Introduction

This assignment was a great challenge to test many of the techniques that we have learned in the class thus far. The goal for the second part of this project was to create more accurate models for the Ames, IA housing market. I did this by using multiple linear regression techniques on various combinations of variables for the models. The building blocks for each model were based upon shell code from class and the models from the first part of the assignment. The goal of adding additional variables to the model is to minimize the mean square root errors while also increasing the precision of the model. This will be measured by R squared scores and AIC and BIC values.

Section 1. Modeling & More

Model 1

```
  OLS Regression Results
==============================================================================
Dep. Variable:                      Y   R-squared:                       0.808
Model:                            OLS   Adj. R-squared:                  0.803
Method:                 Least Squares   F-statistic:                     167.4
Date:                Thu, 14 Feb 2019   Prob (F-statistic):               0.00
Time:                        00:25:51   Log-Likelihood:                -24204.
No. Observations:                2039   AIC:                         4.851e+04
Df Residuals:                    1988   BIC:                         4.880e+04
Df Model:                          50
Covariance Type:            nonrobust
==============================================================================================
                                 coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------------------
Intercept                  -1.093e+06   1.23e+05     -8.903      0.000   -1.33e+06   -8.52e+05
C(lotconfig)[T.CulDSac]     9959.0566   3853.710      2.584      0.010    2401.323    1.75e+04
C(lotconfig)[T.FR2]        -9229.1512   5358.716     -1.722      0.085   -1.97e+04    1280.137
C(lotconfig)[T.FR3]        -4.164e+04   1.14e+04     -3.654      0.000    -6.4e+04   -1.93e+04
C(lotconfig)[T.Inside]      1090.6206   2122.872      0.514      0.607   -3072.667    5253.909
C(housestyle)[T.1.5Unf]     3571.6500   9857.072      0.362      0.717   -1.58e+04    2.29e+04
C(housestyle)[T.1Story]    -3608.3476   3057.079     -1.180      0.238   -9603.762    2387.067
C(housestyle)[T.2.5Fin]     1.207e+04     1.5e+04      0.805      0.421   -1.73e+04    4.15e+04
C(housestyle)[T.2.5Unf]    -3655.5504   9215.417     -0.397      0.692   -2.17e+04    1.44e+04
C(housestyle)[T.2Story]    -3197.4247   3239.242     -0.987      0.324   -9550.090    3155.241
C(housestyle)[T.SFoyer]    -1.251e+04   5437.443     -2.302      0.021   -2.32e+04   -1851.083
C(housestyle)[T.SLvl]       -1.08e+04   4842.278     -2.231      0.026   -2.03e+04   -1306.732
C(roofstyle)[T.Gable]      -5849.0281   1.08e+04     -0.542      0.588    -2.7e+04    1.53e+04
C(roofstyle)[T.Gambr]      -4787.4578   1.34e+04     -0.357      0.721   -3.11e+04    2.15e+04
C(roofstyle)[T.Hip]         9712.8899   1.09e+04      0.890      0.374   -1.17e+04    3.11e+04
C(roofstyle)[T.Mansa]       5865.3970   1.65e+04      0.354      0.723   -2.66e+04    3.83e+04
C(roofstyle)[T.Shed]       -8503.5956   2.05e+04     -0.415      0.678   -4.87e+04    3.17e+04
C(heating)[T.GasA]          9710.3288   3.55e+04      0.274      0.784   -5.98e+04    7.92e+04
C(heating)[T.GasW]          2.029e+04   3.62e+04      0.560      0.576   -5.08e+04    9.14e+04
C(heating)[T.Grav]          6528.5477   3.78e+04      0.173      0.863   -6.76e+04    8.06e+04
C(heating)[T.OthW]           -1.5e+04   5.02e+04     -0.299      0.765   -1.13e+05    8.34e+04
C(heating)[T.Wall]          2.924e+04   4.33e+04      0.675      0.500   -5.57e+04    1.14e+05
C(neighborhood)[T.Blueste] -3.636e+04   1.57e+04     -2.311      0.021   -6.72e+04   -5508.840
C(neighborhood)[T.BrDale]  -4.718e+04   1.17e+04     -4.020      0.000   -7.02e+04   -2.42e+04
C(neighborhood)[T.BrkSide] -1.747e+04   1.01e+04     -1.732      0.083   -3.73e+04    2308.281
C(neighborhood)[T.ClearCr]  7050.8946   1.11e+04      0.637      0.524   -1.46e+04    2.88e+04
C(neighborhood)[T.CollgCr] -1057.3237   8718.998     -0.121      0.903   -1.82e+04     1.6e+04
C(neighborhood)[T.Crawfor]  1.409e+04   9833.075      1.433      0.152   -5195.611    3.34e+04
C(neighborhood)[T.Edwards] -2.617e+04   9219.795     -2.839      0.005   -4.43e+04   -8092.035
C(neighborhood)[T.Gilbert]  -795.6399   9079.647     -0.088      0.930   -1.86e+04     1.7e+04
C(neighborhood)[T.Greens]  -2.381e+04   1.67e+04     -1.425      0.154   -5.66e+04    8957.083
C(neighborhood)[T.GrnHill]  1.029e+05    3.6e+04      2.857      0.004    3.23e+04    1.74e+05
C(neighborhood)[T.IDOTRR]  -1.597e+04   1.05e+04     -1.528      0.127   -3.65e+04    4529.173
C(neighborhood)[T.MeadowV] -4.371e+04   1.13e+04     -3.868      0.000   -6.59e+04   -2.15e+04
C(neighborhood)[T.Mitchel] -1.809e+04   9393.775     -1.925      0.054   -3.65e+04     336.029
C(neighborhood)[T.NAmes]   -2.392e+04   8949.379     -2.673      0.008   -4.15e+04   -6373.808
C(neighborhood)[T.NPkVill]  -3.32e+04   1.22e+04     -2.728      0.006   -5.71e+04   -9335.589
C(neighborhood)[T.NWAmes]  -2.214e+04   9352.744     -2.367      0.018   -4.05e+04   -3798.909
C(neighborhood)[T.NoRidge]  5.368e+04   9976.588      5.381      0.000    3.41e+04    7.32e+04
C(neighborhood)[T.NridgHt]  7.071e+04   9023.361      7.836      0.000     5.3e+04    8.84e+04
C(neighborhood)[T.OldTown] -1.739e+04   9824.114     -1.770      0.077   -3.67e+04    1878.279
C(neighborhood)[T.SWISU]    -1.96e+04   1.16e+04     -1.686      0.092   -4.24e+04    3202.449
C(neighborhood)[T.Sawyer]  -2.548e+04   9361.979     -2.721      0.007   -4.38e+04   -7118.135
C(neighborhood)[T.SawyerW] -1.445e+04   9185.627     -1.573      0.116   -3.25e+04    3569.249
C(neighborhood)[T.Somerst]  1.697e+04   8900.968      1.907      0.057    -482.153    3.44e+04
C(neighborhood)[T.StoneBr]  5.574e+04   1.05e+04      5.323      0.000    3.52e+04    7.63e+04
C(neighborhood)[T.Timber]   2.038e+04   9532.920      2.138      0.033    1684.484    3.91e+04
C(neighborhood)[T.Veenker]  8445.5088   1.28e+04      0.659      0.510   -1.67e+04    3.36e+04
qualityindex                2135.8233     99.771     21.407      0.000    1940.156    2331.490
totalsqftcalc                 39.7080      1.274     31.162      0.000      37.209      42.207
yearbuilt                    569.4023     58.348      9.759      0.000     454.973     683.832
==============================================================================
Omnibus:                      605.595   Durbin-Watson:                   2.040
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            47418.402
Skew:                          -0.429   Prob(JB):                         0.00
Kurtosis:                      26.609   Cond. No.                     4.70e+05
==============================================================================
```

