Sunayu Tech Task
Multivariate Linear Regression: Predicting House Prices

Michael Vatt

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```
# Create a Function to Check for Installed Packages and Install if They Are Not Installed

install <- function(packages){
  new.packages <- packages[!(packages %in% installed.packages()[, "Package"])]
  if (length(new.packages))
    install.packages(new.packages, dependencies = TRUE, repos = "http://cran.us.r-project.org")
  sapply(packages, require, character.only = TRUE)
```

```
}

# Install

packages <- c("caTools", "car", "caret", "cluster", "Clustering", "corpus", "corrplot", "data.table",
              "dendextend", "doParallel", "dplyr", "e1071", "factoextra", "FactoMineR", "fpc",
              "GGally", "ggplot2", "ggthemes", "gridExtra", "kableExtra", "knitr", "ldatuning",
              "magrittr", "mclust", "NbClust", "petro.One", "plotly", "plotrix", "qdap", "qdapTools",
              "quanteda", "randomForest", "readxl", "RColorBrewer", "rlist", "RWeka", "scales",
              "SentimentAnalysis", "sentimentr", "SnowballC", "stm", "stringr", "syuzhet",
              "tensorflow", "tidyr", "tidytext", "tidyverse", "tm", "topicmodels", "viridisLite",
              "wordcloud", "xlsx", "zoo")

install(packages)
```

```
# Call the installed packages

#library(plyr) # plyr is required to be loaded before dplyr or issues may arise
library(dplyr) # dplyr needed for efficient loading of loadApp()

loadApp <- function() {

my_library <- c("caTools", "car", "caret", "cluster", "Clustering", "corpus", "corrplot", "data.table",
              "dendextend", "doParallel", "dplyr", "e1071", "factoextra", "FactoMineR", "fpc",
              "GGally", "ggplot2", "ggthemes", "gridExtra", "kableExtra", "knitr", "ldatuning",
              "magrittr", "mclust", "NbClust", "petro.One", "plotly", "plotrix", "qdap", "qdapTools",
              "quanteda", "randomForest", "readxl", "RColorBrewer", "rlist", "RWeka", "scales",
              "SentimentAnalysis", "sentimentr", "SnowballC", "stm", "stringr", "syuzhet",
              "tensorflow", "tidyr", "tidytext", "tidyverse", "tm", "topicmodels", "viridisLite",
              "wordcloud", "xlsx", "zoo")

install.lib <- my_library[!my_library %>% installed.packages()]

for(lib in install.lib) install.packages(lib, dependencies = TRUE)

sapply(my_library, require, character = TRUE)

}

loadApp()
```

Overview of Multivariate Linear Regression Housing Prediction

This data set includes the following variables:

Variables
Income
House_Age
Number_Rooms
Number_Bedrooms
Area_Population
Price
Address

Objective

This was a task issued by Sunayu as an evaluation of approach, style, ability, and performance. The R script will analyze a house price data set to predict the price of a house via different independent variables. It will move through data familiarization, preprocessing, splitting the training and testing data, exploratory data analysis, model evaluation, predictions, and results. The R Markdown report is the same script, maybe a little more refined, prettier, and a one stop shop to read the results.

Dataset

```
split <- detectCores(TRUE)
cl <- makePSOCKcluster(split)
registerDoParallel(cl)
```

```
dataset <- read.csv("https://raw.githubusercontent.com/huzaifsayed/Linear-Regression-Model-for-House-Pr
```

Familiarization

Let's take an initial look to familiarize with the data set and to ensure it was properly read in.

```
class(dataset) # Need to coerce into data frame if it is not
```

```
## [1] "data.frame"
```

```
dim(dataset) #  For familiarity and a quick visualization to determine if something went wrong
```

```
## [1] 5000    7
```

```
summary(dataset) # Does anything look strange? Any variable(s) requiring pre-processing?
```

```
##  Avg..Area.Income Avg..Area.House.Age Avg..Area.Number.of.Rooms
##  Min.   : 17797   Min.   :2.644       Min.   : 3.236
##  1st Qu.: 61481   1st Qu.:5.322       1st Qu.: 6.299
##  Median : 68804   Median :5.970       Median : 7.003
##  Mean   : 68583   Mean   :5.977       Mean   : 6.988
##  3rd Qu.: 75783   3rd Qu.:6.651       3rd Qu.: 7.666
##  Max.   :107702   Max.   :9.519       Max.   :10.760
##
##  Avg..Area.Number.of.Bedrooms Area.Population       Price
##  Min.   :2.000                Min.   :  172.6   Min.   :  15939
##  1st Qu.:3.140                1st Qu.:29403.9   1st Qu.: 997577
##  Median :4.050                Median :36199.4   Median :1232669
##  Mean   :3.981                Mean   :36163.5   Mean   :1232073
##  3rd Qu.:4.490                3rd Qu.:42861.3   3rd Qu.:1471210
##  Max.   :6.500                Max.   :69621.7   Max.   :2469066
##
##                                                 Address
##  000 Adkins Crescent\nSouth Teresa, AS 49642-1348:   1
##  000 Todd Pines\nAshleyberg, KY 90207-1179       :   1
##  001 Steve Plaza\nJessicastad, UT 25190          :   1
##  0010 Gregory Loaf\nSouth Ericfort, VA 34651-0718:   1
##  00149 Raymond Knolls\nNew Jason, UT 75026       :   1
##  002 Katherine Flat\nHartmanland, AZ 37973-3049  :   1
##  (Other)                                         :4994
```

```
str(dataset)  # There are 6 variables of numerical and 1 variable factor
```

```
## 'data.frame':    5000 obs. of  7 variables:
##  $ Avg..Area.Income            : num  79545 79249 61287 63345 59982 ...
##  $ Avg..Area.House.Age         : num  5.68 6 5.87 7.19 5.04 ...
##  $ Avg..Area.Number.of.Rooms   : num  7.01 6.73 8.51 5.59 7.84 ...
##  $ Avg..Area.Number.of.Bedrooms: num  4.09 3.09 5.13 3.26 4.23 4.04 3.41 2.42 2.3 6.1 ...
##  $ Area.Population             : num  23087 40173 36882 34310 26354 ...
##  $ Price                       : num  1059034 1505891 1058988 1260617 630943 ...
##  $ Address                     : Factor w/ 5000 levels "000 Adkins Crescent\nSouth Teresa, AS 49642-
```

```
head(dataset) # Numerical variables need scaling? Should we not include any variables?
```

```
##   Avg..Area.Income Avg..Area.House.Age Avg..Area.Number.of.Rooms
## 1         79545.46            5.682861                  7.009188
## 2         79248.64            6.002900                  6.730821
## 3         61287.07            5.865890                  8.512727
## 4         63345.24            7.188236                  5.586729
## 5         59982.20            5.040555                  7.839388
## 6         80175.75            4.988408                  6.104512
##   Avg..Area.Number.of.Bedrooms Area.Population     Price
## 1                         4.09        23086.80 1059033.6
## 2                         3.09        40173.07 1505890.9
## 3                         5.13        36882.16 1058988.0
## 4                         3.26        34310.24 1260616.8
## 5                         4.23        26354.11  630943.5
## 6                         4.04        26748.43 1068138.1
##                                            Address
```

```
## 1 208 Michael Ferry Apt. 674\nLaurabury, NE 37010-5101
## 2 188 Johnson Views Suite 079\nLake Kathleen, CA 48958
## 3  9127 Elizabeth Stravenue\nDanieltown, WI 06482-3489
## 4                            USS Barnett\nFPO AP 44820
## 5                           USNS Raymond\nFPO AE 09386
## 6 06039 Jennifer Islands Apt. 443\nTracyport, KS 16077
```

```
colnames(dataset) <- c("Income", "House_Age", "Number_Rooms", "Number_Bedrooms", "Area_Population",
                       "Price", "Address") # For easier handling and better visualization
names(dataset) # Ensure that the variable names changed
```

```
## [1] "Income"          "House_Age"       "Number_Rooms"    "Number_Bedrooms"
## [5] "Area_Population" "Price"           "Address"
```

Preprocessing

Here, we will limit our regression model to the first 6 variable columns and remove *Address* for the predictions. *Address* would require encoding but since it would create 1 dummy variable per observation (5000), encoding would be trivial and inconsequential for a prediction.

