Reselection of Continuous Variables

Now that I've gotten a firm grasp of the iterative process of developing starting data values, I would like to simplify my approach so I can concentrate on learning. Before I had selected most of the variables to implement in my model, but there were a few issues.

1. It became overwhelming to try to understand the effects of those variables in the model.
2. I could not tell which variables were adding nothing to the model.
3. A lot of those variables were repeated information (ie, totalsqft and 1fltotalsqft)

So the update I will be making from my previous selection is EDA is I will choose what I believe to be the four most critical continuous variables that do not overlap each other.

1. LotArea – I did not include this in the previous analysis and I think that was a mistake. The price of the house most certainly includes the amount of yard included with it.
2. FirstFlrSF – This will represent all square footage for the house. Below I will present my drop conditions for this selection.
3. GarageArea – This is the final variable which represents another value adder.
4. TotalBsmtSF – I only include basements because there were so few houses available without basements.

It total, all four, according to my drop conditions, will represent all possible area that has value.

Drop Conditions

1. LotArea > 0
2. HouseStyle = 1Story
3. BldType = 1Fam
4. TotalBsmtSF > 0
5. GarageArea > 0

These drop conditions ensure that all houses selected will be single story family residences, a ranch style, with basements and garages.

I will also be selecting TotRmsAbvGrd, FullBath, HalfBath, and Neighbourhood for their categorical and quantitative values

Histograms

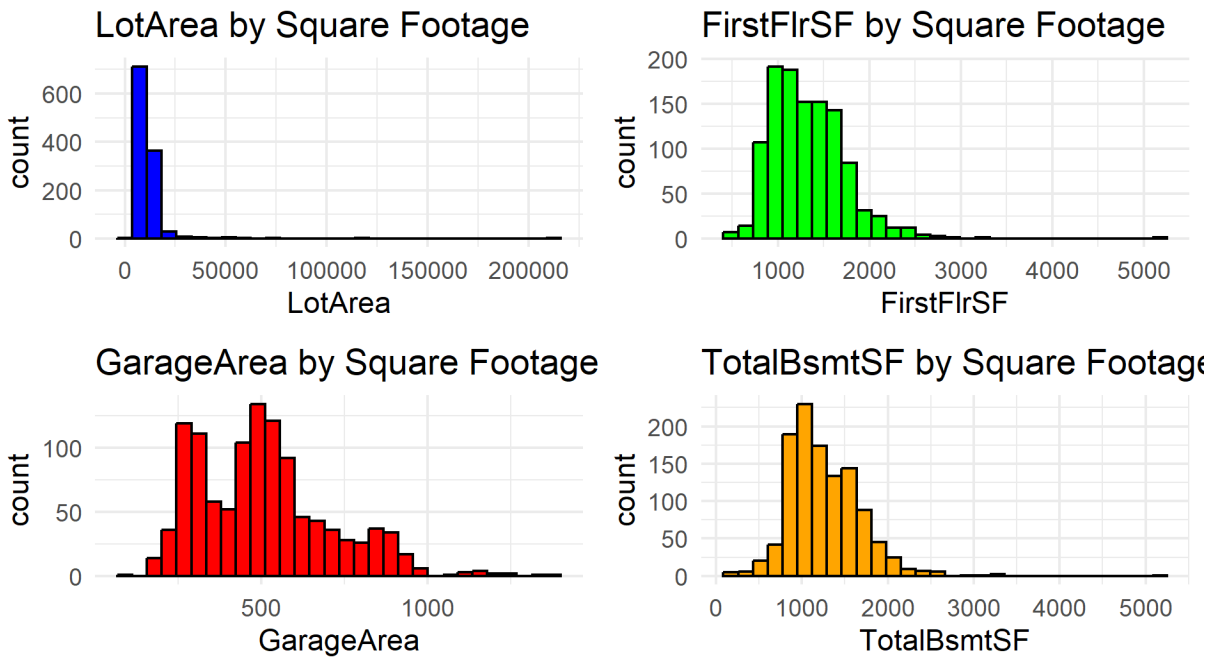


Figure 1

The four continuous variables I selected shown in Figure 1, include outliers which could show a right skew, meaning people prefer smaller areas. Total basement square footage mirrors the first floor showing that the foundations of these houses are built using the basement. Lot area shows most houses have reasonably sized lots, just enough for a front and back yard, while several have several acres of land, but do not constitute the majority of the houses.

Garages have a bimodal distribution, most likely single and double wide garages.

Summary

Statistic	LotArea	FirstFlrSF	GarageArea	TotalBsmtSF
Mean	11308.17	1325.80	507.45	1256.78
Median	9991.00	1266.00	484.00	1188.00
Min	2887.00	407.00	100.00	105.00
Max	215245.00	5095.00	1390.00	5095.00
SD	8660.32	406.37	201.47	419.88

Figure 2

What stands out in the Ames region, is that there are clearly wealthy people who own lots of land twenty times larger than the mean. These are still ranch style homes, so it is likely the larger areas are farms.

Most lots are around 11,308 sqft, first floor areas of 1325 sqft, and basements just a bit smaller.