My first model above used: qualityindex, totalsqftcalc, yearbuilt, neighborhood, heating, roofstyle, housestyle and lotconfig. I choose these variables based off of correlation matrix python produced. It has a good R-Squared score and low AIC and BIC scored. Overall most of the nominal variables like heating, seemed to have less significant p-values.

Model 2

```
OLS Regression Results
==============================================================================
Dep. Variable:                      Y   R-squared:                       0.802
Model:                            OLS   Adj. R-squared:                  0.798
Method:                 Least Squares   F-statistic:                     245.6
Date:                Thu, 14 Feb 2019   Prob (F-statistic):               0.00
Time:                        00:53:05   Log-Likelihood:                -24237.
No. Observations:                2039   AIC:                         4.854e+04
Df Residuals:                    2005   BIC:                         4.873e+04
Df Model:                          33
Covariance Type:            nonrobust
=============================================================================================
                                coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------------------
Intercept                 -1.031e+06   1.12e+05     -9.217      0.000   -1.25e+06   -8.12e+05
C(lotconfig)[T.CulDSac]    9938.0849   3867.921      2.569      0.010    2352.520    1.75e+04
C(lotconfig)[T.FR2]       -8986.4899   5393.883     -1.666      0.096   -1.96e+04    1591.712
C(lotconfig)[T.FR3]       -4.599e+04   1.15e+04     -4.003      0.000   -6.85e+04   -2.35e+04
C(lotconfig)[T.Inside]     1375.5535   2134.445      0.644      0.519   -2810.408    5561.515
C(neighborhood)[T.Blueste] -3.917e+04   1.59e+04     -2.470      0.014   -7.03e+04   -8070.036
C(neighborhood)[T.BrDale]  -4.974e+04   1.17e+04     -4.260      0.000   -7.26e+04   -2.68e+04
C(neighborhood)[T.BrkSide] -1.868e+04   1.01e+04     -1.849      0.065   -3.85e+04    1136.236
C(neighborhood)[T.ClearCr]  5848.2137   1.09e+04      0.534      0.593   -1.56e+04    2.73e+04
C(neighborhood)[T.CollgCr] -2813.0286   8794.937     -0.320      0.749   -2.01e+04    1.44e+04
C(neighborhood)[T.Crawfor]  1.307e+04   9913.581      1.318      0.188   -6371.445    3.25e+04
C(neighborhood)[T.Edwards]  -2.68e+04   9270.142     -2.891      0.004    -4.5e+04   -8616.638
C(neighborhood)[T.Gilbert] -3368.6064   9037.078     -0.373      0.709   -2.11e+04    1.44e+04
C(neighborhood)[T.Greens]  -2.797e+04   1.69e+04     -1.656      0.098   -6.11e+04    5148.418
C(neighborhood)[T.GrnHill]  9.827e+04   3.65e+04      2.696      0.007    2.68e+04     1.7e+05
C(neighborhood)[T.IDOTRR]  -1.708e+04   1.05e+04     -1.625      0.104   -3.77e+04    3532.006
C(neighborhood)[T.MeadowV] -4.851e+04   1.13e+04     -4.311      0.000   -7.06e+04   -2.64e+04
C(neighborhood)[T.Mitchel] -2.115e+04   9428.589     -2.244      0.025   -3.96e+04   -2664.022
C(neighborhood)[T.NAmes]   -2.345e+04   9004.978     -2.604      0.009   -4.11e+04   -5785.905
C(neighborhood)[T.NPkVill] -3.653e+04   1.22e+04     -2.982      0.003   -6.06e+04   -1.25e+04
C(neighborhood)[T.NWAmes]   -2.34e+04   9415.411     -2.486      0.013   -4.19e+04   -4938.379
C(neighborhood)[T.NoRidge]  5.517e+04   9990.785      5.522      0.000    3.56e+04    7.48e+04
C(neighborhood)[T.NridgHt]  7.439e+04   9100.565      8.174      0.000    5.65e+04    9.22e+04
C(neighborhood)[T.OldTown] -1.889e+04   9895.376     -1.909      0.056   -3.83e+04     512.709
C(neighborhood)[T.SWISU]   -1.994e+04   1.16e+04     -1.717      0.086   -4.27e+04    2835.356
C(neighborhood)[T.Sawyer]  -2.689e+04   9392.435     -2.863      0.004   -4.53e+04   -8472.736
C(neighborhood)[T.SawyerW] -1.735e+04   9240.592     -1.877      0.061   -3.55e+04     776.689
C(neighborhood)[T.Somerst]  1.558e+04   8954.068      1.740      0.082   -1982.433    3.31e+04
C(neighborhood)[T.StoneBr]  5.678e+04   1.06e+04      5.361      0.000     3.6e+04    7.75e+04
C(neighborhood)[T.Timber]   2.107e+04   9627.659      2.189      0.029    2188.975       4e+04
C(neighborhood)[T.Veenker]  3203.2929   1.29e+04      0.248      0.804   -2.21e+04    2.85e+04
qualityindex               2154.8081     98.905     21.787      0.000    1960.840    2348.776
totalsqftcalc                41.5578      1.230     33.788      0.000      39.146      43.970
yearbuilt                   537.9639     55.761      9.648      0.000     428.609     647.319
==============================================================================
Omnibus:                      590.736   Durbin-Watson:                   2.039
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            48577.684
Skew:                          -0.354   Prob(JB):                         0.00
Kurtosis:                      26.902   Cond. No.                     4.10e+05
==============================================================================
```