```
# Let's Check for Missing Data

data.frame(count_na_values <- colSums(is.na(dataset))) # Need to appraise if any greater than 0.
```

```
##                 count_na_values....colSums.is.na.dataset..
## Income                                                   0
## House_Age                                                0
## Number_Rooms                                             0
## Number_Bedrooms                                          0
## Area_Population                                          0
## Price                                                    0
## Address                                                  0
```

```
# Split the Data set into a Training Set and Test Set

set.seed(1234)
val_ind <- createDataPartition(dataset$Price, times = 1, p = 0.2, list = FALSE) # Split 80/20
train_set <- dataset[-val_ind,] # 4000 observations for training data
test_set <- dataset[val_ind,] # 1000 observations to test upon

# Let's Make Sure the Split Operated Correctly

dim(train_set); dim(test_set) # 80% and 20% of the data set respectively
```

```
## [1] 4000    7
```

```
## [1] 1000    7
```

```r
class(train_set); class(test_set) # Should be data.frames
```

```
## [1] "data.frame"
```

```
## [1] "data.frame"
```

```r
# Remove Address From Data set for Prediction

train_set <- train_set[,(1:6)] # Only keep numerical variables significant to the prediction
test_set <- test_set[,(1:6)] # Only keep numerical variables significant to the prediction
names(train_set); names(test_set) # Ensure proper variables were kept
```

```
## [1] "Income"          "House_Age"       "Number_Rooms"    "Number_Bedrooms"
## [5] "Area_Population" "Price"
```

```
## [1] "Income"          "House_Age"       "Number_Rooms"    "Number_Bedrooms"
## [5] "Area_Population" "Price"
```

Methods and Analysis

First Model

```r
## Model Will Not Need to Perform Feature Scaling - Linear Regression Function lm()
  ## Handles that Inherently

# Fitting Multiple Linear Regression to the Training Set

model1 <- lm(formula = Price ~ ., data = train_set) # Price is the dependent variable as a function
summary(model1)                                     # of all dependent variables via '.'
```

```
##
## Call:
## lm(formula = Price ~ ., data = train_set)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -327301  -70435     367   68818  346229
##
## Coefficients:
##                   Estimate Std. Error  t value Pr(>|t|)
## (Intercept)     -2.630e+06  1.890e+04 -139.151   <2e-16 ***
## Income           2.157e+01  1.508e-01  143.026   <2e-16 ***
## House_Age        1.649e+05  1.601e+03  103.047   <2e-16 ***
## Number_Rooms     1.211e+05  1.768e+03   68.498   <2e-16 ***
## Number_Bedrooms  1.696e+03  1.458e+03    1.163    0.245
## Area_Population  1.508e+01  1.607e-01   93.845   <2e-16 ***
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 100600 on 3994 degrees of freedom
## Multiple R-squared:  0.9191, Adjusted R-squared:  0.919
## F-statistic:  9079 on 5 and 3994 DF,  p-value: < 2.2e-16
```

```
## We see that Number_Bedrooms is not statistically significant
  ## Would removing this variable aid prediction accuracy?