Correlations

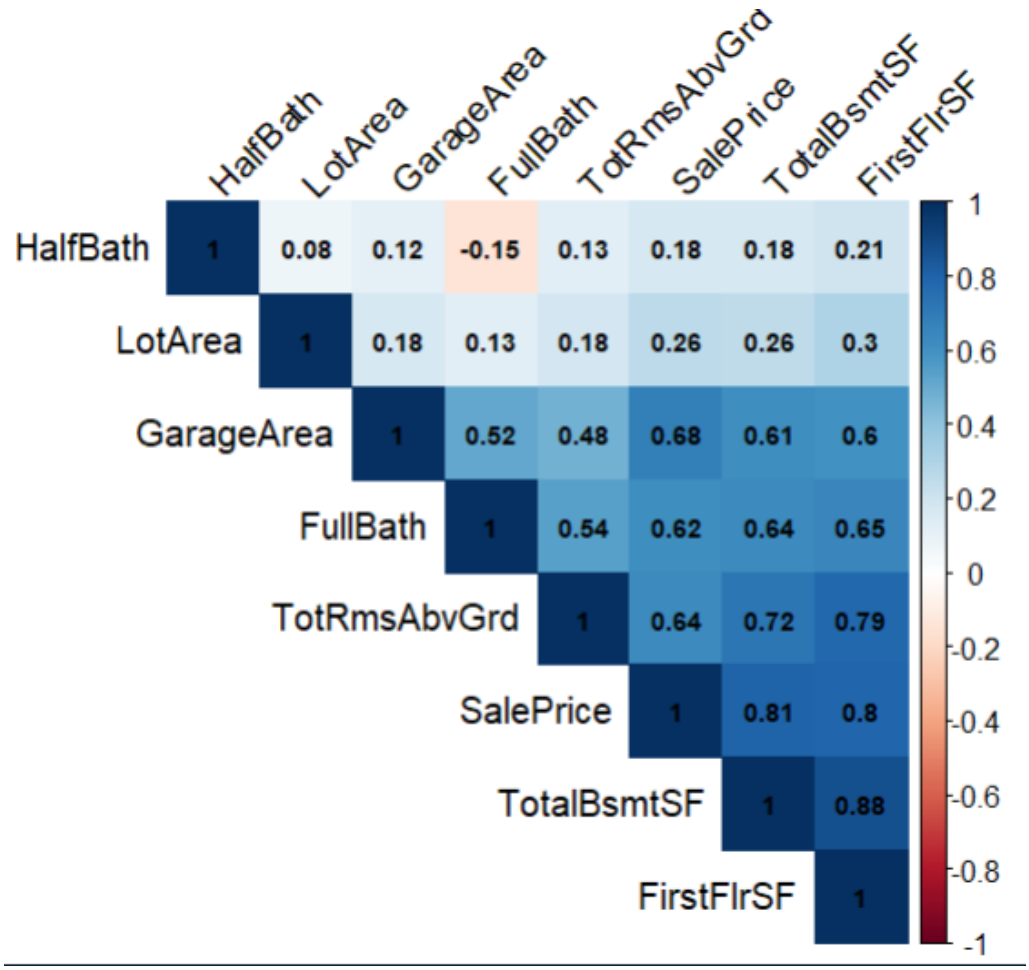


Figure 3

Like earlier, Total Basement square footage and First Floor square footage are highly correlated. All variables exceed 0.6 concerning Sale Price, but Lot Area and Half Bath are only slightly correlated. Size seems to matter the most and the number of Full Baths.

Size based variables correlate with other ones which gives me confidence our model will be able to predict Sale Price nicely.

Scatterplots

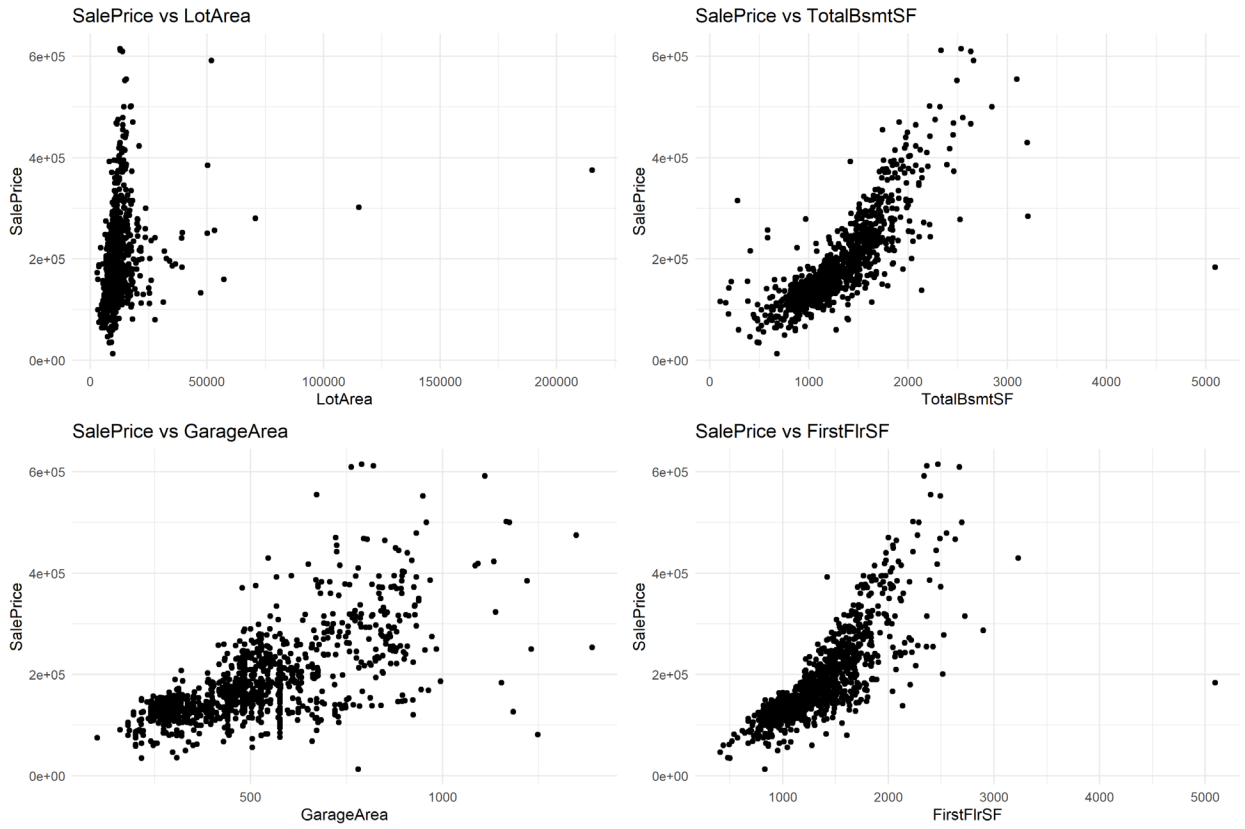


Figure 4

Figure 4 shows all continuous variables have positive relationship. Although there are strong correlations between each one there is noticeable variability especially with Lot Area, a few of the outliers could throw off the model as well.