My second model above used: qualityindex, totalsqftcalc, yearbuilt, neighborhood, and lotconfig. I dropped heating, roof style and housestyle from this model due to high p-values. Unfortunately, it did not improve my model and the AIC and BIC scores went up, along with a decrease in the R-Squared score.

Model 3

```
    OLS Regression Results
==============================================================================
Dep. Variable:                      Y   R-squared:                       0.802
Model:                            OLS   Adj. R-squared:                  0.800
Method:                 Least Squares   F-statistic:                     471.9
Date:                Thu, 14 Feb 2019   Prob (F-statistic):               0.00
Time:                        01:05:22   Log-Likelihood:                -19255.
No. Observations:                1645   AIC:                         3.854e+04
Df Residuals:                    1630   BIC:                         3.862e+04
Df Model:                          14
Covariance Type:            nonrobust
===========================================================================================
                              coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------------------
Intercept              -1.514e+06   5.77e+04    -26.219      0.000   -1.63e+06    -1.4e+06
C(lotconfig)[T.CulDSac] -2794.1488   3603.313     -0.775      0.438   -9861.760    4273.463
C(lotconfig)[T.FR2]     -1.473e+04   4685.372     -3.144      0.002   -2.39e+04   -5541.025
C(lotconfig)[T.FR3]     -1.149e+04   1.06e+04     -1.083      0.279   -3.23e+04    9323.235
C(lotconfig)[T.Inside]  -1227.8088   1973.864     -0.622      0.534   -5099.386    2643.768
C(housestyle)[T.1.5Unf]   1.03e+04   8513.429      1.210      0.227   -6398.895     2.7e+04
C(housestyle)[T.1Story] -2862.0665   2608.078     -1.097      0.273   -7977.605    2253.472
C(housestyle)[T.2.5Fin]  2.658e+04     1.5e+04      1.772      0.077   -2840.752     5.6e+04
C(housestyle)[T.2.5Unf]  7862.9373   8506.186      0.924      0.355   -8821.270    2.45e+04
C(housestyle)[T.2Story] -5676.1508   2798.566     -2.028      0.043   -1.12e+04    -186.987
C(housestyle)[T.SFoyer] -2.695e+04   4844.866     -5.563      0.000   -3.65e+04   -1.74e+04
C(housestyle)[T.SLvl]   -1.747e+04   4168.740     -4.191      0.000   -2.56e+04   -9294.063
qualityindex             2301.0798     88.532     25.991      0.000    2127.431    2474.729
totalsqftcalc              56.0250      1.267     44.229      0.000      53.540      58.509
yearbuilt                 764.7805     30.206     25.319      0.000     705.534     824.027
==============================================================================
Omnibus:                      251.950   Durbin-Watson:                   1.974
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              583.201
Skew:                           0.864   Prob(JB):                    2.29e-127
Kurtosis:                       5.350   Cond. No.                     2.23e+05
==============================================================================
```

The above model produced a better model for me. The p-values from house style are the main concerns I have. I also used the lotconfig, qualityindex, totalsqftcalc and yearbuilt as my other variables. The R-Squared scores are consistent from previous models, but the AIC and BIC scores are also much more improved and help to show evidence of a potentially better model. I did a VIF for this model as well for comparison purposes. Due to high values of correlation for housestyle and lotconfig, I dropped those and did another Model that I call four.

