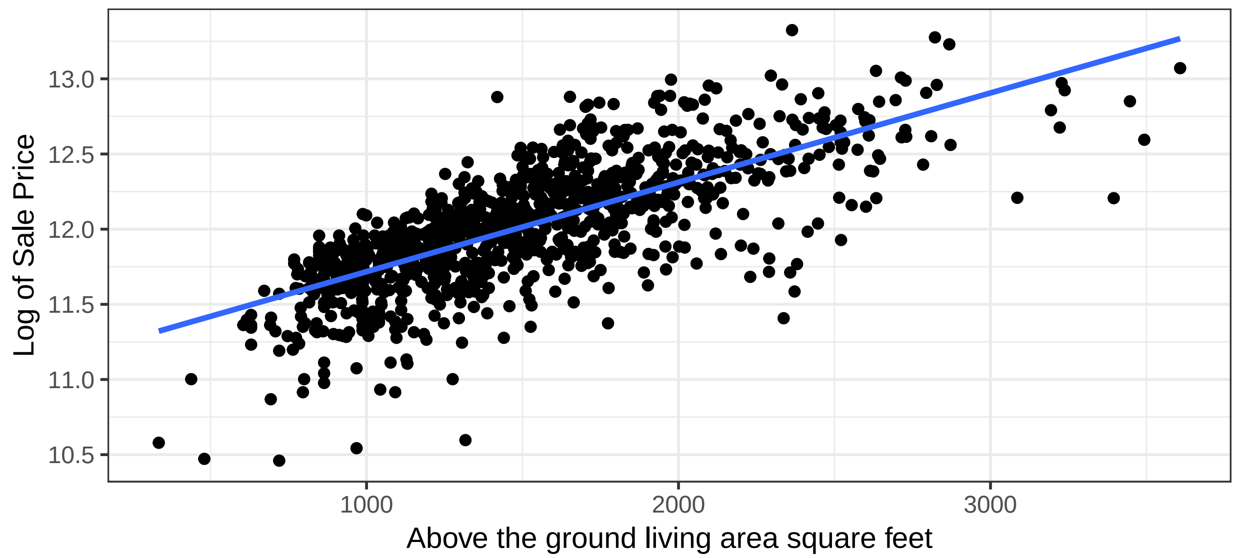
While data exploration we noticed that the variable ‘GrLiveArea’ has outlier.

From the 1st graph above, we can see there are outliers at ‘GrLivArea’ greater than 4000. We decided to remove these outliers.

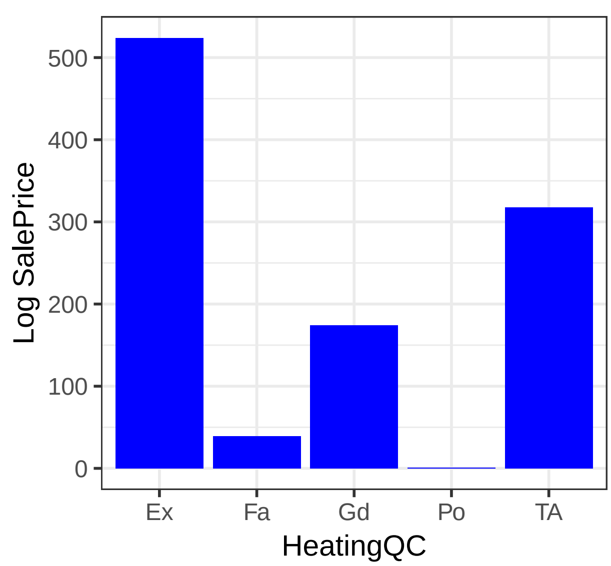
There might be more outliers in other variables, but removing all of them might affect our model. such as less observation, and there might be outliers in our test data as well. Therefore, we just removed the outliers for variable "GrlivArea".

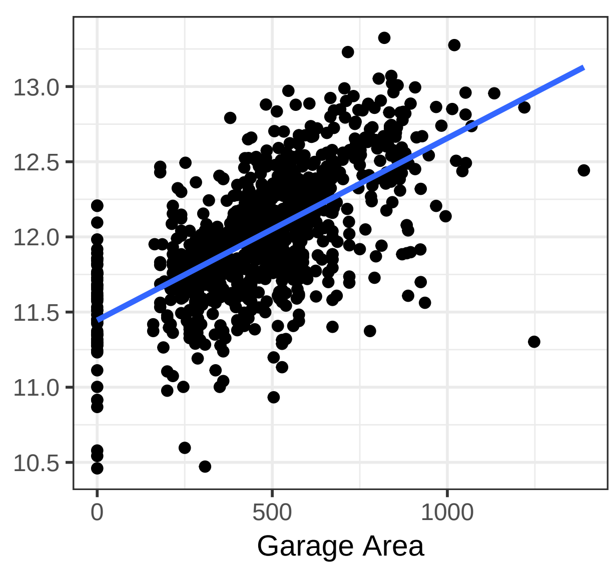
VARIABLE SELECTION

When selecting our variables, we decided first to see which predictors would someone who was buying a house choose. The ones that stood out right away were Living Area, Bathroom, number of bedrooms, and total rooms. When most people speak about houses, one of the first things they mention is the number of bedrooms and bathrooms so we assumed those would be important factors in buying a house. For Living Area and total Basement Square Footage, we knew we did not need to use the 1st and 2nd floor breakdowns because they were added for total living area and total basement square footage. Below graph shows comparison between log of sale price and above the ground living area square feet. We can see some strong pattern between them.