New Variables

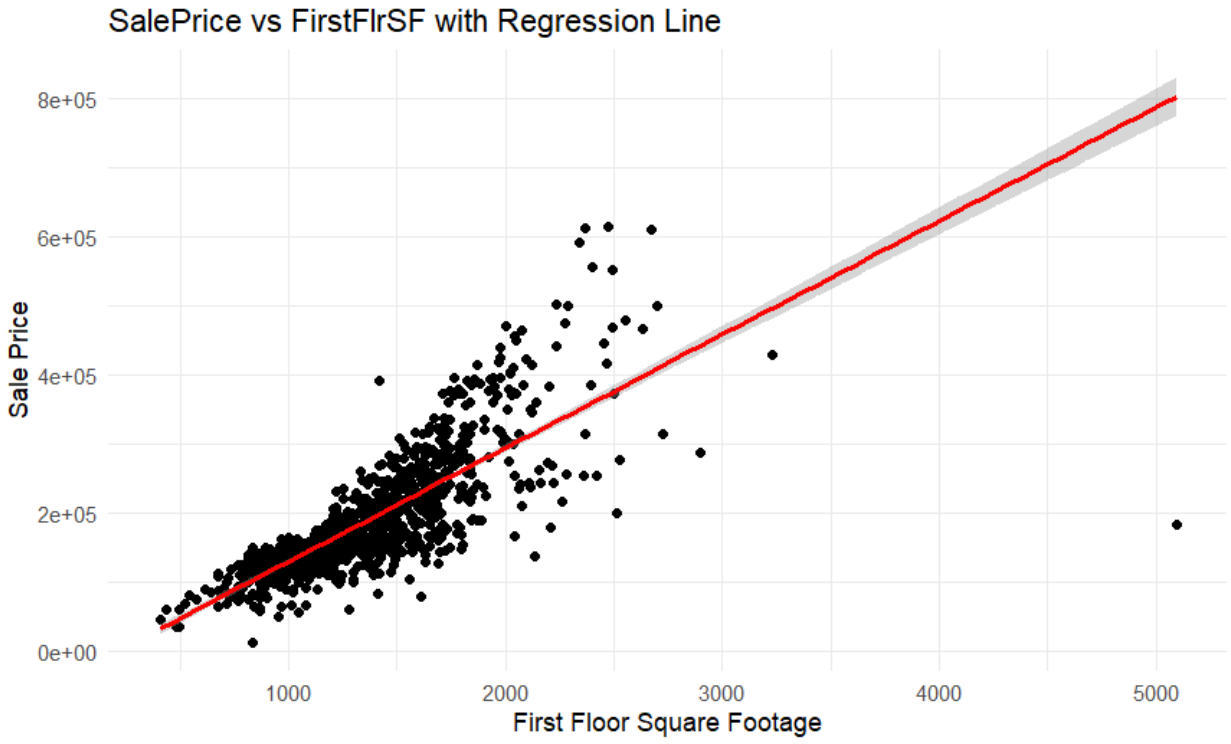
I created one new variable type named Square Foot Per Dollar. The calculation is SalePrice / (LotArea + TotalBsmtSF + GarageArea + FirstFlrSF)) so that each house has all square footage included in the calculation. My hope is it will give the most accurate indication by smoothing out how much each square foot is worth.

Assignment Tasks

1.

I've selected FirstFlrSF as the best continuous explanatory variable to predict Y (SalePrice). I think it's a straightforward and well known variable, and although when I ran the correlations, basement square footage beat it out slightly at 0.81 to 0.8, if I were to ever expand this model to include more, lots of basements can vary in size, but most people buy a house for its living area. Also, the quality of the basement could affect it as many basements are not livable.

A.




```
Call:
lm(formula = SalePrice ~ FirstFlrSF, data = ames_data_w_saleprice)

Residuals:
    Min      1Q  Median      3Q     Max
-618669  -22042    -856   18901  257684

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -34294.900   5100.923  -6.723 2.82e-11 ***
FirstFlrSF     164.242      3.679  44.647  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 50210 on 1127 degrees of freedom
Multiple R-squared:  0.6388,    Adjusted R-squared:  0.6385
F-statistic:  1993 on 1 and 1127 DF,  p-value: < 2.2e-16
```

B. The model in equation form is SalePrice = -34294 + 164.242 * FirstFlrSF
The intercept (-34294.9) is the estimated Sale Price when FirstFlrSF is zero. Obviously when there is no square footage, the house will be less than worthless. The slope (164.242) is that each square footage that increases in the house, the amount of the price will increase by $164.24

C. 63.88% of the variation in Sale Price can be explained by the variation in the First Floor Square Footage of houses. This means the prices of houses can be predicted by knowing just the First Floor Square footage. There is still a large percentage that is unaccounted for, however this is huge.

D.