This is the VIF for Model 3

```
Intercept                  6321.423581
C(lotconfig)[T.CulDSac]       1.286576
C(lotconfig)[T.FR2]           1.155319
C(lotconfig)[T.FR3]           1.033131
C(lotconfig)[T.Inside]        1.415540
C(housestyle)[T.1.5Unf]       1.077486
C(housestyle)[T.1Story]       3.223679
C(housestyle)[T.2.5Fin]       1.034751
C(housestyle)[T.2.5Unf]       1.075653
C(housestyle)[T.2Story]       3.105904
C(housestyle)[T.SFoyer]       1.337091
C(housestyle)[T.SLvl]         1.470230
qualityindex                  1.185466
totalsqftcalc                 1.351872
yearbuilt                     1.498649
```

Model 4

```
OLS Regression Results
==============================================================================
Dep. Variable:                      Y   R-squared:                       0.794
Model:                            OLS   Adj. R-squared:                  0.793
Method:                 Least Squares   F-statistic:                     2103.
Date:                Thu, 14 Feb 2019   Prob (F-statistic):               0.00
Time:                        01:14:28   Log-Likelihood:                -19289.
```

```
No. Observations:                1645   AIC:                         3.859e+04
Df Residuals:                    1641   BIC:                         3.861e+04
Df Model:                           3
Covariance Type:            nonrobust
================================================================================
                    coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
Intercept      -1.399e+06   5.24e+04    -26.730      0.000    -1.5e+06    -1.3e+06
qualityindex    2312.9261     88.300     26.194      0.000    2139.733    2486.120
totalsqftcalc     56.4671      1.262     44.753      0.000      53.992      58.942
yearbuilt        702.9255     26.917     26.114      0.000     650.130     755.721
==============================================================================
Omnibus:                      269.946   Durbin-Watson:                   1.972
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              635.477
Skew:                           0.914   Prob(JB):                    1.02e-138
Kurtosis:                       5.435   Cond. No.                     1.99e+05
==============================================================================
```

The above model performed better in regards to having better p-values and better BIC score. This model scored in the lower part of the 40,000 RMSE.

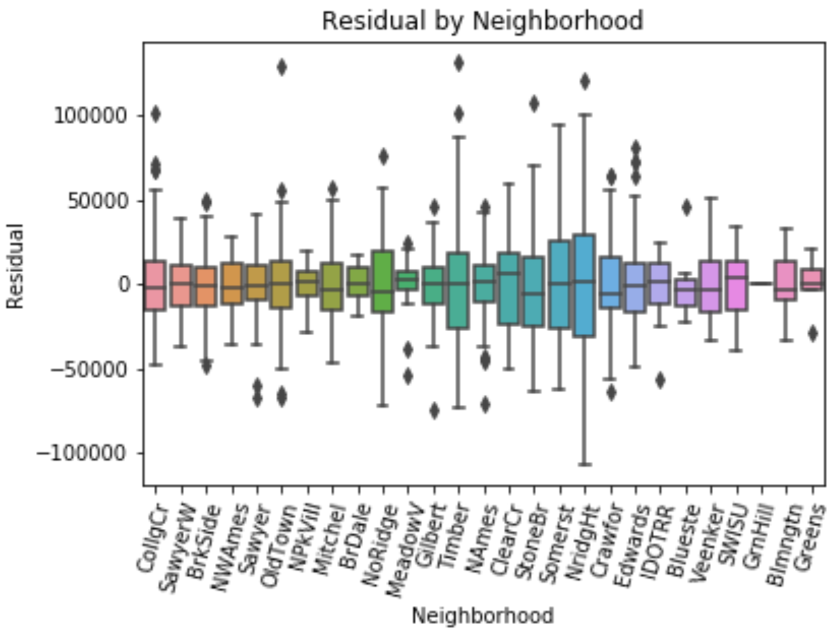
Model 5

```
OLS Regression Results
==============================================================================
Dep. Variable:              saleprice   R-squared:                       0.896
Model:                            OLS   Adj. R-squared:                  0.894
Method:                 Least Squares   F-statistic:                     435.3
Date:                Thu, 14 Feb 2019   Prob (F-statistic):               0.00
Time:                        01:19:46   Log-Likelihood:                -18723.
No. Observations:                1645   AIC:                         3.751e+04
Df Residuals:                    1612   BIC:                         3.769e+04
Df Model:                          32
Covariance Type:            nonrobust
===========================================================================================
                                coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------------------
Intercept                 -8.341e+05   7.85e+04    -10.623      0.000   -9.88e+05    -6.8e+05
neighborhood[T.Blueste] -1.713e+04   1.09e+04     -1.572      0.116   -3.85e+04    4239.347
neighborhood[T.BrDale]  -2.471e+04   9000.007     -2.745      0.006   -4.24e+04   -7052.075
neighborhood[T.BrkSide] -1532.4518   8096.964     -0.189      0.850   -1.74e+04    1.43e+04
neighborhood[T.ClearCr]  8014.4751   8662.334      0.925      0.355   -8976.144      2.5e+04
neighborhood[T.CollgCr]    87.4515   7385.889      0.012      0.991   -1.44e+04    1.46e+04
neighborhood[T.Crawfor]  1.561e+04   8040.486      1.942      0.052    -158.060    3.14e+04
neighborhood[T.Edwards] -8651.3826   7681.778     -1.126      0.260   -2.37e+04    6415.938
neighborhood[T.Gilbert]  2292.6064   7583.504      0.302      0.762   -1.26e+04    1.72e+04
neighborhood[T.Greens]   -391.6243    1.14e+04     -0.034      0.973   -2.28e+04      2.2e+04
neighborhood[T.GrnHill]  1.171e+05    2.26e+04     5.172      0.000    7.27e+04    1.62e+05
neighborhood[T.IDOTRR]  -8670.2039   8490.853     -1.021      0.307   -2.53e+04    7984.067
neighborhood[T.MeadowV] -2.211e+04   8677.187     -2.548      0.011   -3.91e+04   -5088.364
neighborhood[T.Mitchel] -8381.0179   7719.579     -1.086      0.278   -2.35e+04    6760.447
neighborhood[T.NAmes]   -1.281e+04   7502.862     -1.708      0.088   -2.75e+04    1903.047
neighborhood[T.NPkVill] -2.497e+04   9031.525     -2.764      0.006   -4.27e+04   -7250.268
neighborhood[T.NWAmes]  -1.741e+04   7701.140     -2.261      0.024   -3.25e+04   -2308.925
neighborhood[T.NoRidge]  2.984e+04   8021.701      3.720      0.000    1.41e+04    4.56e+04
neighborhood[T.NridgHt]  4.205e+04   7700.404      5.461      0.000    2.69e+04    5.72e+04
neighborhood[T.OldTown]  -1.18e+04   7998.975     -1.475      0.141   -2.75e+04    3894.200
neighborhood[T.SWISU]   -1.393e+04   9062.906     -1.537      0.124   -3.17e+04    3845.856
neighborhood[T.Sawyer]  -1.182e+04   7707.552     -1.533      0.125   -2.69e+04    3299.222
neighborhood[T.SawyerW] -8603.3201   7619.053     -1.129      0.259   -2.35e+04    6340.971
neighborhood[T.Somerst]  1.368e+04   7582.818      1.804      0.071   -1196.262    2.86e+04
neighborhood[T.StoneBr]  2.836e+04   8440.220      3.360      0.001    1.18e+04    4.49e+04
neighborhood[T.Timber]   1.622e+04   8007.961      2.026      0.043     513.577    3.19e+04
neighborhood[T.Veenker]  8500.2699   9774.036      0.870      0.385   -1.07e+04    2.77e+04
qualityindex             1677.5519     67.639     24.801      0.000    1544.882    1810.222
totalsqftcalc              55.5622      1.530     36.320      0.000      52.562      58.563
totalbsmtsf                -8.2319      2.549     -3.230      0.001     -13.231      -3.233
garagearea                 39.6388      3.510     11.292      0.000      32.754      46.524
bsmtunfsf                  32.0698      1.997     16.059      0.000      28.153      35.987
yearbuilt                 415.4386     39.110     10.622      0.000     338.728     492.149
==============================================================================
Omnibus:                      204.301   Durbin-Watson:                   1.957
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              853.462
Skew:                           0.533   Prob(JB):                    4.71e-186
Kurtosis:                       6.364   Cond. No.                     4.61e+05
==============================================================================
```