# Using Fitted model1 for Predicting the Test Set Results

y_pred1 <- predict(model1, newdata = test_set)
visual_comparison <- data.frame(test_set$Price, y_pred1, residuals = test_set$Price - y_pred1)
visual_comparison[1:10,]
```

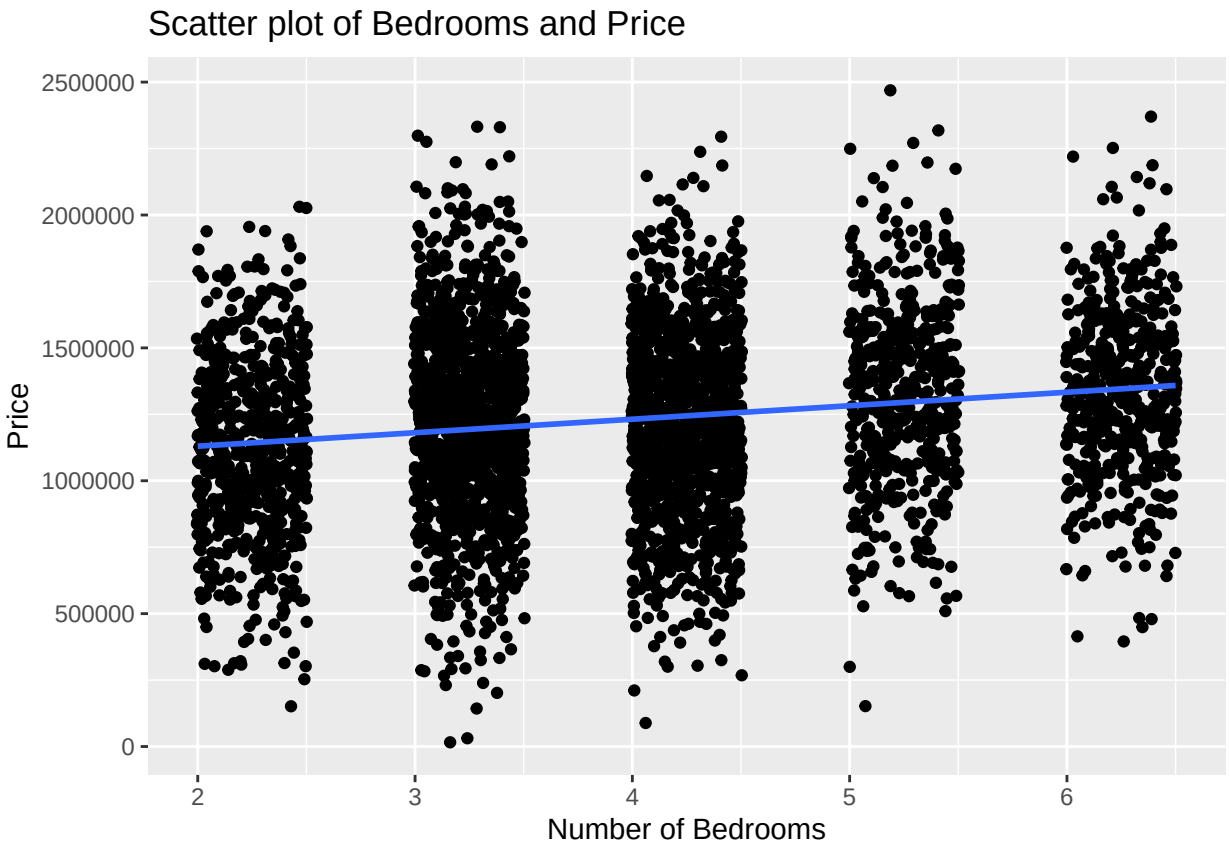
```
##    test_set.Price   y_pred1  residuals
## 18       528485.2  490640.3   37844.98
## 29      1240763.8 1405751.4 -164987.61
## 34       534305.1  614277.9  -79972.79
## 38      1081150.1 1167072.0  -85921.85
## 45      1153871.5  944404.6  209466.87
## 58      1186688.5 1009474.6  177213.92
## 61      1111085.0  935228.2  175856.81
## 71      1146532.5 1052267.4   94265.01
## 75      1534479.9 1357417.2  177062.70
## 78      1204598.0 1349876.4 -145278.38
```

Despite the model returning statistically significant p-value and R-squared values, we can see the model did not fit quite well on the test data set. Many of the predicted values have a noticeable difference. It is possible to make the model more robust and vigorous through more advanced models. Checking for multicollinearity may also help improve the algorithm.

Exploratory Data Analysis

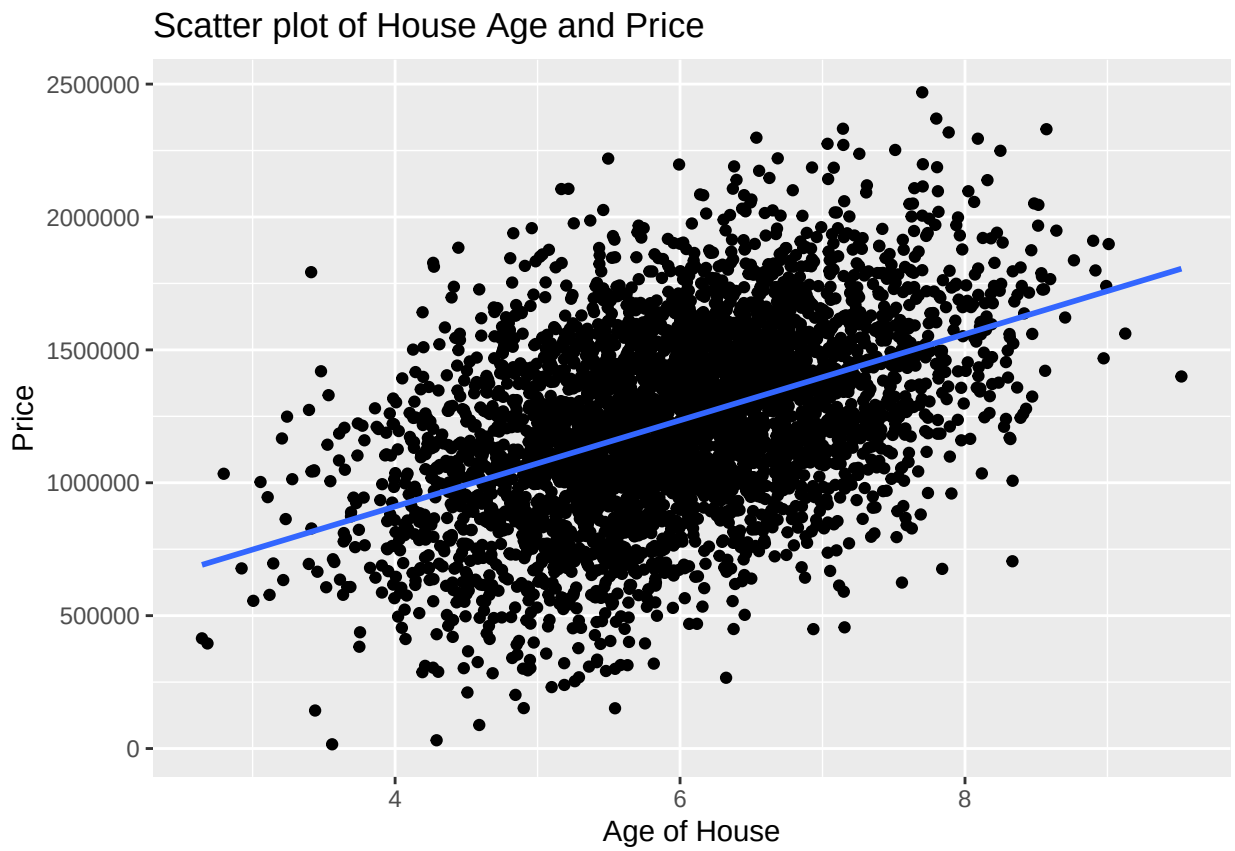
```
# Let's try to Evaluate Associations between Variables

correlation <- cor(train_set)
corrplot(correlation, method = "color")
```


```
## Price is positively correlated with Income, House_Age, Number_Rooms, and Area_Population
## Price has a slight positive correlation with Number_Bedrooms

# Let's Make Scatter Plots to Determine the Relationship(s) between the Variables

bedroom_plot <- ggplot(data = train_set, aes(x = Number_Bedrooms, y = Price)) + geom_jitter() +
  geom_smooth(method = "lm", se = FALSE) +
  labs(title = "Scatter plot of Bedrooms and Price", x = "Number of Bedrooms", y = "Price")

bedroom_plot # We see that the relationship is linear
```

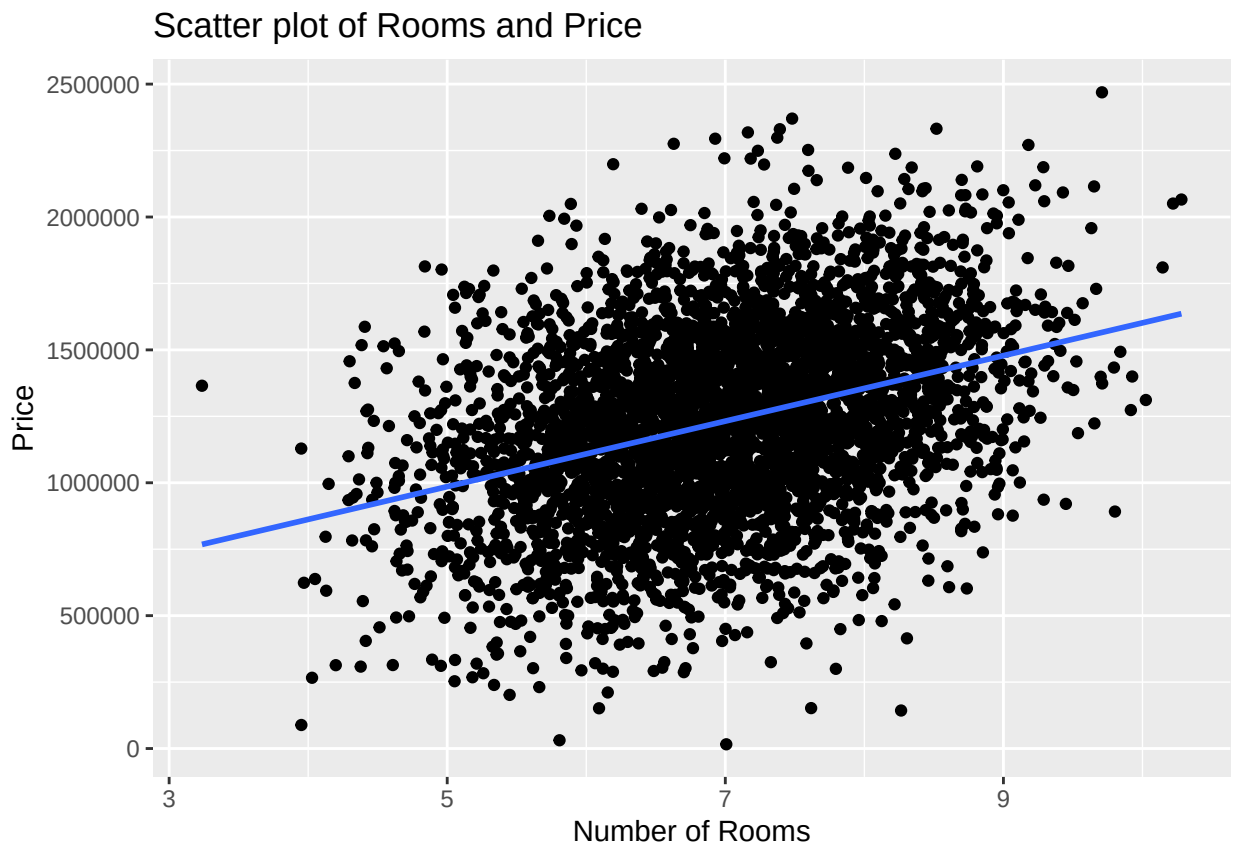