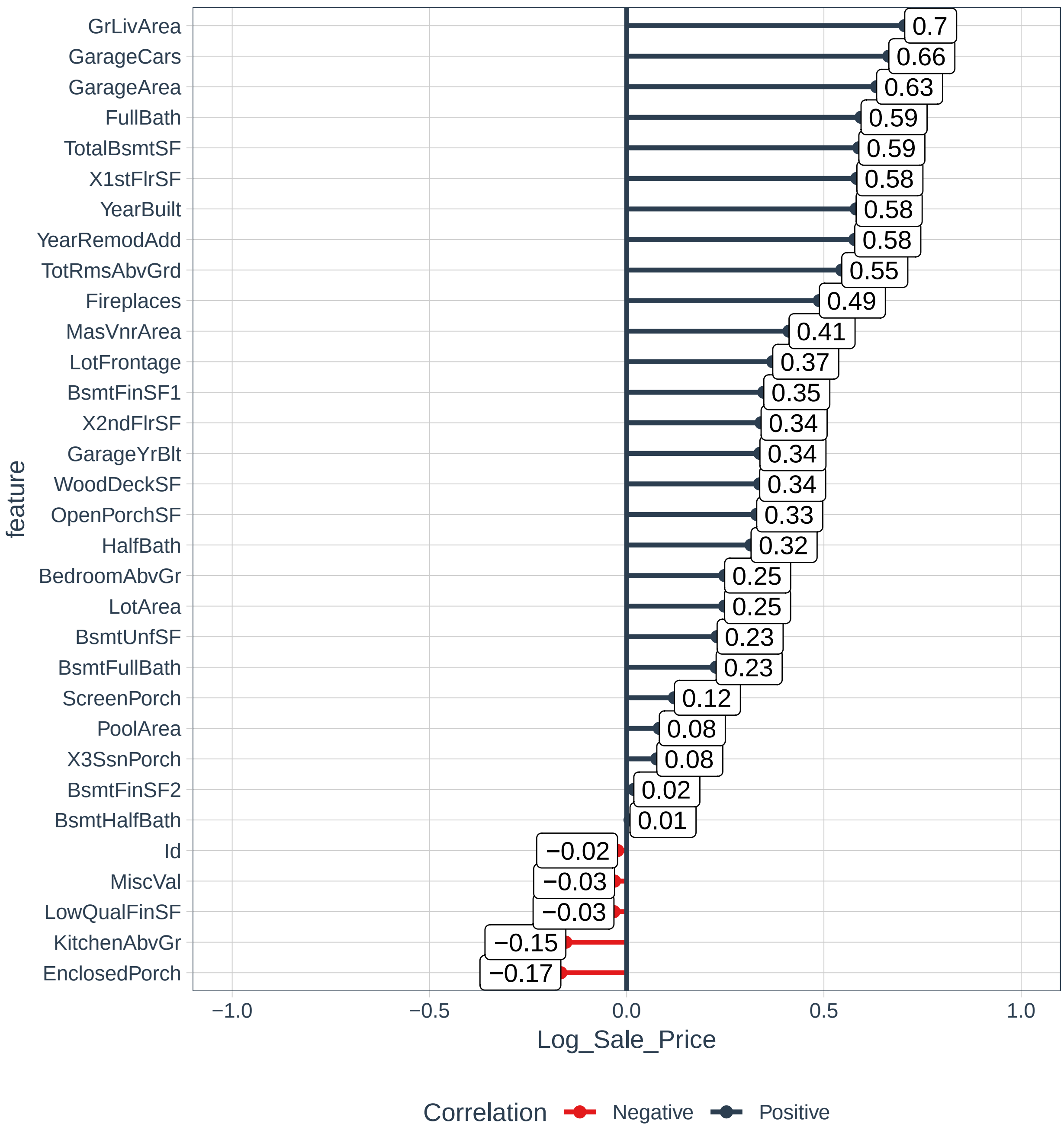


Next we included garage area and garage cars because of location, Iowa is a state that most people drive in so there will be a need for cars. Also, Iowa snows regularly, so an enclosed space, such as a garage, would be very beneficial for whomever is buying the house. This factor also made us include heating quality because Iowa is known to get very cold in the winters.





CORRELATION PLOT



The above chart shows correlation plot between numerical variables and log of sale price. We choose top 10 variables which had correlation above 50 percent to reduce our total number of variables to enter into the model.

NEW VARIABLE CREATION AND TRANSFORMATION

The data set contains rich information about all the factors which a home buyer will consider while buying a house. We created new intuitive variables to draw more meaningful insights.

- Total number of bathrooms : we decided to create our own variable for bathrooms, by adding up basement half and full bathroom, and above ground half and full bathroom. The reason why we decided to create a new variable called total bathroom, was because we felt they each were important but we also just didn't need four separate variables for bathroom.

- Two categories for year of built: Year of built had many different years. We decided to split it into two variables, old and new. If a house was built before 1950, it was considered old and if it was built after 1950, we considered it new. The reason we chose 1950 was because when we compared year built with sales price, we saw a huge increase in sale price after 1950.

MODEL

Our final list of variables is as follows

- GrLivArea(1st + 2nd SF): Above the ground living surface area.
- GarageArea: Size of garage in square feet.
- TotalBsmtSF(BSMT 1st + 2nd): Total square feet of basement area.
- Total Bathroom: Add 4 bathroom variables up
- GarageCars: Size of garage in car capacity.
- TotRmsAbvGrd: Total rooms above the ground does not include bathroom
- BedroomAbvGr: Number of bedrooms
- YearBuilt(categorical): Divided this variable in two categories old and new based.
- ExterQual(categorical): Exterior material quality
- Neighborhood(categorical): Physical location
- BldgType(categorical): Type of dwelling
- OverallQual(categorical): Overall material and finish quality
- HeatingQC(categorical) : Heating quality and condition

We decide to split categorical variables into dummy variables except the predictor "OverallQual". In total we had fourteen variables chosen, but after making dummy variables, this number increased to 43.

MODEL DEVELOPMENT.

We fitted a multiple linear regression model with all 43 variables. The R Square is 0.8869 and Adjust R Square is 0.8812.