The above model was the best one I created. It scored a 41,973 on Kaggle. I used neighborhood, qualityindex, totalsqftcalc, totalbsmtsf, garagearea, bsmtunfsf and yearbuilt. It was also the same model I did the log transformation on with the response variable. Overall, this model had the best R-Squared, AIC and BIC scores.

Neighborhood Accuracy

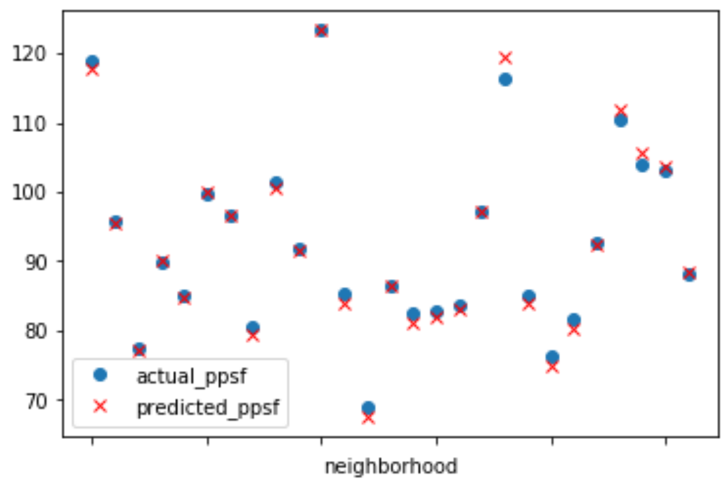
The neighborhood accuracy was the most challenging and rewarding part of the assignment. The python code I used allowed me to map the neighborhoods to indicator variables. This was done after looking at the boxplot of residuals below. According to the box plot NridgHt,Crawfor and StoneBr were some of the most overpredicted markets. Timber was one of the most underpredicted markets. OldTown and Sawyer appear to have some of the better fits by residual.



Below is the actual and estimated mean price per square foot for each neighborhood that I was able to get through python. I grouped the neighborhoods by three groups and went in descending order based on actual price per sq. foot. Below is the output table. I also did a plot of actual vs. predicted below to help with a visual of the data.

	neighborhood	actual_ppsf	predicted_ppsf	Neighborhood_Group
0	GrnHill	123.318386	123.318386	1
1	Blmngtn	118.892612	117.839159	1
2	NridgHt	116.384053	119.373685	1
3	Somerst	110.542232	111.702139	1
4	StoneBr	103.866523	105.737218	1
5	Timber	103.230292	103.698200	1
6	Gilbert	101.491760	100.569597	1
7	CollgCr	99.736694	99.986461	1
8	NoRidge	97.265357	97.242276	1
9	Crawfor	96.726724	96.512449	2
10	Blueste	95.722814	95.435617	2
11	SawyerW	92.704506	92.312512	2