```
income_plot <- ggplot(data = train_set, aes(x = Income, y = Price)) + geom_jitter() +
  geom_smooth(method = "lm", se = FALSE) +
  labs(title = "Scatter plot of Income and Price", x = "Income", y = "Price")

income_plot # We see that the relationship is linear
```

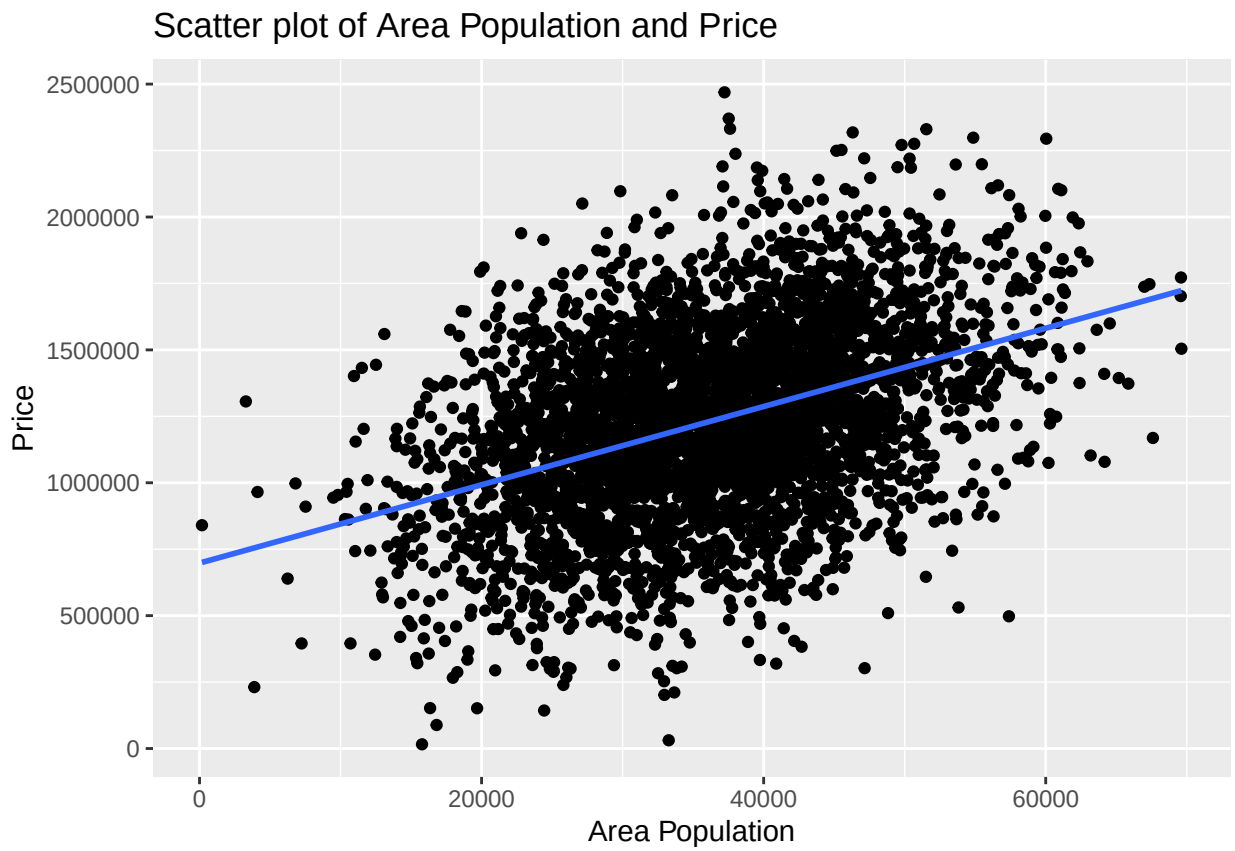

```
age_plot <- ggplot(data = train_set, aes(x = House_Age, y = Price)) + geom_jitter() +
  geom_smooth(method = "lm", se = FALSE) +
  labs(title = "Scatter plot of House Age and Price", x = "Age of House", y = "Price")

age_plot # We see that the relationship is linear
```



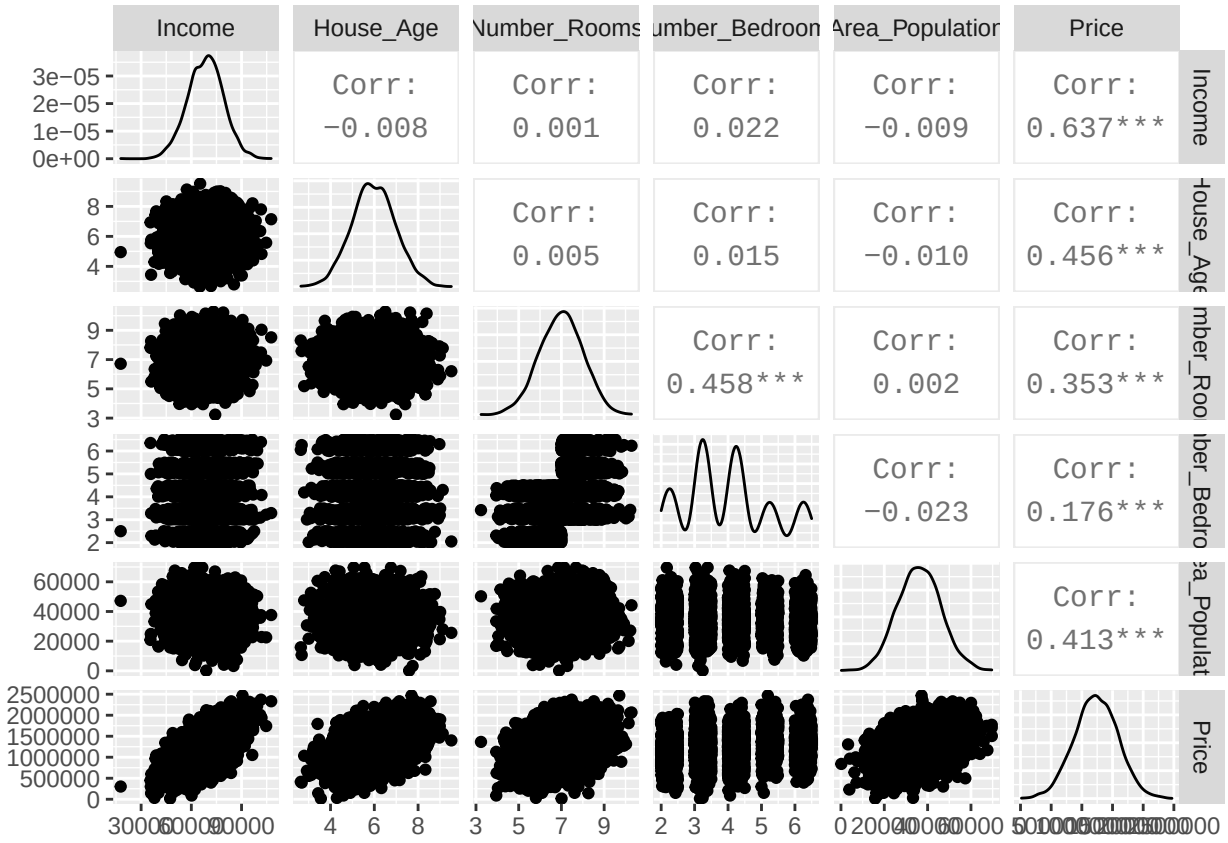