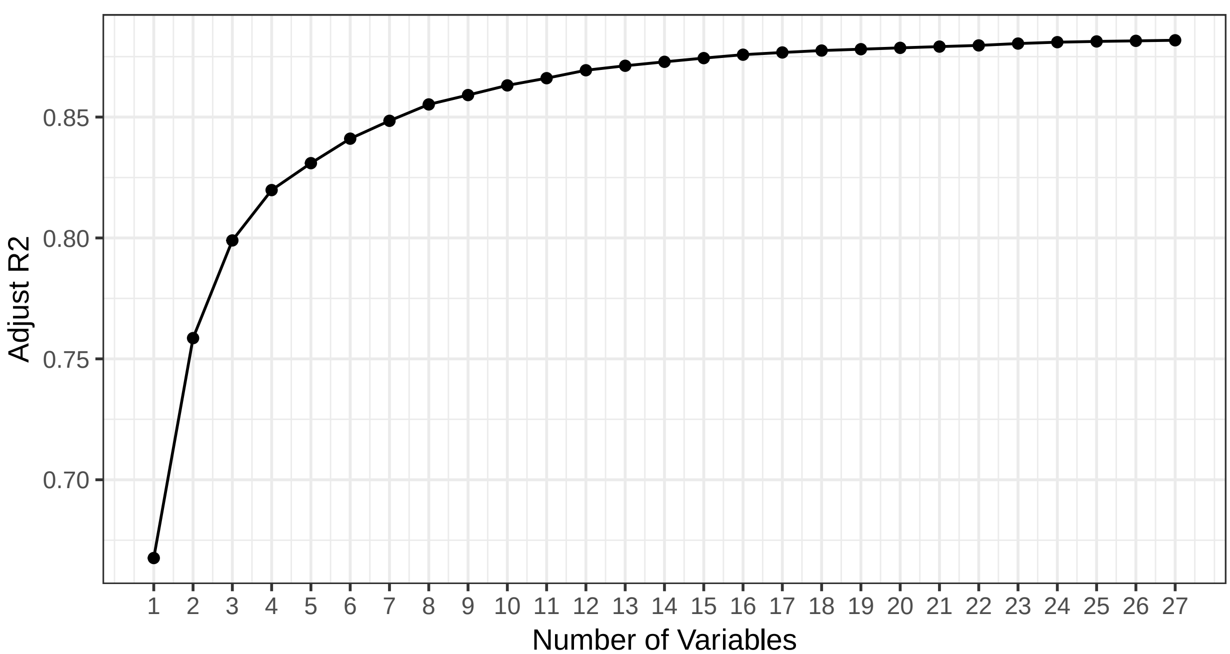
The model was too complexity and was hard to explain. we performed a stepwise AIC forward regression on these 43 variables and reduced number of variables to 27. The new model would be less complexity while retained predictive power. The stepwise AIC forward regression will iteratively adding variable to the model until the AIC would not be decrease. In our case, the stepwise AIC forward regression stop at variable #27 'Neighborhood_BrkSide' with Adjust R Square 0.88176 (base on the result below) .

Below is the results of Stepwise AIC Forward Regression

```
##
##                               Selection Summary
## ------------------------------------------------------------------------------
## Variable                    AIC       Sum Sq      RSS       R-Sq      Adj. R-Sq
## ------------------------------------------------------------------------------
## OverallQual              -74.830    114.769    56.411    0.67046      0.66762
## GrLivArea               -411.480    130.246    40.935    0.76087      0.75858
```

```
## YearBuilt_Old           -603.859    137.128    34.053    0.80107      0.79898
## TotalBsmtSF             -718.366    140.685    30.496    0.82185      0.81980
## GarageArea              -784.750    142.598    28.583    0.83302      0.83094
## Total_Bathroom          -849.046    144.337    26.844    0.84318      0.84107
## Neighborhood_Crawfor    -898.291    145.608    25.572    0.85061      0.84846
## HeatingQC_TA            -945.601    146.775    24.406    0.85743      0.85523
## BldgType_Twnhs          -973.257    147.451    23.730    0.86138      0.85910
## BldgType_Duplex        -1002.696    148.147    23.034    0.86544      0.86311
## Neighborhood_IDOTRR    -1024.945    148.670    22.511    0.86850      0.86608
## Neighborhood_OldTown   -1050.180    149.243    21.938    0.87184      0.86937
## Neighborhood_ClearCr   -1064.274    149.575    21.606    0.87378      0.87122
## HeatingQC_Fa           -1076.788    149.870    21.311    0.87551      0.87285
## Neighborhood_BrDale    -1088.642    150.148    21.033    0.87713      0.87439
## Neighborhood_MeadowV   -1099.602    150.404    20.777    0.87863      0.87580
## Neighborhood_NridgHt   -1106.464    150.578    20.603    0.87964      0.87672
## Neighborhood_Veenker   -1112.356    150.731    20.450    0.88054      0.87752
## HeatingQC_Gd           -1116.191    150.844    20.337    0.88120      0.87808
## Neighborhood_Edwards   -1120.014    150.956    20.225    0.88185      0.87863
## ExterQual_Fa           -1123.581    151.062    20.119    0.88247      0.87915
## BldgType_TwnhsE        -1126.912    151.163    20.018    0.88306      0.87964
## BedroomAbvGr           -1132.699    151.310    19.870    0.88392      0.88041
## Neighborhood_StoneBr   -1136.787    151.425    19.756    0.88459      0.88098
## Neighborhood_Timber    -1138.606    151.496    19.685    0.88501      0.88129
## Neighborhood_Somerst   -1139.732    151.554    19.627    0.88534      0.88153
## Neighborhood_BrkSide   -1140.862    151.612    19.569    0.88568      0.88176
## -----------------------------------------------------------------------------------
```

From the result above, we can see that the variable 'OverallQual' is most important variable with R square 0.67046. A single variable explained 67% of variance of the data! Follow by "GrLivArea", "YearBuilt_Old", and so on. With all 27 variables, the model explained 88% of variances. Which is around same as the 43 variables model.



In the plot above, we plotted all 27 variables that was chosen by stepwise AIC forward regression corresponding to adjusted R square. The plot shows as the number of variables increased, the adjust R-Squared increased as well. we know that adjusted R-Squared is modified version of R-squared that has been adjusted for the number of predictors in the model, and it penalized number of predictors was added. In conclusion, we decided to keep all 27 variables.