12	Greens	91.696116	91.476015	2
13	BrkSide	89.799890	90.008079	2
14	Veenker	88.186158	88.504960	2
15	Mitchel	86.356609	86.364205	2
16	IDOTRR	85.426961	83.905890	2
17	OldTown	85.169046	83.848181	2
18	ClearCr	85.027752	84.657259	3
19	NWAmes	83.790941	83.103876	3
20	NPkVill	82.931444	82.055189	3
21	NAmes	82.390030	81.178871	3
22	Sawyer	81.652367	80.182541	3
23	Edwards	80.688669	79.396191	3
24	BrDale	77.510648	77.060749	3
25	SWISU	76.376106	75.010812	3
26	MeadowV	68.985885	67.620480	3



In order to get a clear idea of how my groupings affected the model, I refit the new variables against the response variable and compared the results below. My group 1 (highest cost per square foot0 ended up being selected as the reference. Overall the AIC and BIC stayed consistent, but the R-squared score decreased and was not good.

```
OLS Regression Results
==============================================================================
Dep. Variable:                      Y   R-squared:                       0.313
Model:                            OLS   Adj. R-squared:                  0.313
Method:                 Least Squares   F-statistic:                     374.7
Date:                Thu, 14 Feb 2019   Prob (F-statistic):          8.74e-135
Time:                        01:51:37   Log-Likelihood:                -20278.
No. Observations:                1645   AIC:                         4.056e+04
Df Residuals:                    1642   BIC:                         4.058e+04
Df Model:                           2
Covariance Type:            nonrobust
=========================================================================================
                            coef    std err          t      P>|t|      [0.025      0.975]
-----------------------------------------------------------------------------------------
Intercept              2.284e+05   2444.625     93.419      0.000    2.24e+05    2.33e+05
Neighborhood_Group[T.2] -7.531e+04  3473.028    -21.686      0.000   -8.21e+04   -6.85e+04
Neighborhood_Group[T.3] -8.333e+04  3247.329    -25.661      0.000   -8.97e+04    -7.7e+04
==============================================================================
Omnibus:                      379.662   Durbin-Watson:                   1.984
```

```
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              947.769
Skew:                           1.234   Prob(JB):                    1.57e-206
Kurtosis:                       5.781   Cond. No.                         3.91
==============================================================================
```

Section 2. Model Comparison of Y versus log(y)

I went back and used my best performing Kaggle model, which was number five for the log comparison section. I will re-copy the table down below here for reference along with the log transformed one. The corresponding VIF scores are also right below the print outs. The VIF scores were the same for both versions of the model and nothing was significant enough to justify dropping any attributes. Overall, the log transformed model had the highest R-squared score but also had high AIC and BIC scores. I was not able to test that model on Kaggle and get a proper score to compare to the one that I got for the non-log version. Overall, I believe that the log transformation does a good job of normalizing the variables as witnessed by the improved p-values. Due to the high AIC and BIC scores of the log transformed model, I would have to keep the original as the better fitting model. After seeing the results below, I can't justify doing another log transform to a response variable. It would change what this model is trying to predict as well. Overall, I think that log transforms are best done on large continuous variables that have a significant variance. That could improve the model fit, depending on the situation.

```
OLS Regression Results (non-log)
==============================================================================
Dep. Variable:              saleprice   R-squared:                       0.896
Model:                            OLS   Adj. R-squared:                  0.894
Method:                 Least Squares   F-statistic:                     435.3
Date:                Thu, 14 Feb 2019   Prob (F-statistic):               0.00
Time:                        01:19:46   Log-Likelihood:                -18723.
No. Observations:                1645   AIC:                         3.751e+04
Df Residuals:                    1612   BIC:                         3.769e+04
Df Model:                          32
Covariance Type:            nonrobust
===========================================================================================
                              coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------------------
Intercept               -8.341e+05   7.85e+04    -10.623      0.000   -9.88e+05    -6.8e+05
neighborhood[T.Blueste] -1.713e+04   1.09e+04     -1.572      0.116   -3.85e+04    4239.347
neighborhood[T.BrDale]  -2.471e+04   9000.007     -2.745      0.006   -4.24e+04   -7052.075
neighborhood[T.BrkSide] -1532.4518   8096.964     -0.189      0.850   -1.74e+04    1.43e+04
neighborhood[T.ClearCr]  8014.4751   8662.334      0.925      0.355   -8976.144     2.5e+04
neighborhood[T.CollgCr]    87.4515   7385.889      0.012      0.991   -1.44e+04    1.46e+04
neighborhood[T.Crawfor]  1.561e+04   8040.486      1.942      0.052    -158.060    3.14e+04
neighborhood[T.Edwards] -8651.3826   7681.778     -1.126      0.260   -2.37e+04    6415.938
neighborhood[T.Gilbert]  2292.6064   7583.504      0.302      0.762   -1.26e+04    1.72e+04
neighborhood[T.Greens]   -391.6243    1.14e+04     -0.034      0.973   -2.28e+04     2.2e+04
neighborhood[T.GrnHill]  1.171e+05    2.26e+04     5.172      0.000    7.27e+04    1.62e+05
neighborhood[T.IDOTRR]  -8670.2039   8490.853     -1.021      0.307   -2.53e+04    7984.067
neighborhood[T.MeadowV] -2.211e+04   8677.187     -2.548      0.011   -3.91e+04   -5088.364
neighborhood[T.Mitchel] -8381.0179   7719.579     -1.086      0.278   -2.35e+04    6760.447
neighborhood[T.NAmes]   -1.281e+04   7502.862     -1.708      0.088   -2.75e+04    1903.047
neighborhood[T.NPkVill] -2.497e+04   9031.525     -2.764      0.006   -4.27e+04   -7250.268
neighborhood[T.NWAmes]  -1.741e+04   7701.140     -2.261      0.024   -3.25e+04   -2308.925
neighborhood[T.NoRidge]  2.984e+04   8021.701      3.720      0.000    1.41e+04    4.56e+04
neighborhood[T.NridgHt]  4.205e+04   7700.404      5.461      0.000    2.69e+04    5.72e+04
neighborhood[T.OldTown]  -1.18e+04   7998.975     -1.475      0.141   -2.75e+04    3894.200
neighborhood[T.SWISU]   -1.393e+04   9062.906     -1.537      0.124   -3.17e+04    3845.856
neighborhood[T.Sawyer]  -1.182e+04   7707.552     -1.533      0.125   -2.69e+04    3299.222
neighborhood[T.SawyerW] -8603.3201   7619.053     -1.129      0.259   -2.35e+04    6340.971
neighborhood[T.Somerst]  1.368e+04   7582.818      1.804      0.071   -1196.262    2.86e+04
neighborhood[T.StoneBr]  2.836e+04   8440.220      3.360      0.001    1.18e+04    4.49e+04
neighborhood[T.Timber]   1.622e+04   8007.961      2.026      0.043     513.577    3.19e+04
```

```
neighborhood[T.Veenker]  8500.2699   9774.036      0.870      0.385   -1.07e+04    2.77e+04
qualityindex             1677.5519     67.639     24.801      0.000    1544.882    1810.222
totalsqftcalc              55.5622      1.530     36.320      0.000      52.562      58.563
totalbsmtsf                -8.2319      2.549     -3.230      0.001     -13.231      -3.233
garagearea                 39.6388      3.510     11.292      0.000      32.754      46.524
bsmtunfsf                  32.0698      1.997     16.059      0.000      28.153      35.987
yearbuilt                 415.4386     39.110     10.622      0.000     338.728     492.149
==============================================================================
Omnibus:                      204.301   Durbin-Watson:                   1.957
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              853.462
Skew:                           0.533   Prob(JB):                    4.71e-186
Kurtosis:                       6.364   Cond. No.                     4.61e+05
```