```
room_plot <- ggplot(data = train_set, aes(x = Number_Rooms, y = Price)) + geom_jitter() +
  geom_smooth(method = "lm", se = FALSE) +
  labs(title = "Scatter plot of Rooms and Price", x = "Number of Rooms", y = "Price")

room_plot # We see that the relationship is linear
```



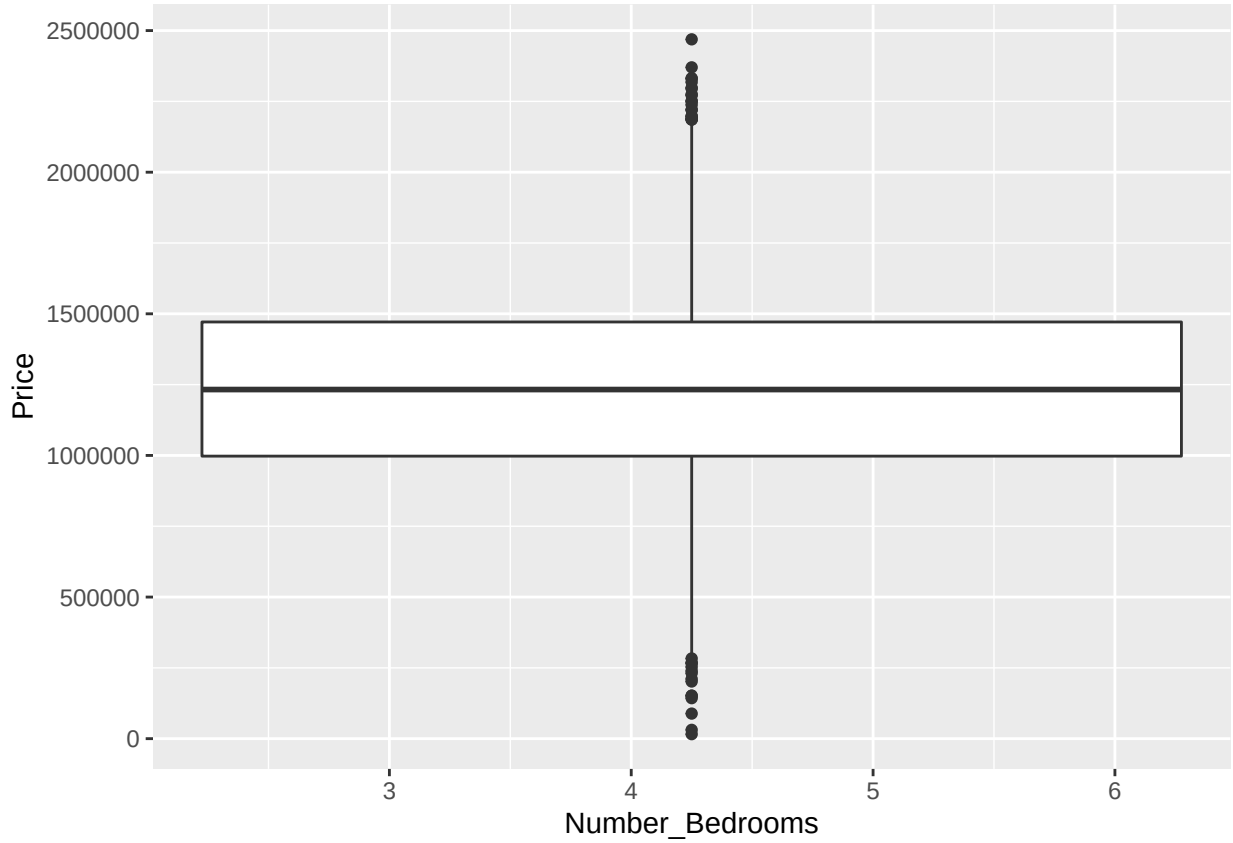

```
pop_plot <- ggplot(data = train_set, aes(x = Area_Population, y = Price)) + geom_jitter() +
  geom_smooth(method = "lm", se = FALSE) +
  labs(title = "Scatter plot of Area Population and Price", x = "Area Population", y = "Price")