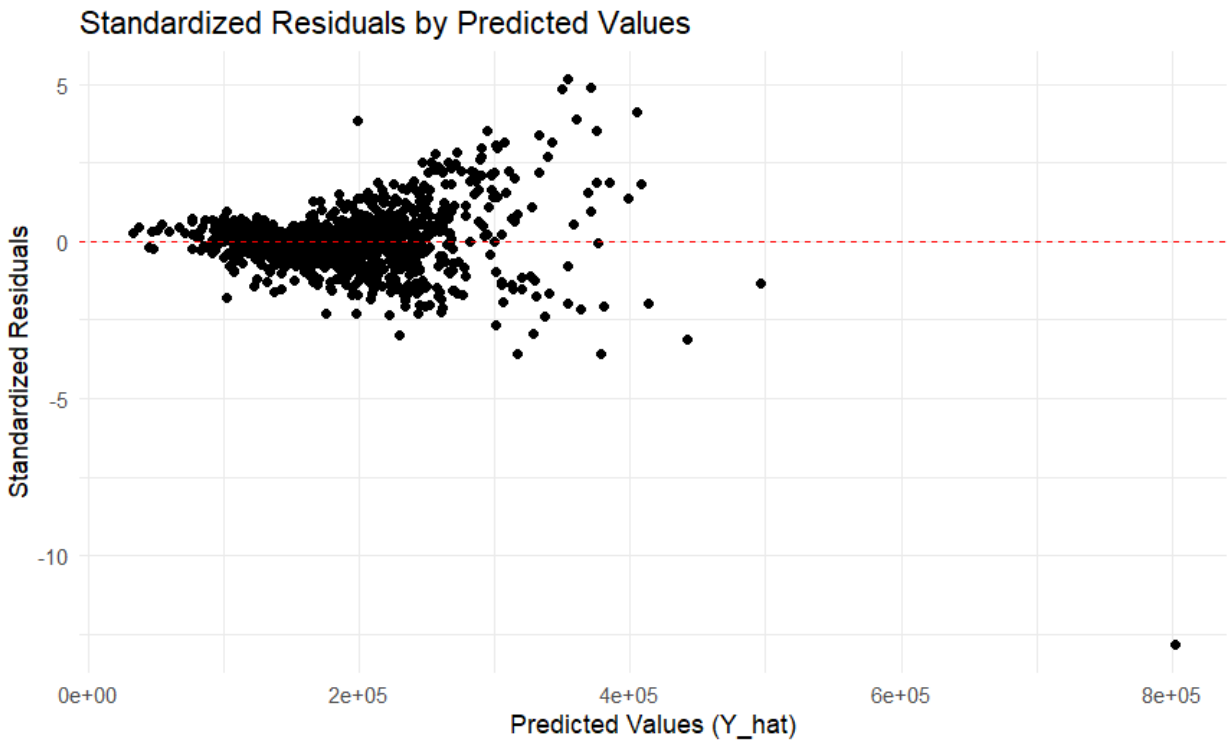
```
Analysis of Variance Table

Response: SalePrice
             Df     Sum Sq    Mean Sq F value    Pr(>F)
FirstFlrSF    1 5.0248e+12 5.0248e+12  1993.4 < 2.2e-16 ***
Residuals  1127 2.8409e+12 2.5208e+09
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Null Hypothesis H0: B1 = 0 : There is no relationship between FirstFlrSF and SalePrice
Alternative Hypothesis HA: B1 != 0: There is a relationship between FirstFlrSF and SalePrice

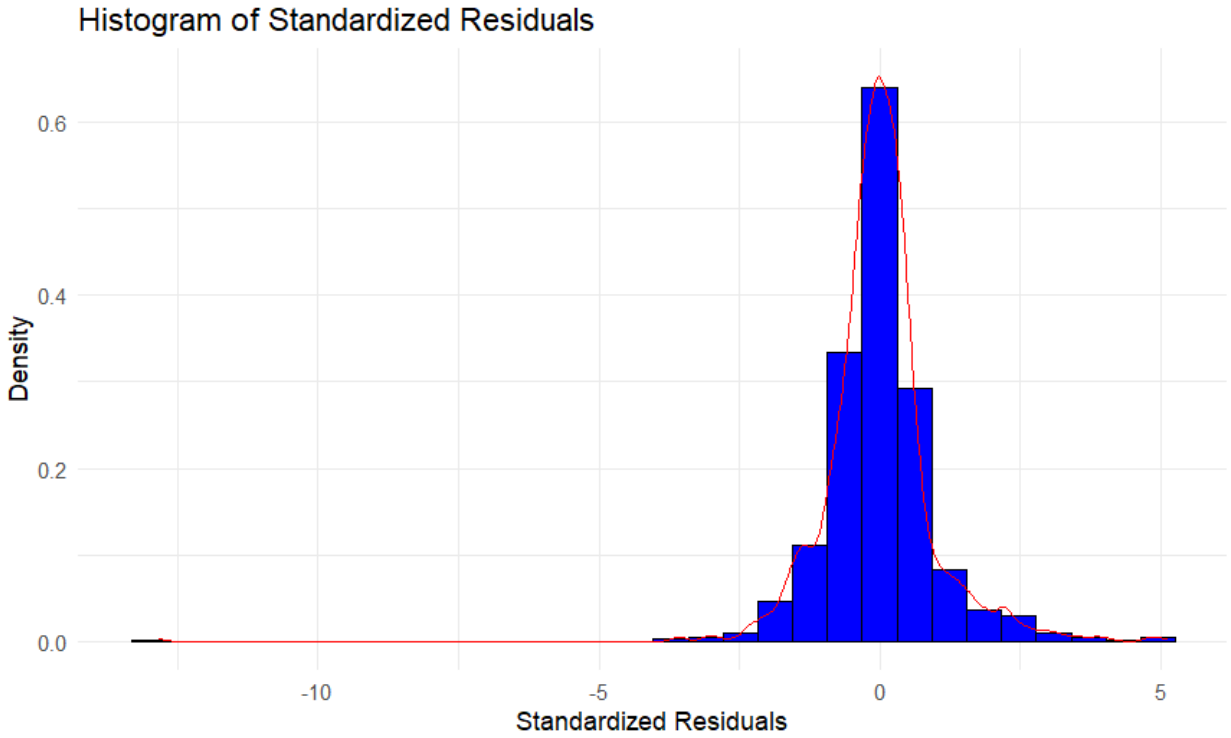
The P-Value is well below the accepted value of 0.05 as 2.2e-16, therefore we must reject the Null hypothesis.

Overall Omnibus Model
Null Hypothesis H0: B1 = 0 The model provides no explanatory power.
Alternative Hypothesis: HA: B1 != 0 The model does provide explanatory power.

A larger F value provides a better fit and explanatory power of B1. Again, our value of 2.2e-16 is well below the 0.05 needed, and we must reject the null hypothesis and say that it does have explanatory power.

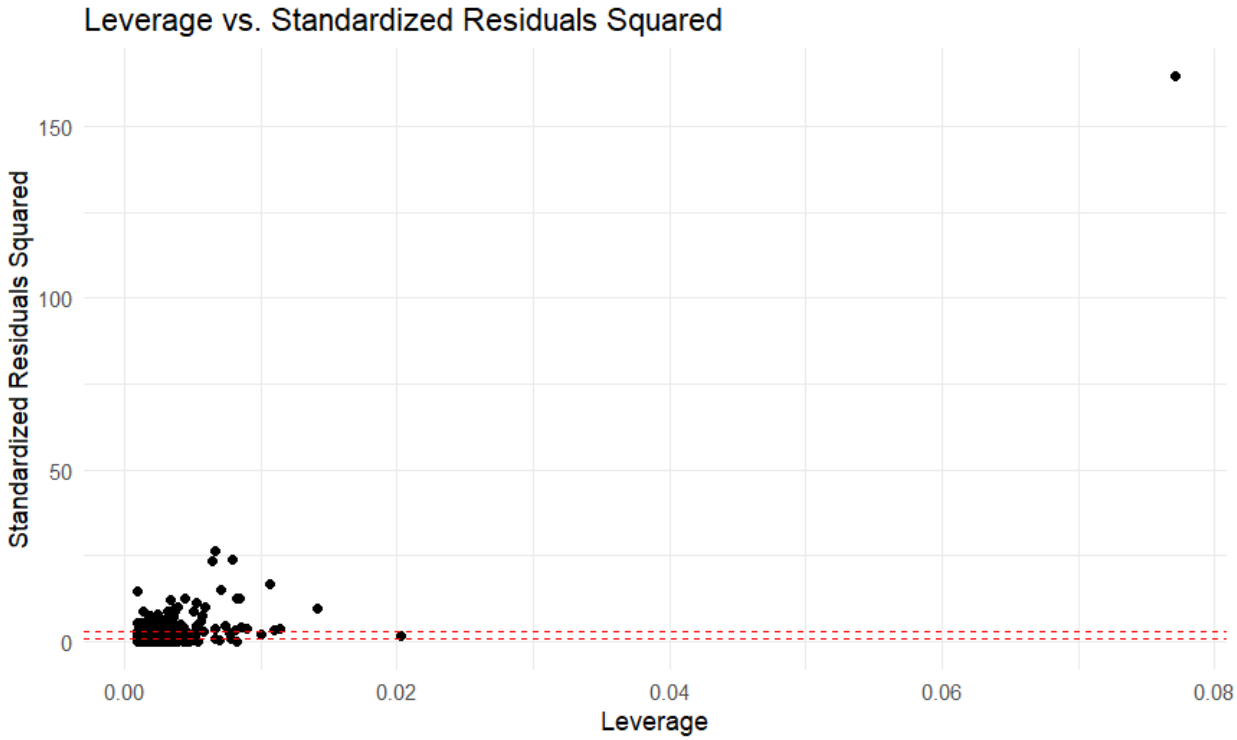


E.



F. The histogram shows a nice curve for normality, and the scatterplot is nicely evenly distributed. Although there are a few outliers, it does not seem to affect much.
I do not believe I will need to fix this by re weighing the variable for heteroscedasticity.

G.



Nothing is too concerning looking at the leverage vs standardized R^2 plot. I see this one over represented house popping up over and over again, it probably is not going to affect too much, however it could cause problems, and dropping it in the future may improve the model

2.

A.