This is the VIF for Model 5 non-log

```
Intercept                  22053.844215
neighborhood[T.Blueste]        1.800078
neighborhood[T.BrDale]         2.963730
neighborhood[T.BrkSide]        9.946482
neighborhood[T.ClearCr]        3.542099
neighborhood[T.CollgCr]       16.752300
neighborhood[T.Crawfor]        8.777780
neighborhood[T.Edwards]       14.713771
neighborhood[T.Gilbert]       10.193750
neighborhood[T.Greens]         1.694636
neighborhood[T.GrnHill]        1.114889
neighborhood[T.IDOTRR]         5.670744
neighborhood[T.MeadowV]        3.554256
neighborhood[T.Mitchel]        8.210373
neighborhood[T.NAmes]         27.629309
neighborhood[T.NPkVill]        2.810689
neighborhood[T.NWAmes]         9.115227
neighborhood[T.NoRidge]        5.992755
neighborhood[T.NridgHt]        7.932105
neighborhood[T.OldTown]       19.082966
neighborhood[T.SWISU]          3.529132
neighborhood[T.Sawyer]        10.876325
neighborhood[T.SawyerW]        9.036756
neighborhood[T.Somerst]        9.404371
neighborhood[T.StoneBr]        3.663966
neighborhood[T.Timber]         5.044072
neighborhood[T.Veenker]        2.270085
qualityindex                   1.305557
totalsqftcalc                  3.637908
totalbsmtsf                    1.917187
grlivarea                      3.053692
garagearea                     1.765713
yearbuilt                      4.740209
```

```
OLS Regression Results Log Version
==============================================================================
Dep. Variable:          log_saleprice   R-squared:                       0.918
Model:                            OLS   Adj. R-squared:                  0.917
Method:                 Least Squares   F-statistic:                     565.4
Date:                Thu, 14 Feb 2019   Prob (F-statistic):               0.00
Time:                        02:31:08   Log-Likelihood:                 1424.0
No. Observations:                1645   AIC:                            -2782.
Df Residuals:                    1612   BIC:                            -2604.
Df Model:                          32
Covariance Type:            nonrobust
===========================================================================================
                              coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------------------
Intercept                   5.3755      0.377     14.274      0.000       4.637       6.114
neighborhood[T.Blueste]    -0.1215      0.052     -2.324      0.020      -0.224      -0.019
neighborhood[T.BrDale]     -0.2343      0.043     -5.427      0.000      -0.319      -0.150
neighborhood[T.BrkSide]    -0.0546      0.039     -1.406      0.160      -0.131       0.022
neighborhood[T.ClearCr]     0.0473      0.042      1.138      0.255      -0.034       0.129
neighborhood[T.CollgCr]    -0.0113      0.035     -0.320      0.749      -0.081       0.058
```