pop_plot # We see that the relationship is linear
```



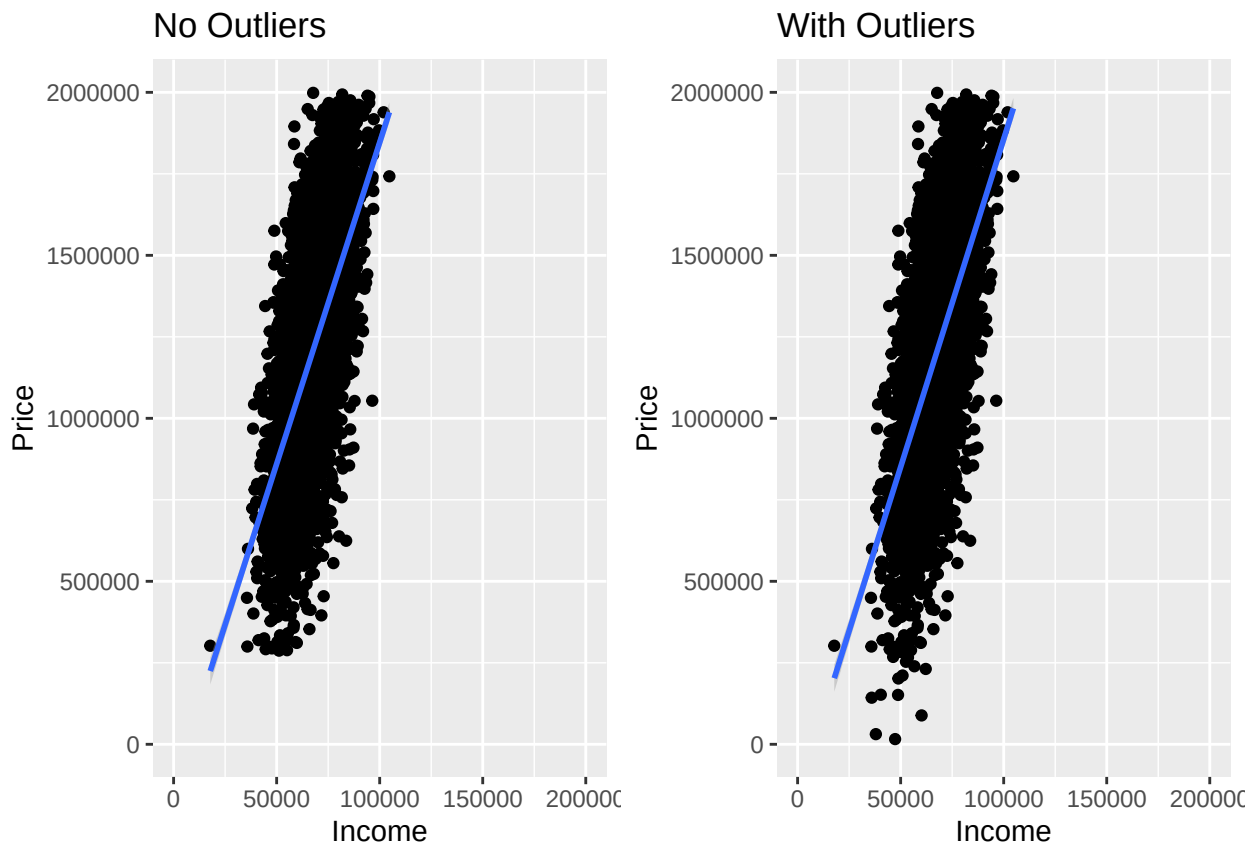

```
# Evaluate Correlations Amongst Variables

ggpairs(train_set, columns = c(1:6))
```




```
## Correlation evaluation appears to support that Number_Bedrooms has a much lower correlation
## and statistical significance towards Price.

# Check for Outliers

ggplot(data = train_set) + geom_boxplot(aes(x = Number_Bedrooms, y = Price)) # Some outliers exist
```




```
train_set_without_outliers <- train_set[-which(train_set$Price %in%
                                                 boxplot(train_set$Price, plot = FALSE)$out),]

## There were 34 outliers, uncertain if their removal will significantly impact overall prediction

# Visualize Outlier Differences

rounded_without_outliers <- round(train_set_without_outliers)
rounded_with_outliers <- round(train_set)

plot1 <- ggplot(data = rounded_without_outliers, aes(x = Income, y = Price)) +
  geom_point() + geom_smooth(method = lm) + xlim(0, 200000) + ylim(0, 2000000) +
  ggtitle("No Outliers")

plot2 <- ggplot(data = rounded_with_outliers, aes(x = Income, y = Price)) +
  geom_point() + geom_smooth(method = lm) + xlim(0, 200000) + ylim(0, 2000000) +
  ggtitle("With Outliers")

grid.arrange(plot1, plot2, ncol = 2)
```



Second Model

Let's try our second model and see if it performs any better.

```
# Fitting Multiple Linear Regression to the Training set Without Number_Bedrooms

train_set_without_outliers <- train_set_without_outliers[,c(1:3,5:6)] # Remove Number_Bedrooms

model2 <- lm(formula = Price ~ ., data = train_set_without_outliers) # Price is the dependent
summary(model2)                          # variable as a function of all dependent variables via '.'
```

```
##
## Call:
## lm(formula = Price ~ ., data = train_set_without_outliers)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -325927  -70218     -77   68094  344474
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)     -2.608e+06  1.947e+04 -133.97   <2e-16 ***
## Income           2.143e+01  1.535e-01  139.60   <2e-16 ***
## House_Age        1.642e+05  1.612e+03  101.85   <2e-16 ***
```

```
## Number_Rooms     1.213e+05  1.581e+03   76.72   <2e-16 ***
## Area_Population  1.499e+01  1.617e-01   92.69   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 100400 on 3961 degrees of freedom
## Multiple R-squared:  0.9138, Adjusted R-squared:  0.9137
## F-statistic: 1.05e+04 on 4 and 3961 DF,  p-value: < 2.2e-16
```

```
## All independent variables are now statistically dependent. R-squared and p-values remain
## statistically significant, however, they both actually decreased by approximately 0.005

# Using Fitted model2 for Predicting the Test Set Results

y_pred2 <- predict(model2, newdata = test_set)
visual_comparison2 <- data.frame(test_set$Price, y_pred2, residuals = test_set$Price - y_pred2)
visual_comparison2[1:10,]
```

```
##    test_set.Price   y_pred2  residuals
## 18       528485.2  492630.8   35854.40
## 29      1240763.8 1403825.0 -163061.19
## 34       534305.1  614597.5  -80292.33
## 38      1081150.1 1168880.7  -87730.62
## 45      1153871.5  942585.7  211285.78
## 58      1186688.5 1009277.6  177410.94
## 61      1111085.0  939507.8  171577.19
## 71      1146532.5 1054453.6   92078.83
## 75      1534479.9 1353139.0  181340.90
## 78      1204598.0 1349202.8 -144604.77
```

Predictions were slightly different but essentially returned no improvement.

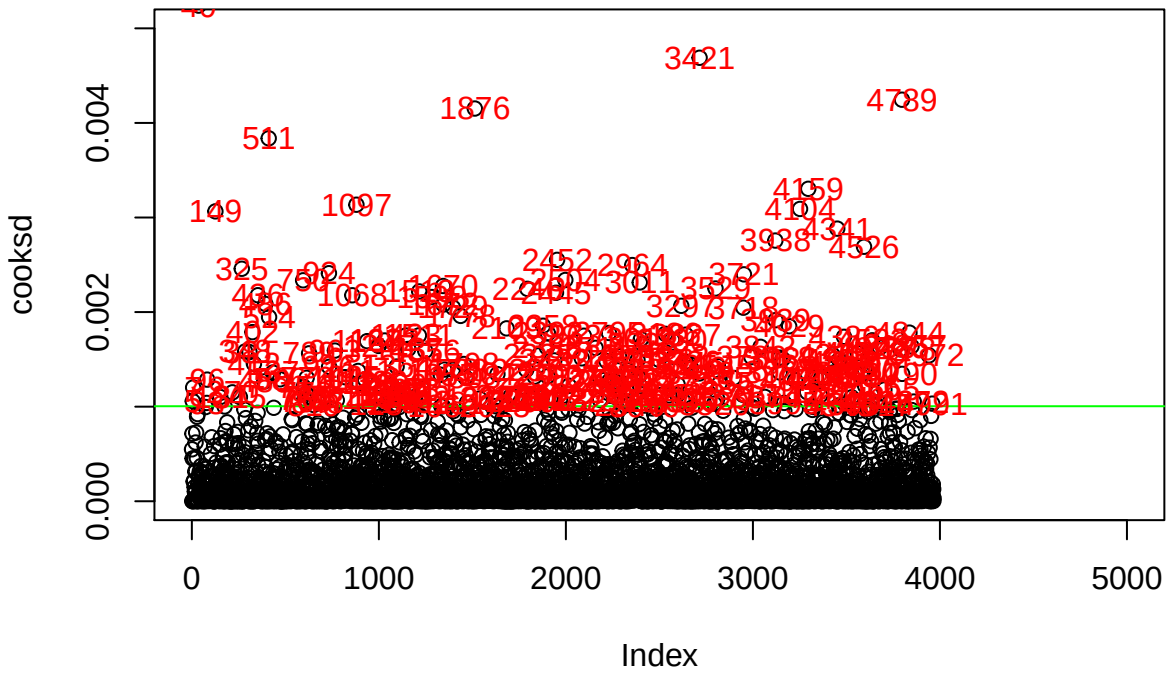
Influential Data Points

Since there was essentially no improvement, let's detect influential data points with Cook's Distance to see if this may improve our model.