THE RESPONSE FUNCTION

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	10.73	0.149	71.99	0
OverallQual2	0.1014	0.1645	0.6164	0.5377
OverallQual3	0.3856	0.1503	2.565	0.01046
OverallQual4	0.4933	0.1485	3.321	0.0009277
OverallQual5	0.59	0.1489	3.963	7.913e-05
OverallQual6	0.6613	0.1491	4.435	1.022e-05
OverallQual7	0.7453	0.1497	4.979	7.485e-07
OverallQual8	0.8337	0.1509	5.527	4.145e-08
OverallQual9	0.9797	0.1532	6.395	2.437e-10
OverallQual10	0.9975	0.1597	6.248	6.109e-10
GrLivArea	0.000247	1.652e-05	14.95	7.292e-46
YearBuilt__Old	-0.1066	0.01748	-6.095	1.55e-09
TotalBsmtSF	0.0001171	1.343e-05	8.719	1.125e-17
GarageArea	0.0002069	2.765e-05	7.484	1.559e-13
Total__Bathroom	0.0602	0.006669	9.027	8.624e-19
Neighborhood__Crawfor	0.1851	0.02549	7.263	7.511e-13
HeatingQC__TA	-0.0742	0.01164	-6.373	2.807e-10
BldgType__Twnhs	-0.1449	0.03064	-4.73	2.565e-06
BldgType__Duplex	-0.1187	0.02278	-5.212	2.258e-07
Neighborhood__IDOTRR	-0.1622	0.03145	-5.157	3.015e-07
Neighborhood__OldTown	-0.08257	0.02128	-3.881	0.0001108
Neighborhood__ClearCr	0.1245	0.03154	3.947	8.44e-05
HeatingQC__Fa	-0.1058	0.02493	-4.246	2.376e-05
Neighborhood__BrDale	-0.1592	0.04734	-3.362	0.0008012
Neighborhood__MeadowV	-0.1075	0.04406	-2.439	0.0149
Neighborhood__NridgHt	0.1014	0.02392	4.239	2.446e-05
Neighborhood__Veenker	0.2062	0.07009	2.942	0.003333
HeatingQC__Gd	-0.03576	0.01303	-2.745	0.006166
Neighborhood__Edwards	-0.03334	0.01841	-1.811	0.07043
ExterQual__Fa	-0.1066	0.04307	-2.475	0.01349
BldgType__TwnhsE	-0.06654	0.01942	-3.427	0.0006356
BedroomAbvGr	-0.01939	0.007505	-2.583	0.009923
Neighborhood__StoneBr	0.1272	0.04506	2.822	0.004859
Neighborhood__Timber	0.05862	0.02692	2.177	0.02969
Neighborhood__Somerst	0.03764	0.02095	1.796	0.07272
Neighborhood__BrkSide	0.04589	0.02637	1.74	0.08217

Table 2: Fitting linear model: paste(response, "~", paste(preds, collapse = " + "))

Observations	Residual Std. Error	R^2	Adjusted R^2
1056	0.1385	0.8857	0.8818

We can see from the responded function that neighbourhood like StoneBr, Timber, Brkside, Somrest shows a posi-tive relationship with sale price whereas neighbor like meadow and Brdale shows negative relationship with log sale price. We have R Square of 0.8857 and adjust R Square 0.8818.

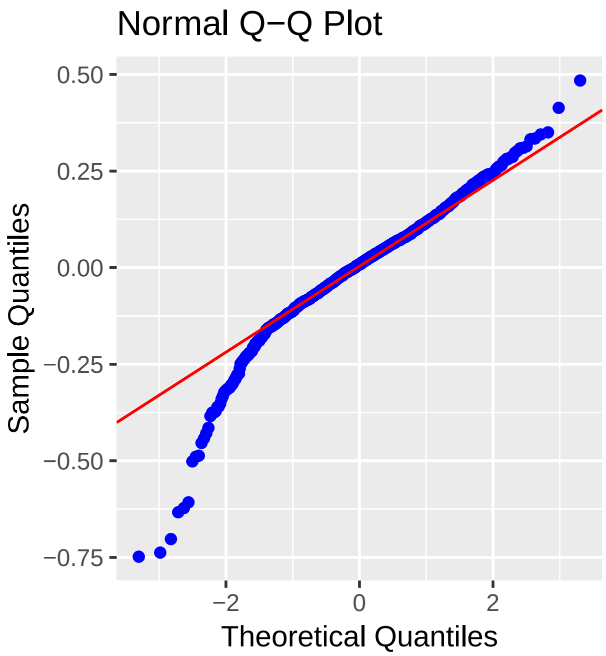
MODEL DIAGNOSTICS

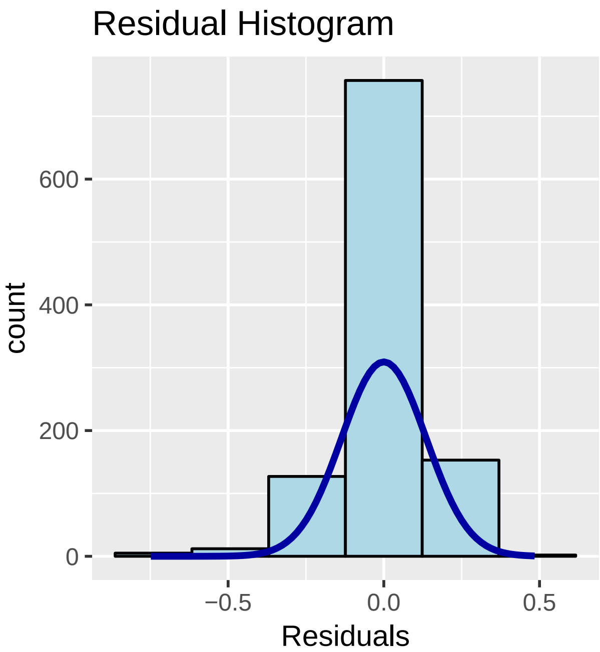
We need to check the assumptions below.

Multiple Linear Regression Assumptions:

- The errors has normal distribution
- The errors has mean 0
- Homoscedasticity of errors or equal variance
- The errors are independent.