```
Residuals:
    Min      1Q  Median      3Q     Max
-430755  -21320   -1136   16059  248672

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -1.180e+05  4.882e+03  -24.17   <2e-16 ***
FirstFlrSF   8.029e+01  4.075e+00   19.70   <2e-16 ***
OverallQual  3.235e+04  1.138e+03   28.43   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 38330 on 1126 degrees of freedom
Multiple R-squared:  0.7897,    Adjusted R-squared:  0.7893
F-statistic:  2114 on 2 and 1126 DF,  p-value: < 2.2e-16
```

Prediction equation: SalePrice = -103.464 + 0.107*FirstFlrSF + 3.948*OverallQual
The intercept (-118,000) represents the estimated Sale Price when both FirstFlrSF and OverallQual are at 0.
FirstFlrSF (80.29) says that for each additional square foot in the first floor square footage, while overall quality remains the same, will increase by $80.29.
OverallQual (32,350) says for every one-unit increase in overall quality, assuming FirstFlrSF remains constant, the price will increase by 32,350.
The largest change is that I must assume that the other coefficients will not change to get an accurate prediction for any given coefficient. Another large change is that FirstFlrSF coefficient has halved compared to model 2.

B. The R^2 was 0.79 which means with the addition of OverallQual the variability can be explained by the combination of FirstFlrSF and OverallQual, which is higher than 63.88% in Model 2. This means that this model works better as a predicator compared to just FirstFlrSF.

C.

```
Analysis of Variance Table

Response: SalePrice
              Df     Sum Sq    Mean Sq F value    Pr(>F)
FirstFlrSF     1 5.0248e+12 5.0248e+12 3420.79 < 2.2e-16 ***
OverallQual    1 1.1869e+12 1.1869e+12  808.01 < 2.2e-16 ***
Residuals   1126 1.6540e+12 1.4689e+09
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

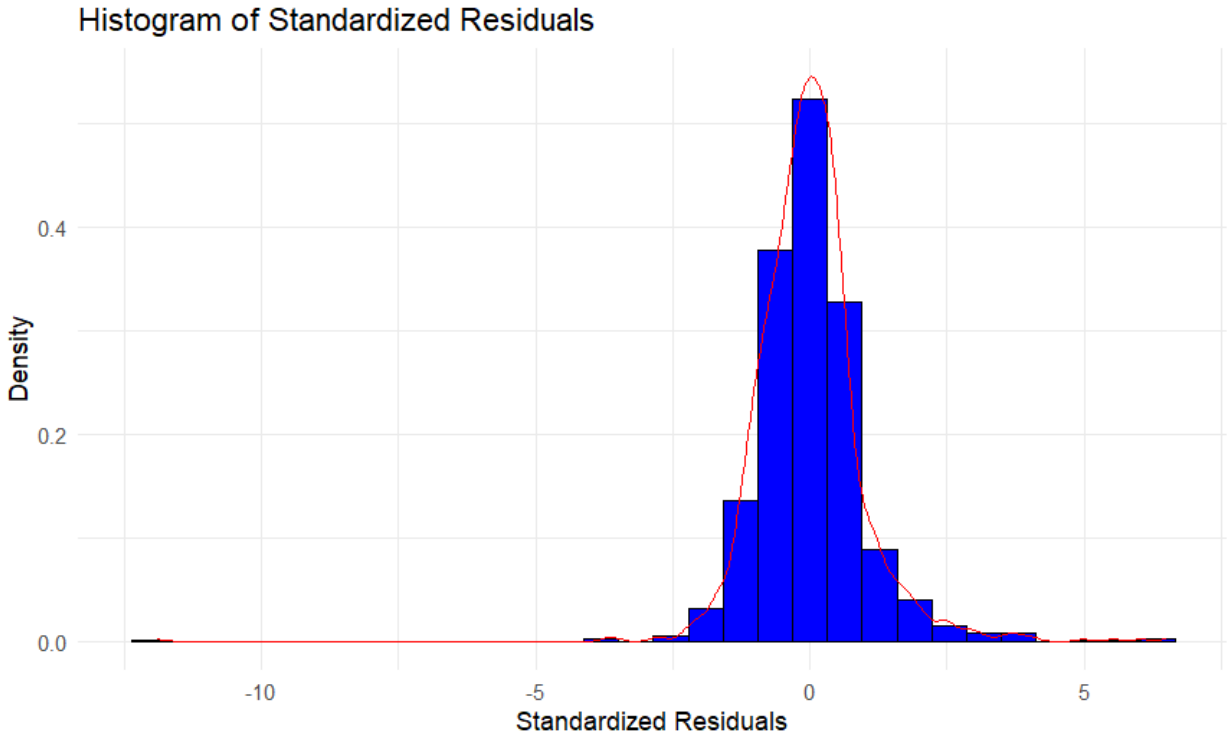
D.
Null Hypothesis: H0: Bi = 0
Alternative Hypothesis: HA: Bi != 0
The null hypothesis states that any given variable has no affect on the response variable.
The alternative hypothesis states that any given variable does have an effect on the response variable.
FirstFlrSF: The p-value is less than 0.05 with a value of 2.2e-16 so we must reject the null hypothesis.
OverallQual: The p-value is less than 0.05 with a value of 2.2e-16 so we must reject the null hypothesis.

Overall Omnibus Model
Null Hypothesis H0: Bi = 0 The model provides no explanatory power.
Alternative Hypothesis: HA: Bi != 0 The model does provide explanatory power.