```
# Let's Detect Influential Data Points with Cook's Distance
# These are more influential than simple outliers

cooksd <- cooks.distance(model2)
mean(cooksd)
```

```
## [1] 0.0002511019
```

```
plot(cooksd, main = "Influential Observations by Cook's Distance",
     xlim = c(0,5000), ylim = c(0,0.005))
abline(h = 4 * mean(cooksd, na.rm=T), col = "green")  # Creates cutoff to find influential points
text(x = 1:length(cooksd) + 1, y = cooksd,
     labels = ifelse(cooksd > 4 * mean(cooksd, na.rm = T), names(cooksd), ""), col = "red")
```




```
influential <- as.numeric(names(cooksd)[(cooksd > 4 * mean(cooksd, na.rm=T))])
      # influential row numbers
head(train_set_without_outliers[influential, ]) # Take a peek at a few influntial observations
```

```
##       Income House_Age Number_Rooms Area_Population     Price
## 5   59982.20  5.040555     7.839388        26354.11  630943.5
## 7   64698.46  6.025336     8.147760        60828.25 1502055.8
## 44  70421.48  6.907083     7.634319        43183.93 1744932.2
## 107 78633.97  5.465393     7.531143        43728.80 1555320.5
## 111 55472.65  4.822147     5.855972        15353.96  340605.2
## 181 61526.97  6.593963     9.180401        27307.95 1381430.6
```

```
train_set_without_outliers_influential <- train_set_without_outliers[-influential, ]
nrow(train_set_without_outliers_influential)
```

```
## [1] 3807
```

```
plot3 <- ggplot(data = rounded_without_outliers, aes(x = Income, y = Price)) + geom_point() +
  geom_smooth(method = lm) + xlim(0, 200000) + ylim(0, 2000000) +  ggtitle("Without Outliers")

plot4 <- ggplot(data = train_set_without_outliers_influential, aes(x = Income, y = Price)) +
  geom_point() + geom_smooth(method = lm) + xlim(0, 200000) + ylim(0, 2000000) +
  ggtitle("Without Outliers + Influential")

grid.arrange(plot3, plot4, ncol = 2)
```

Third Model

Let's try our third model and see if it performs any better.

```
# Fitting Multiple Linear Regression to the train_set3

model3 <- lm(formula = Price ~ ., data = train_set_without_outliers_influential) # Price is the
summary(model3)                  #dependent variable as a function of all dependent variables via '.'
```

```
##
## Call:
## lm(formula = Price ~ ., data = train_set_without_outliers_influential)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -324600  -70410     331   68563  344430
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)     -2.602e+06  1.988e+04 -130.90   <2e-16 ***
## Income           2.136e+01  1.567e-01  136.33   <2e-16 ***
## House_Age        1.641e+05  1.649e+03   99.49   <2e-16 ***
## Number_Rooms     1.214e+05  1.621e+03   74.94   <2e-16 ***
## Area_Population  1.493e+01  1.649e-01   90.56   <2e-16 ***
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 100500 on 3802 degrees of freedom
## Multiple R-squared:  0.9136, Adjusted R-squared:  0.9135
## F-statistic: 1.005e+04 on 4 and 3802 DF,  p-value: < 2.2e-16
```

```
## Initial review, model3 virtually fit the same as model2

# Predicting the Test Set Results on train_set3

y_pred3 <- predict(model3, newdata = test_set)
visual_comparison3 <- data.frame(test_set$Price, y_pred3, residuals = test_set$Price - y_pred3)
visual_comparison3[1:10,]
```

```
##    test_set.Price   y_pred3  residuals
## 18       528485.2  493336.9   35148.38
## 29      1240763.8 1401712.6 -160948.87
## 34       534305.1  616754.6  -82449.42
## 38      1081150.1 1168679.7  -87529.60
## 45      1153871.5  943443.6  210427.83
## 58      1186688.5 1010048.6  176639.87
## 61      1111085.0  939620.9  171464.13
## 71      1146532.5 1054445.7   92086.75
## 75      1534479.9 1352694.3  181785.65
## 78      1204598.0 1348511.3 -143913.31
```

Predictions were slightly different but essentially no improvement still. This is likely due to the fact that we had 4000 observations in the training set where outliers and influential only accounted for 193 total observations.

- (model1 = 4000; model2 = 3966; model3 = 3807)

Thus not enough change to influence the overall algorithm. Other models may be even more accurate if we attempted to remove other independent variables as well.

Results

Accuracy of the Models

Since removing variables can be intensive and time-consuming, let's evaluate our models to see how accurately they performed.

```
# Accuracy of the Models on the Different Training Sets

pred1 <- model1$fitted.values
pred2 <- model2$fitted.values
pred3 <- model3$fitted.values

tally_table <- data.frame(actual = train_set$Price, predicted = pred1)
```

```
mape <- mean(abs(tally_table$actual - tally_table$predicted) / tally_table$actual)
accuracy1 <- 1 - mape

tally_table <- data.frame(actual = train_set_without_outliers$Price, predicted = pred2)
mape <- mean(abs(tally_table$actual - tally_table$predicted) / tally_table$actual)
accuracy2 <- 1 - mape

tally_table <- data.frame(actual = train_set_without_outliers_influential$Price, predicted = pred3)
mape <- mean(abs(tally_table$actual - tally_table$predicted) / tally_table$actual)
accuracy3 <- 1 - mape

mape_preds <- data.frame(Method_on_Training_Set =
                    c("Full Training Set", "Without Outliers", "Without Outliers + Influential"),
                    MAPE = percent(c(accuracy1, accuracy2, accuracy3)))
kable(mape_preds, booktabs = T, col.names = c("Method", "MAPE")) %>%
  kable_styling(latex_options = "striped")
```

Method	MAPE
Full Training Set	92.346%
Without Outliers	92.644%
Without Outliers + Influential	92.611%

We see that model2 returned the greatest accuracy on the training set.

```
# Accuracy on test_set

tally_table_2 <- data.frame(actual = test_set$Price, predicted = y_pred1)
mape_test <- mean(abs(tally_table_2$actual - tally_table_2$predicted) / tally_table_2$actual)
accuracy_test1 <- 1 - mape_test

tally_table_2 <- data.frame(actual = test_set$Price, predicted = y_pred2)
mape_test <- mean(abs(tally_table_2$actual - tally_table_2$predicted) / tally_table_2$actual)
accuracy_test2 <- 1 - mape_test

tally_table_2 <- data.frame(actual = test_set$Price, predicted = y_pred3)
mape_test <- mean(abs(tally_table_2$actual - tally_table_2$predicted) / tally_table_2$actual)
accuracy_test3 <- 1 - mape_test

mape_preds_test <- data.frame(Method_on_Test_Set = c("Full Training Set", "Without Outliers",
                                                     "Without Outliers + Influential"),
                    MAPE = percent(c(accuracy_test1, accuracy_test2, accuracy_test3)))
kable(mape_preds_test, booktabs = T, col.names = c("Method", "MAPE")) %>%
  kable_styling(latex_options = "striped")
```

Method	MAPE
Full Training Set	92.3903%
Without Outliers	92.3780%
Without Outliers + Influential	92.3711%

Conclusion

We see that the accuracy values on the test set were virtually the same for each model. Since the accuracy was relatively high, it may not be worth the time spent on testing other models with different independent variable combinations.