Residual QQ plot and Residual Histogram

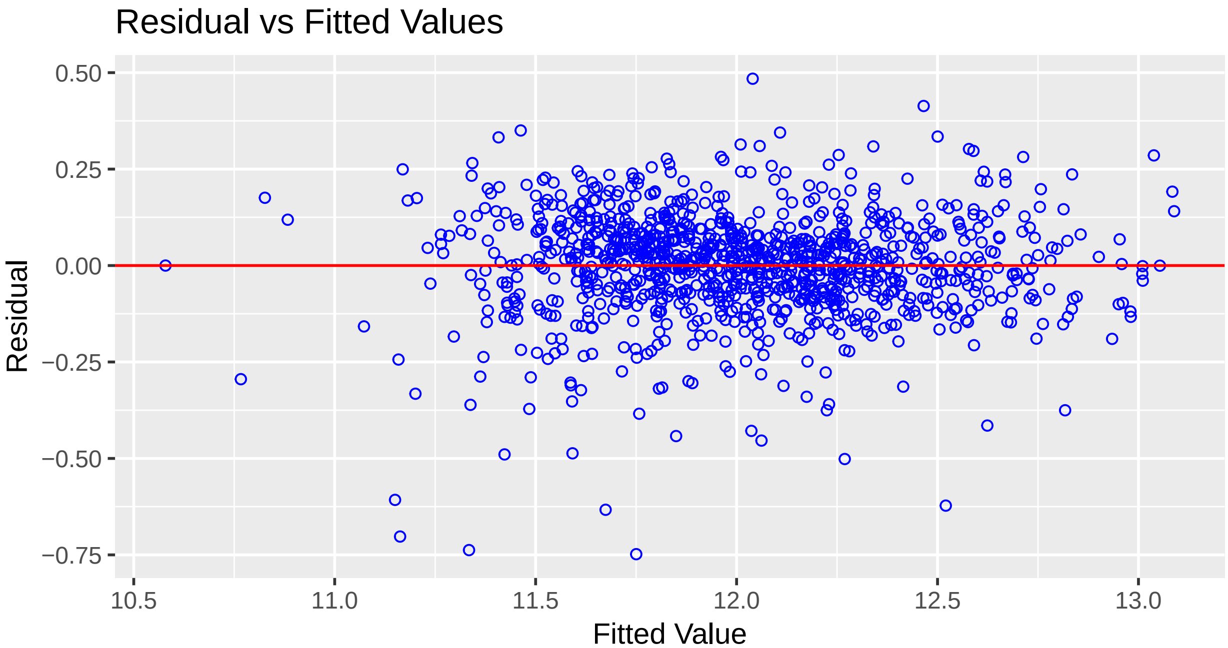




The QQ plot - The residual points roughly lie within the lines. The Q-Q plot of the residuals suggests that the error terms are indeed normally distributed.

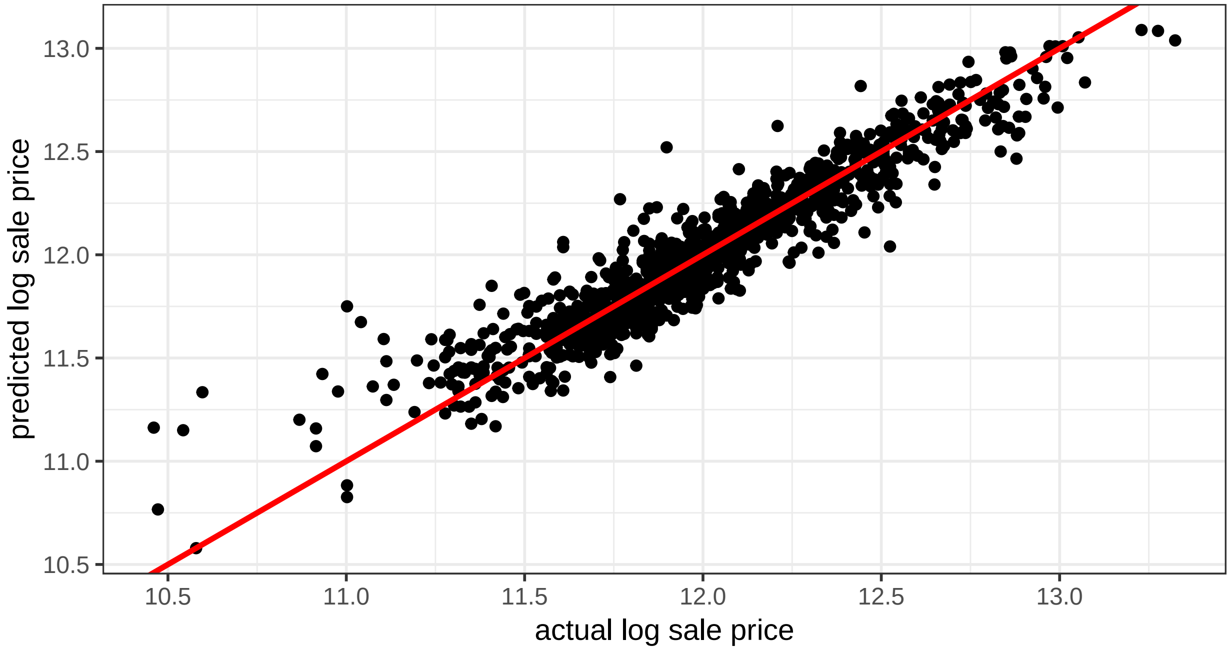
The histogram - The errors terms are indeed normally distributed.

Residual vs Fitted Values Plot.



- The residuals spread randomly around the 0 line indicating that the relationship is linear.
- The residuals roughly horizontal band around the 0 line indicating homogeneity of error variance.(constant variance)
- No residuals are away from random pattern of residuals indicating no outliers.

Correlation between actual log sale price and predicted log sale price on train data




```
## [1] 0.941108
```

Based on the graph above, we can see that our model performed very good. The correlation between actual log sale price and predicted log sale price is 0.94.