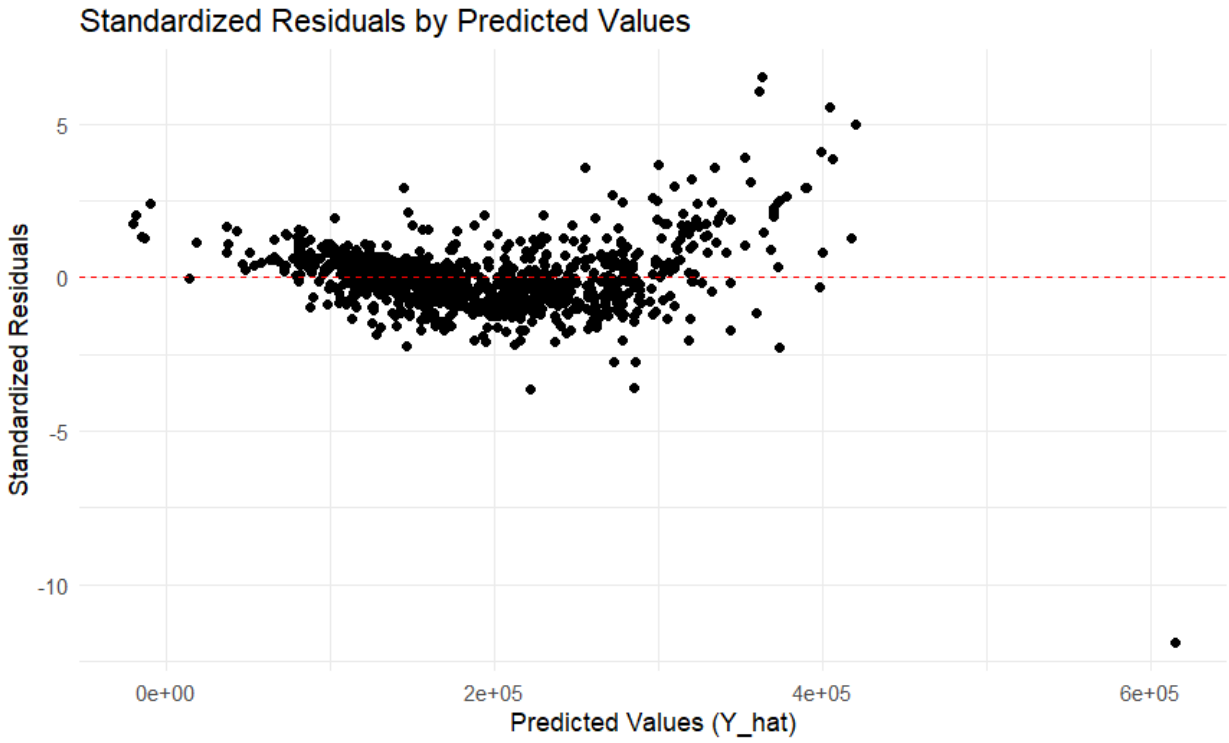
F-statistic
FirstFlrSF = 3420.79
OverallQual = 808.01

Being that all values are well below their p-values, we reject all null hypotheses and accept the alternative hypotheses.

E.



Much like Model 1, we see that the residuals have a nice normal distribution. We



We have a bit of a problem now. The spread of residuals seems to be increasing with the predicted values. This suggests that the variance of the residuals is not constant.

F . The residuals do not appear to be randomly scattered which means the relationship may not be linear. The points that are far away from the red line could be points with high leverage which will affect the slope.
There is also that pesky outlier appearing again.

G. I should retain both variables. Separately they were both better predictors, but together they have an even higher R^2 score. Although this score could be higher just because there are more variables, the score was much higher so I will keep both.

3.

I decided to add Neighborhood for the final variable as that will add the most variety to the different types available.

A.

```
Call:
lm(formula = SalePrice ~ FirstFlrSF + OverallQual + Neighborhood,
    data = ames_data_w_saleprice_3)

Residuals:
    Min      1Q  Median      3Q     Max
-338059  -15548    -361   13964  213735

Coefficients:
                     Estimate Std. Error t value Pr(>|t|)
(Intercept)         -67211.482  20655.812  -3.254  0.00117 **
FirstFlrSF             71.051      3.849  18.461  < 2e-16 ***
OverallQual         22203.310   1310.533  16.942  < 2e-16 ***
NeighborhoodBrkSide   -781.418  20762.277  -0.038  0.96998
NeighborhoodClearCr  38707.718  20561.749   1.883  0.06003 .
NeighborhoodCollgCr  24487.361  19402.570   1.262  0.20719
NeighborhoodCrawfor  25095.236  20322.850   1.235  0.21716
NeighborhoodEdwards   5080.664  19830.576   0.256  0.79784
NeighborhoodGilbert  16753.434  20372.596   0.822  0.41105
NeighborhoodIDOTRR   -3288.616  20523.647  -0.160  0.87272
NeighborhoodMitchel  25886.868  19905.454   1.300  0.19370
NeighborhoodNAmes     8909.534  19398.380   0.459  0.64611
NeighborhoodNoRidge  74428.858  22692.951   3.280  0.00107 **
NeighborhoodNridgHt  97338.338  19726.852   4.934 9.28e-07 ***
NeighborhoodNWAmes    3433.562  19710.509   0.174  0.86174
NeighborhoodOldTown    994.788  19854.433   0.050  0.96005
NeighborhoodSawyer   14241.211  19637.004   0.725  0.46847
NeighborhoodSawyerW   8436.592  20118.528   0.419  0.67505
NeighborhoodSomerst  37308.066  19617.033   1.902  0.05745 .
NeighborhoodStoneBr 127198.039  21121.358   6.022 2.34e-09 ***
NeighborhoodSWISU    -6807.704  22568.470  -0.302  0.76298
NeighborhoodTimber   43450.336  19833.422   2.191  0.02868 *
NeighborhoodVeenker  45845.344  21518.180   2.131  0.03335 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 33230 on 1106 degrees of freedom
Multiple R-squared:  0.8447,    Adjusted R-squared:  0.8416
F-statistic: 273.5 on 22 and 1106 DF,  p-value: < 2.2e-16
```

Model = SalePrice = -67211.48 + 71.05(FirstFlrSF) + 22203.31(OverallQual) + SUM(Neighborhood Coefficients)

The largest different here is since it uses categorical variables, it must add each Neighborhood sub-variable to the model, hence why we must sum them.

B.

The R^2 value increased from 0.79 to 0.8447 which, although not as large as from Model 1 to 2, still increased enough to make a difference. It absolutely helps the model's explanatory ability.