```
sessionInfo()
```

```
## R version 3.6.3 (2020-02-29)
## Platform: x86_64-w64-mingw32/x64 (64-bit)
## Running under: Windows 10 x64 (build 19042)
##
## Matrix products: default
##
## locale:
## [1] LC_COLLATE=English_United States.1252
## [2] LC_CTYPE=English_United States.1252
## [3] LC_MONETARY=English_United States.1252
## [4] LC_NUMERIC=C
## [5] LC_TIME=English_United States.1252
##
## attached base packages:
## [1] parallel  stats     graphics  grDevices utils     datasets  methods
## [8] base
##
## other attached packages:
##  [1] zoo_1.8-8               xlsx_0.6.4.2            wordcloud_2.6
##  [4] viridisLite_0.3.0       topicmodels_0.2-11      tm_0.7-7
##  [7] NLP_0.2-0               forcats_0.5.0           purrr_0.3.4
## [10] readr_1.3.1             tibble_3.0.1            tidyverse_1.3.0
## [13] tidytext_0.2.6          tidyr_1.1.2             tensorflow_2.2.0
## [16] syuzhet_1.0.4           stringr_1.4.0           stm_1.3.5
## [19] SnowballC_0.7.0         sentimentr_2.7.1        SentimentAnalysis_1.3-3
## [22] scales_1.1.1            RWeka_0.4-43            rlist_0.4.6.1
## [25] readxl_1.3.1            randomForest_4.6-14     quanteda_2.1.1
## [28] qdap_2.4.3              RColorBrewer_1.1-2      qdapTools_1.3.5
## [31] qdapRegex_0.7.2         qdapDictionaries_1.0.7  plotrix_3.7-8
## [34] plotly_4.9.2.1          petro.One_0.2.3         NbClust_3.0
## [37] mclust_5.4.6            magrittr_1.5            ldatuning_1.0.2
## [40] knitr_1.30              kableExtra_1.2.1        gridExtra_2.3
## [43] ggthemes_4.2.0          GGally_2.0.0            fpc_2.2-8
## [46] FactoMineR_2.3          factoextra_1.0.7        e1071_1.7-3
## [49] dplyr_1.0.0             doParallel_1.0.15       iterators_1.0.12
## [52] foreach_1.5.0           dendextend_1.14.0       data.table_1.12.8
## [55] corrplot_0.84           corpus_0.10.1           Clustering_1.6
## [58] cluster_2.1.0           caret_6.0-86            ggplot2_3.3.2
## [61] lattice_0.20-41         car_3.0-10              carData_3.0-4
## [64] caTools_1.18.0
##
## loaded via a namespace (and not attached):
##   [1] ClusterR_1.2.2       prabclus_2.3-2       ModelMetrics_1.2.2.2
##   [4] stopwords_2.0        bit64_4.0.5          rpart_4.1-15
```

```
##   [7] RCurl_1.98-1.2       generics_0.0.2       openNLP_0.2-7
##  [10] usethis_1.6.3        gama_1.0.3           RSQLite_2.2.0
##  [13] openNLPdata_1.5.3-4  chron_2.3-56         bit_4.0.4
##  [16] tokenizers_0.2.1     webshot_0.5.2        xml2_1.3.2
##  [19] lubridate_1.7.9      assertthat_0.2.1     viridis_0.5.1
##  [22] gower_0.2.1          amap_0.8-18          xfun_0.17
##  [25] hms_0.5.3            rJava_0.9-12         evaluate_0.14
##  [28] DEoptimR_1.0-8       fansi_0.4.1          dbplyr_1.4.4
##  [31] igraph_1.2.5         DBI_1.1.0            htmlwidgets_1.5.1
##  [34] reshape_0.8.8        apcluster_1.4.8      stats4_3.6.3
##  [37] ellipsis_0.3.1       backports_1.1.10     RcppParallel_5.0.2
##  [40] vctrs_0.3.2          abind_1.4-5          withr_2.2.0
##  [43] robustbase_0.93-6    lazyeval_0.2.2       crayon_1.3.4
##  [46] labeling_0.3         recipes_0.1.12       pkgconfig_2.0.3
##  [49] slam_0.1-47          nlme_3.1-148         nnet_7.3-14
##  [52] rlang_0.4.7          diptest_0.75-7       lifecycle_0.2.0
##  [55] lexicon_1.2.1        modelr_0.1.8         cellranger_1.1.0
##  [58] Matrix_1.2-18        reprex_0.3.0         base64enc_0.1-3
##  [61] whisker_0.4          bitops_1.0-6         advclust_0.4
##  [64] pROC_1.16.2          blob_1.2.1           venneuler_1.1-0
##  [67] leaps_3.1            memoise_1.1.0        plyr_1.8.6
##  [70] compiler_3.6.3       pvclust_2.2-0        clue_0.3-57
##  [73] cli_2.0.2            janeaustenr_0.1.5    mgcv_1.8-31
##  [76] MASS_7.3-51.6        tidyselect_1.1.0     stringi_1.4.6
##  [79] yaml_2.2.1           ggrepel_0.8.2        grid_3.6.3
##  [82] fastmatch_1.1-0      tools_3.6.3          rio_0.5.16
##  [85] rstudioapi_0.11      foreign_0.8-75       prodlim_2019.11.13
##  [88] farver_2.0.3         scatterplot3d_0.3-41 digest_0.6.25
##  [91] pracma_2.2.9         lava_1.6.7           proto_1.0.0
##  [94] Rcpp_1.0.5           broom_0.7.0          gender_0.5.4
##  [97] httr_1.4.2           kernlab_0.9-29       colorspace_1.4-1
## [100] rvest_0.3.6          XML_3.99-0.3         fs_1.5.0
## [103] reticulate_1.16      splines_3.6.3        RWekajars_3.9.3-2
## [106] xlsxjars_0.6.1       flexmix_2.3-17       xtable_1.8-4
## [109] gmp_0.6-0            jsonlite_1.7.1       timeDate_3043.102
## [112] flashClust_1.01-2    modeltools_0.2-23    ipred_0.9-9
## [115] R6_2.4.1             gsubfn_0.7           pillar_1.4.4
## [118] htmltools_0.5.0      glue_1.4.1           class_7.3-17
## [121] codetools_0.2-16     utf8_1.1.4           sqldf_0.4-11
## [124] curl_4.3             tfruns_1.4           gtools_3.8.2
## [127] zip_2.1.1            openxlsx_4.1.5       survival_3.2-3
## [130] textclean_0.9.3      rmarkdown_2.3        munsell_0.5.0
## [133] haven_2.3.1          reshape2_1.4.4       gtable_0.3.0

## Time difference of 18.70521 secs
```