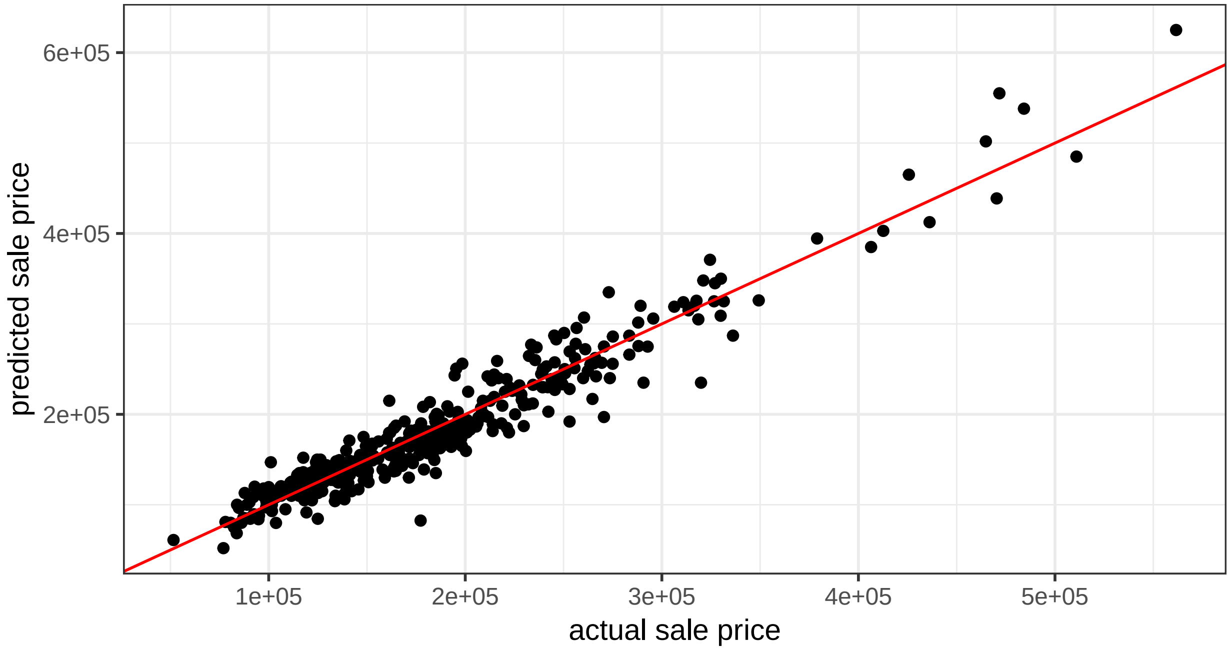
Overall, our model satisfied the linear regression assumptions.

PREDICTION ON TEST SET

We are going to use the 4 metrics below to measure performance of our model on the test data set(using sale price). We transformed log sale price back to sale price.

- Bias
- Maximum Deviation
- Mean Absolute Deviation
- Mean Square Error

Correlation between actual sale price and predicted sale price on test data




```
## [1] 0.9624428
```

From the plot above, we can see the actual sale price and predicted sale price are highly correlated with correlation 0.96. In other words, our model has very good prediction power on the test data set.

Table 1. The metrics on the full model with 44 variables

measure	value
Bias	736.9
Maximum_Deviation	93348
Mean_Absolute_Deviation	15192
Mean_Square_Error	433396722

Table 2. The metrics on the reduced model with 27 variables

measure	value
Bias	751.8
Maximum_Deviation	94781
Mean_Absolute_Deviation	15563
Mean_Square_Error	448613544

Table 1 and Table 2 are the performance metrics of full model(43 variables) and the reduced model(27 variables) on the test data set. We can see that the full model has bias 736.9 and the reduced model has bias 751.8. The reason is the full model has 44 variables and explained more variances than the reduced model. The same idea apply for Mean Square Error. In term of Maximum Deviation and Mean Absolute Deviation, both model has similar metrics. Overall, we chose reduced model as our final model. The performance metrics for both model are very closed, and the reduced model are less complex.

CONCLUSION

In conclusion, by running a linear model with our 27 variables, we found that our adjusted R-square was .88176. We determined that the error terms were normally distributed and that our relationship was linear, which supported the choice of our model. We found a strong correlation between actual log sale price and predicted log sale price. The model performance on our test set is shown above and in the end we found a good combination of numeric and categorical variables led to the best prediction for Sales Price. Overall Quality was the most important predictor, followed by Living Area and Year Built. These three variables lay the foundation of buying a house, with many accessories after which increase the Sales Price of a house after. There were many variables that highly correlate with one another, which makes sense as people who buy houses often look at similar qualities of houses when choosing.

In the end, there were a few variables that we also considered using such as MS Zone and Sales Type which we thought could also also influenced Sale Price, but they were either too difficult to interpret or code to get the most out of the data so we did not include them. But in the end of the day, these would also be more "accessories" than foundations that would help explain the Sale Price of a house.