C.

```
Analysis of Variance Table

Response: SalePrice
               Df     Sum Sq    Mean Sq  F value    Pr(>F)
FirstFlrSF      1 5.0248e+12 5.0248e+12 4549.826 < 2.2e-16 ***
OverallQual     1 1.1869e+12 1.1869e+12 1074.693 < 2.2e-16 ***
Neighborhood   20 4.3253e+11 2.1626e+10   19.582 < 2.2e-16 ***
Residuals    1106 1.2215e+12 1.1044e+09
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

D.

H0: B_FirstFlrSF = 0

HA: B_FirstFlrSF != 0

H0: B_OverallQual = 0

HA: B_OverallQual != 0

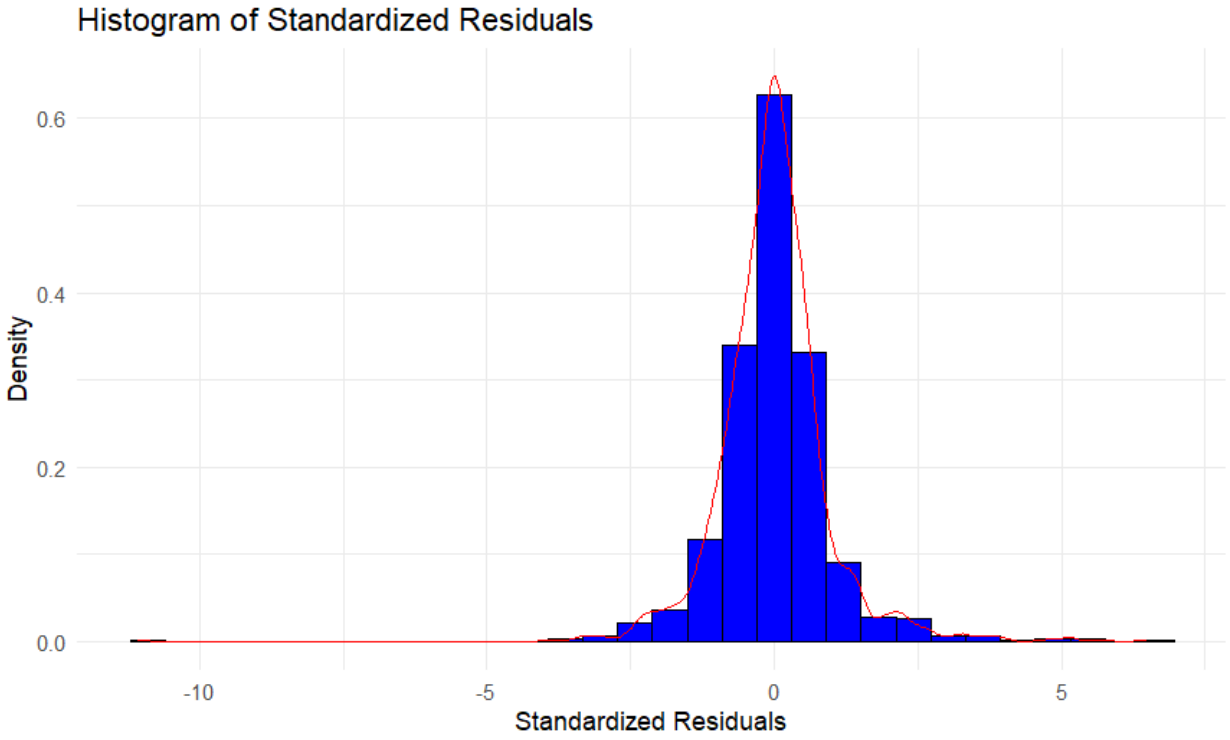
H0: B_Neighborhood[i] = 0

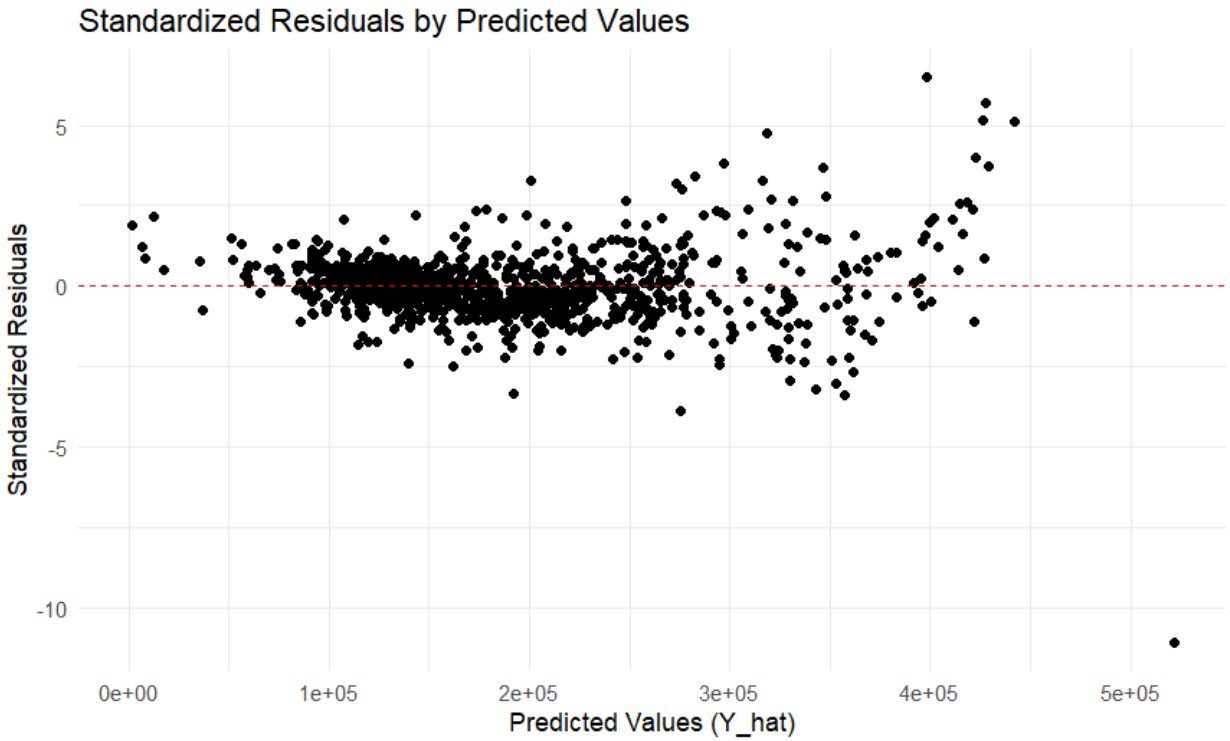
HA: B_Neighborhood[i] != 0

All the other variables are like before, but B_Neighborhood will be different as the null hypothesis is for any given variable inside.

For all three, the p-values are well below the required 0.05 at 2.2e-16 so we must reject the null hypotheses for all three.

E.





Even with the added values, we still have a fairly normal distribution, however the scatterplot does indicate that it may not be totally linear although it seems to have evened out a bit compared to Model 2.

F. My concerns are the same with Model 2.

G. The F-statistic for Neighborhood is only 19.582 compared with FirstFlrSF at 4549.826 and OverallQual at 1074.693. Although its P-value is extremely significant, it does not appear to have affected the model. I'm unsure whether I should keep it in since most of that information is probably already present in the quality of houses. I would assume that higher quality homes are also in nicer neighborhoods.

4.

```
Call:
lm(formula = log(SalePrice) ~ FirstFlrSF + OverallQual + Neighborhood,
    data = ames_data_w_saleprice_3)

Residuals:
     Min       1Q   Median       3Q      Max
-1.68131 -0.07181  0.00951  0.08724  0.53740

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)
(Intercept)         10.7989355  0.0998208 108.183  < 2e-16 ***
FirstFlrSF           0.0003347  0.0000186  17.994  < 2e-16 ***
OverallQual          0.1235398  0.0063333  19.507  < 2e-16 ***
NeighborhoodBrkSide -0.1498640  0.1003353  -1.494 0.135557
NeighborhoodClearCr  0.1906861  0.0993662   1.919 0.055238 .
NeighborhoodCollgCr  0.0978054  0.0937644   1.043 0.297131
NeighborhoodCrawfor  0.1087716  0.0982117   1.108 0.268309
NeighborhoodEdwards -0.0678456  0.0958328  -0.708 0.479121
NeighborhoodGilbert  0.0716988  0.0984521   0.728 0.466608
NeighborhoodIDOTRR  -0.2545714  0.0991821  -2.567 0.010398 *
NeighborhoodMitchel  0.1032071  0.0961946   1.073 0.283550
NeighborhoodNAmes    0.0079172  0.0937441   0.084 0.932710
NeighborhoodNoRidge  0.1928369  0.1096654   1.758 0.078954 .
NeighborhoodNridgHt  0.2528257  0.0953315   2.652 0.008114 **
NeighborhoodNWAmes   0.0171154  0.0952525   0.180 0.857433
NeighborhoodOldTown -0.1868097  0.0959480  -1.947 0.051789 .
NeighborhoodSawyer   0.0188585  0.0948973   0.199 0.842514
NeighborhoodSawyerW  0.0119350  0.0972243   0.123 0.902321
NeighborhoodSomerst  0.1454166  0.0948008   1.534 0.125336
NeighborhoodStoneBr  0.3437510  0.1020706   3.368 0.000784 ***
NeighborhoodSWISU   -0.1966319  0.1090638  -1.803 0.071675 .
NeighborhoodTimber   0.1510887  0.0958465   1.576 0.115229
NeighborhoodVeenker  0.1749304  0.1039882   1.682 0.092810 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1606 on 1106 degrees of freedom
Multiple R-squared:  0.8508,    Adjusted R-squared:  0.8478
F-statistic: 286.6 on 22 and 1106 DF,  p-value: < 2.2e-16
```

Comparing both R^2 and adjusted R^2 we see a small improved fit from 0.8447 to 0.8508. The largest difference is the RSE dropped from 33230 to 0.1606. I'm at a loss why it would have changed so much because of the log() function. The F-statistic increased from 273.5 to 286.6 while keeping several Neighborhood significant p-values.

Technically, the model fits much better than the previous, however I'm afraid I may have done something wrong with the log() function.

For the moment, I will say that the new model is superior to the other, but I would have to verify at the end that is the case.

5.

```
Call:
lm(formula = log(SalePrice) ~ FirstFlrSF + OverallQual + Neighborhood,
    data = ames_data_cleaned)

Residuals:
     Min       1Q   Median       3Q      Max
-0.40007 -0.06623  0.00396  0.07273  0.29733

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)
(Intercept)         1.090e+01  2.875e-02 379.328  < 2e-16 ***
FirstFlrSF          4.246e-04  1.519e-05  27.953  < 2e-16 ***
OverallQual         1.039e-01  4.945e-03  21.016  < 2e-16 ***
NeighborhoodCrawfor 1.091e-02  2.485e-02   0.439  0.66076
NeighborhoodEdwards -1.460e-01  1.905e-02  -7.662 4.55e-14 ***
NeighborhoodMitchel 2.452e-03  1.921e-02   0.128  0.89845
NeighborhoodNAmes   -9.645e-02  1.241e-02  -7.769 2.06e-14 ***
NeighborhoodNridgHt 1.398e-01  1.805e-02   7.748 2.42e-14 ***
NeighborhoodNWAmes  -7.963e-02  1.691e-02  -4.709 2.87e-06 ***
NeighborhoodOldTown -2.443e-01  1.902e-02 -12.842  < 2e-16 ***
NeighborhoodSawyer  -7.719e-02  1.600e-02  -4.823 1.65e-06 ***
NeighborhoodSawyerW -6.641e-02  2.230e-02  -2.978  0.00298 **
NeighborhoodSomerst 5.308e-02  1.656e-02   3.206  0.00139 **
NeighborhoodTimber  4.572e-02  1.881e-02   2.431  0.01525 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1078 on 941 degrees of freedom
Multiple R-squared:  0.9133,    Adjusted R-squared:  0.9121
F-statistic: 762.3 on 13 and 941 DF,  p-value: < 2.2e-16
```

Comparing to the log() model 4 with influential points, the new one with less significant points lowers the RSE from 0.1606 to 0.1078. What's more, the R^2 and residual R^2 increased to 0.913 which means that up until this point, this model has performed best out of the all the previous models. I would assume that this method should be applied every time to help smooth out problems.

6.

I can only assume that this process is automated in a library. I believe researching before, libraries like PyCaret automatically iterate through all possible combinations, applying log(), and finds the best fit. So if I were to iterate through that I would use..

1. Create a list of all the variables
2. Iterate through the list and append the results of the model to another list to compare later.
3. Run through each of those combinations with log(), create a new list of the log results.
4. Any sort of extra model, run every combination of variables.
5. Compare that to removing influential data points.
6. Finally, sort by results and use the best model.

   Again, I'm more than certain this is a much more efficient way to iterate through these as that could be very compute intense depending on the size of the data and the dimensions of it.

```r
#6
#Using leaps let's find the best model
ames_data_numeric <- ames_data %>%
  select(where(is.numeric)) %>%
  select(-SalePrice)
full_model_formula <- as.formula(paste("SalePrice ~ .", sep = ""))

best_subset <- regsubsets(full_model_formula, data = ames_data,
                          nbest = 1,
                          nvmax = 4,
                          method = "exhaustive",
                          really.big = TRUE)
best_models_summary <- summary(best_subset)
```

   I eventually found the leaps library that does just that. Here, I have it setup to find the best model by doing an exhaustive search for the 4 best predictors. However, even with my processor, it was too much for it to handle, meaning that my process would probably not be the best solution.
   I was unable to get it to work so I did not have enough time unfortunately to finish the reports, but I would have run the reports similarly to the rest of the assignment.

7. Overall I learned a great deal from this assignment. At first, I found the process to be very repetitive, but now that I've gone through the process multiple times, I understand everything much better than when I began.

It's obvious that taking the original data and applying algorithms can make it a better predictor by smoothing out data, removing influential points that are going to cause the model to veer too far in a direction we don't want it going. Applying these processes improves the model, or at least has proven that in this example.

I don’t think that these analytical activities cause problems or add difficulties, I think these are great exercises to understand your data better, and to really hammer home which variables have the most impact.

I think there is a reason why statistical hypothesis testing is still around. It absolutely helps with regression and is a cheap and effective way to build quick models on well known and cleaned datasets.

I think the next step is to do what I suggested above and find the absolute best combination of variables to create the most effective models.