CODE APPENDIX

```r
library(recipes)
library(olsrr)
library(tidyverse)
library(pander)
library(recipes)
library(tidyverse)
library(stringr)
library(forcats)
library(tidyquant)
train_df <- read_csv("data/training.csv")
test_df <- read_csv("data/validation.csv")

data_process <- function(data, train = T, test = F, cor_df = F){

  #convert into factor
  df <- data %>%
      mutate(MSSubClass = as.factor(MSSubClass),
             OverallCond = as.factor(OverallCond),
             YrSold = as.factor(YrSold),
             MoSold = as.factor(MoSold),
             OverallQual = as.factor(OverallQual))

  #fill NA's With None ----
  NA_cols_None <- c("PoolQC",
                    "MiscFeature",
                    "Alley",
                    "Fence",
                    "FireplaceQu",
                    "GarageType",
                    "GarageFinish",
                    "GarageQual",
                    "GarageCond",
                    "BsmtQual",
                    "BsmtCond",
```

```r
                  "BsmtExposure",
                  "BsmtFinType1",
                  "BsmtFinType2",
                  "MasVnrType",
                  "MSSubClass")

df[,NA_cols_None][is.na(df[,NA_cols_None])] <- "None"

#fill NA's with median of LotFrontage of Neighborhood ----
df <- df %>%
  group_by(Neighborhood) %>%
  mutate(LotFrontage = replace_na(LotFrontage, replace = median(LotFrontage, na.rm = T))) %>%
  ungroup()


#fill NA's with 0 ----
NA_cols_0 <- (c(
  "GarageYrBlt",
  "GarageArea",
  "GarageCars",
  "BsmtFinSF1",
  "BsmtFinSF2",
  "BsmtUnfSF",
  "TotalBsmtSF",
  "BsmtFullBath",
  "BsmtHalfBath",
  "MasVnrArea"
))

df[,NA_cols_0][is.na(df[,NA_cols_0])] <- 0

#fill NA's with most frequently appear ----
df <- df %>%
  mutate(Electrical = str_replace_na(string = Electrical, replacement = "SBrkr"))

if(train){

  return(

    df %>%
         #filter outlier ----
         filter(GrLivArea < 4000) %>%

      mutate(
        YearBuilt = ifelse(YearBuilt >= 1950, "New", "Old"),
    #Transform SalePrice into LogSalePrice ----
        Log_Sale_Price = log(SalePrice),
    #Create New Variable for TotalBathroom ----
        Total_Bathroom = BsmtFullBath + BsmtHalfBath + FullBath + HalfBath) %>%

      select(
        GrLivArea, GarageArea, TotalBsmtSF, TotRmsAbvGrd, BedroomAbvGr,
        YearBuilt, ExterQual, Neighborhood, BldgType, OverallQual,
```

```r
          HeatingQC, Total_Bathroom, Log_Sale_Price))
  }

  if(test){

    return(

      df %>%
        mutate(

          YearBuilt = ifelse(YearBuilt >= 1950, "New", "Old"),
      #Transform SalePrice into LogSalePrice ----
          Log_Sale_Price = log(SalePrice),
      #Create New Variable for TotalBathroom ----
          Total_Bathroom = BsmtFullBath + BsmtHalfBath + FullBath + HalfBath) %>%

        select(
          GrLivArea, GarageArea, TotalBsmtSF, TotRmsAbvGrd, BedroomAbvGr,
          YearBuilt, ExterQual, Neighborhood, BldgType, OverallQual,
          HeatingQC, Total_Bathroom, Log_Sale_Price))
  }

  if(cor_df){

    return(
      df %>%
        mutate(Log_Sale_Price = log(SalePrice))
    )
  }

}

# run data_process function on train data
train_processed <- data_process(train_df,train = T)
plot_data <- data_process(train_df, train = F, test = F, cor_df = T)


#create dummy variables for all the nominal variables except variable "overallQual"
rec_obj <- recipe(Log_Sale_Price~., data = train_processed) %>%
  step_dummy(all_nominal(), -OverallQual) %>%
  prep()

#summary(rej_obj)

train_processed_model <- bake(rec_obj, new_data = train_processed)


p1_saleprice_Hist <- plot_data %>%
  ggplot(aes()) +
  geom_histogram(aes(SalePrice), fill = "blue",
                 color = "black", bins = 30)  +
  theme_bw() +
  labs(y = NULL, x = "Sale Price")
```

```r
#QQ plot of SalePrice

p1_saleprice_QQ  <- plot_data %>%
  ggplot(aes(sample = SalePrice)) +
  stat_qq() +
  stat_qq_line() +
  theme_bw() +
  labs(y = "Sale Price")


#Histogram of log SalePrice

p2_log_saleprice_Hist <- plot_data %>%
  ggplot(aes()) +
  geom_histogram(aes(Log_Sale_Price), fill = "blue",
               color = "black", bins = 30)  +
  theme_bw() +
  labs(y = NULL, x = "Log Sale Price")

#QQ plot of log SalePrice

p2_log_saleprice_QQ  <- plot_data %>%
  ggplot(aes(sample = Log_Sale_Price)) +
  stat_qq() +
  stat_qq_line() +
  theme_bw() +
  labs(y = "Log Sale Price")




cowplot::plot_grid(p1_saleprice_Hist, p1_saleprice_QQ,
                   p2_log_saleprice_Hist, p2_log_saleprice_QQ,
                   ncol = 2)

p1_outlier <- plot_data %>%
  ggplot(aes(GrLivArea, SalePrice)) +
  geom_point() +
  geom_vline(xintercept = 4000, color = "red") +
  theme_bw() +
  labs(title = "before removed ouliters")


p2_outlier <- plot_data %>%
  filter(GrLivArea < 4000) %>%
  ggplot(aes(GrLivArea, SalePrice)) +
  geom_point() +
  theme_bw() +
  labs(title = "after removed ouliters")

cowplot::plot_grid(p1_outlier, p2_outlier)

train_processed %>%
```

```r
  ggplot(aes(GrLivArea, Log_Sale_Price)) +
  geom_point() +
  geom_smooth(se = F, method = "lm") +
  labs(x = "Above the ground living area square feet",
       y = "Log of Sale Price") +
  theme_bw()


p1 <- train_processed %>%
  ggplot(aes(HeatingQC)) +
  geom_bar(fill = 'blue') +
  labs(x = "HeatingQC", y = "Log SalePrice") +
  theme_bw()


p2 <- train_processed %>%
  ggplot(aes(GarageArea, Log_Sale_Price)) +
  geom_point() +
  geom_smooth(se = F, method = "lm") +
  labs(x = "Garage Area",
       y =  NULL) +
  theme_bw()

cowplot::plot_grid(p1,p2,label_x = "Log SalePrice")

get_cor <- function(data, target, use = "pairwise.complete.obs",
                    fct_reorder = FALSE, fct_rev = FALSE) {

    feature_expr <- enquo(target)
    feature_name <- quo_name(feature_expr)

    data_cor <- data %>%
        mutate_if(is.character, as.factor) %>%
        mutate_if(is.factor, as.numeric) %>%
        cor(use = use) %>%
        as_tibble() %>%
        mutate(feature = names(.)) %>%
        select(feature, !! feature_expr) %>%
        filter(!(feature == feature_name)) %>%
        mutate_if(is.character, as_factor)

    if (fct_reorder) {
        data_cor <- data_cor %>%
            mutate(feature = fct_reorder(feature, !! feature_expr)) %>%
            arrange(feature)
    }

    if (fct_rev) {
        data_cor <- data_cor %>%
            mutate(feature = fct_rev(feature)) %>%
            arrange(feature)
    }
```

```
    return(data_cor)

}

plot_cor <- function(data, target, fct_reorder = FALSE, fct_rev = FALSE,
                     include_lbl = TRUE, lbl_precision = 2, lbl_position = "outward",
                     size = 2, line_size = 1, vert_size = 1,
                     color_pos = palette_light()[[1]], color_neg = palette_light()[[2]]) {

    feature_expr <- enquo(target)
    feature_name <- quo_name(feature_expr)

    data_cor <- data %>%
        get_cor(!! feature_expr, fct_reorder = fct_reorder, fct_rev = fct_rev) %>%
        mutate(feature_name_text = round(!! feature_expr, lbl_precision)) %>%
        mutate(Correlation = case_when(
            (!! feature_expr) >= 0 ~ "Positive",
            TRUE                   ~ "Negative") %>% as.factor())

    g <- data_cor %>%
        ggplot(aes_string(x = feature_name, y = "feature", group = "feature")) +
        geom_point(aes(color = Correlation), size = size) +
        geom_segment(aes(xend = 0, yend = feature, color = Correlation), size = line_size) +
        geom_vline(xintercept = 0, color = palette_light()[[1]], size = vert_size) +
        expand_limits(x = c(-1, 1)) +
        theme_tq() +
        scale_color_manual(values = c(color_neg, color_pos))

    if (include_lbl) g <- g + geom_label(aes(label = feature_name_text), hjust = lbl_position)

    return(g)

}


plot_data %>%
  select_if(is.numeric) %>%
  select(-SalePrice) %>%
  plot_cor(Log_Sale_Price,fct_reorder = T)

#linear fit on 43 variables
lm_fit <- lm(Log_Sale_Price ~., data = train_processed_model)

summary(lm_fit)

#stepwise aic forward regression on 43 variables
lm_fw_aic <- ols_step_forward_aic(lm_fit)
lm_fw_aic
fd_df <- tibble(
  rank = c(seq(1,27,1)),
  predictor = lm_fw_aic$predictors,
  adj_r2 = lm_fw_aic$arsq)
```

```r
#plot No. of Variables vs Adjust R2

fd_df %>%
  ggplot(aes(rank, adj_r2)) +
  geom_point() +
  geom_line() +
  labs(x = "Number of Variables", y = "Adjust R2") +
  scale_x_continuous(breaks = c(seq(1,27,1))) +
  theme_bw()

#response function for 27 variables selected from forward aic regression
lm_fw_aic$model %>%
  summary() %>%
  pander::pander()
#QQplot
p1_qq <- ols_plot_resid_qq(lm_fw_aic$model)

#Histogram
p2_hist <- ols_plot_resid_hist(lm_fw_aic$model)
#combine those qq and histogram together
cowplot::plot_grid(p1_qq, p2_hist)
#residual vs fitted value
ols_plot_resid_fit(lm_fw_aic$model)
# scatter plot of actual log sale price vs predicted log sale price
tibble(
  actual = train_processed_model$Log_Sale_Price,
  predicted = lm_fw_aic$model$fitted.values
) %>%
  ggplot(aes(actual, predicted)) +
  geom_point() +
  geom_abline(intercept = 0, slope = 1, color = "red", size = 1) +
  labs(x = "actual log sale price", y = "predicted log sale price") +
  theme_bw()

cor(train_processed_model$Log_Sale_Price,
    lm_fw_aic$model$fitted.values)
bias <- function(Y_hat, Y){
  mean(Y_hat - Y)
}

Max_Dev <- function(Y_hat, Y){
  max(abs(Y_hat - Y))
}

Mean_Abs_Dev <- function(Y_hat, Y){
  mean(abs(Y_hat - Y))
}

Mean_sq_err <- function(Y_hat , Y){
  mean((Y_hat - Y)^2)
}

test_processed <- data_process(test_df, train = F, test = T)
```

```r
test_processed_model <- bake(rec_obj, new_data = test_processed)

# predction on log sale price
predicted_value_log <- lm_fw_aic$model %>%
  predict(test_processed_model)

# prediction on sale price
predicted_value <- exp(predicted_value_log)


y_hat_test_full_model = exp(lm_fit %>%
  predict(test_processed_model))


y_hat_test = predicted_value
y_test = test_df$SalePrice
tibble(
  actual = y_hat_test,
  predicted = y_test
) %>%
  ggplot(aes(actual, predicted)) +
  geom_point() +
  geom_abline(intercept = 0, slope = 1, color = "red") +
  labs(x = "actual sale price", y = "predicted sale price") +
  theme_bw()

cor(y_hat_test,
    y_test)
#test performance on full model
tibble(
  Bias = bias(y_hat_test_full_model, y_test),
  Maximum_Deviation = Max_Dev(y_hat_test_full_model, y_test),
  Mean_Absolute_Deviation = Mean_Abs_Dev(y_hat_test_full_model, y_test),
  Mean_Square_Error = Mean_sq_err(y_hat_test_full_model, y_test)
) %>%
  gather(key = "measure", value = "value") %>%
  pander::pander()
#test performance on reduced model
tibble(
  Bias = bias(y_hat_test, y_test),
  Maximum_Deviation = Max_Dev(y_hat_test, y_test),
  Mean_Absolute_Deviation = Mean_Abs_Dev(y_hat_test, y_test),
  Mean_Square_Error = Mean_sq_err(y_hat_test, y_test)
) %>%
  gather(key = "measure", value = "value") %>%
  pander::pander()
```