neighborhood[T.Crawfor]	0.0833	0.039	2.159	0.031	0.008	0.159
neighborhood[T.Edwards]	-0.0958	0.037	-2.600	0.009	-0.168	-0.024
neighborhood[T.Gilbert]	0.0225	0.036	0.620	0.535	-0.049	0.094
neighborhood[T.Greens]	0.0169	0.055	0.309	0.757	-0.090	0.124
neighborhood[T.GrnHill]	0.4632	0.109	4.264	0.000	0.250	0.676
neighborhood[T.IDOTRR]	-0.1277	0.041	-3.136	0.002	-0.208	-0.048
neighborhood[T.MeadowV]	-0.2588	0.042	-6.218	0.000	-0.340	-0.177
neighborhood[T.Mitchel]	-0.0417	0.037	-1.126	0.260	-0.114	0.031
neighborhood[T.NAmes]	-0.0674	0.036	-1.873	0.061	-0.138	0.003
neighborhood[T.NPkVill]	-0.1414	0.043	-3.264	0.001	-0.226	-0.056
neighborhood[T.NWAmes]	-0.0779	0.037	-2.109	0.035	-0.150	-0.005
neighborhood[T.NoRidge]	0.0254	0.038	0.660	0.510	-0.050	0.101
neighborhood[T.NridgHt]	0.0661	0.037	1.789	0.074	-0.006	0.139
neighborhood[T.OldTown]	-0.1186	0.038	-3.091	0.002	-0.194	-0.043
neighborhood[T.SWISU]	-0.0756	0.043	-1.740	0.082	-0.161	0.010
neighborhood[T.Sawyer]	-0.0704	0.037	-1.904	0.057	-0.143	0.002
neighborhood[T.SawyerW]	-0.0502	0.037	-1.373	0.170	-0.122	0.022
neighborhood[T.Somerst]	0.0370	0.036	1.018	0.309	-0.034	0.108
neighborhood[T.StoneBr]	0.0585	0.040	1.444	0.149	-0.021	0.138
neighborhood[T.Timber]	0.0368	0.038	0.959	0.338	-0.039	0.112
neighborhood[T.Veenker]	0.0055	0.047	0.118	0.906	-0.086	0.097
qualityindex	0.0106	0.000	32.798	0.000	0.010	0.011
totalsqftcalc	0.0003	7.34e-06	40.605	0.000	0.000	0.000
totalbsmtsf	-6.66e-05	1.22e-05	-5.448	0.000	-9.06e-05	-4.26e-05
garagearea	0.0002	1.68e-05	13.028	0.000	0.000	0.000
bsmtunfsf	0.0002	9.58e-06	19.992	0.000	0.000	0.000
yearbuilt	0.0028	0.000	15.136	0.000	0.002	0.003

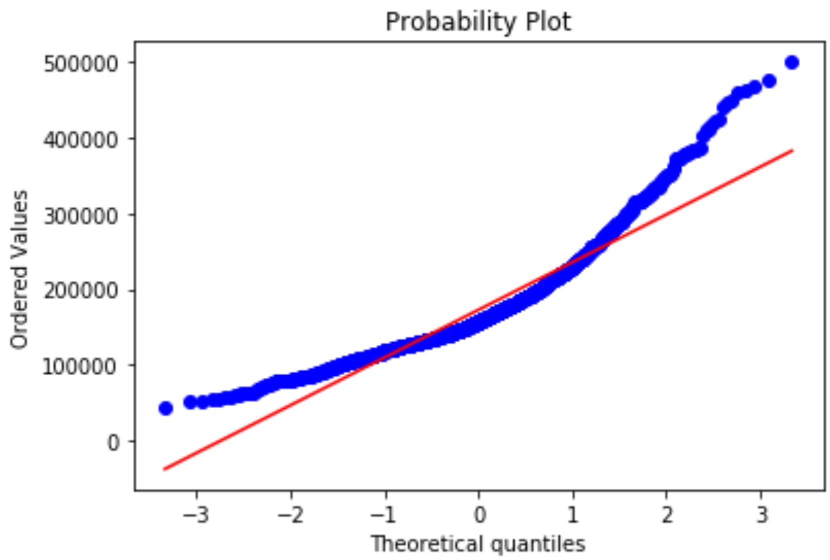
Omnibus:	71.332	Durbin-Watson:	1.969
Prob(Omnibus):	0.000	Jarque-Bera (JB):	197.438
Skew:	-0.158	Prob(JB):	1.34e-43
Kurtosis:	4.668	Cond. No.	4.61e+05

<u>This is the VIF for Model 5 (Log-Transformed Model)</u>

Intercept	22053.844215
neighborhood[T.Blueste]	1.800078
neighborhood[T.BrDale]	2.963730
neighborhood[T.BrkSide]	9.946482
neighborhood[T.ClearCr]	3.542099
neighborhood[T.CollgCr]	16.752300
neighborhood[T.Crawfor]	8.777780
neighborhood[T.Edwards]	14.713771
neighborhood[T.Gilbert]	10.193750
neighborhood[T.Greens]	1.694636
neighborhood[T.GrnHill]	1.114889
neighborhood[T.IDOTRR]	5.670744
neighborhood[T.MeadowV]	3.554256
neighborhood[T.Mitchel]	8.210373
neighborhood[T.NAmes]	27.629309
neighborhood[T.NPkVill]	2.810689
neighborhood[T.NWAmes]	9.115227
neighborhood[T.NoRidge]	5.992755
neighborhood[T.NridgHt]	7.932105
neighborhood[T.OldTown]	19.082966
neighborhood[T.SWISU]	3.529132
neighborhood[T.Sawyer]	10.876325
neighborhood[T.SawyerW]	9.036756
neighborhood[T.Somerst]	9.404371
neighborhood[T.StoneBr]	3.663966
neighborhood[T.Timber]	5.044072
neighborhood[T.Veenker]	2.270085
qualityindex	1.305557
totalsqftcalc	3.720253
totalbsmtsf	3.625469
garagearea	1.765713
bsmtunfsf	2.388449
yearbuilt	4.740209

Goodness of Fit

To check the goodness of fit, I built the QQ plot below. The data looks to be normal distributed with a skewness to the upper half, as the residual line starts to elevate from the regression line. I don't see enough to alarm me that a possible change would need to be made.



Section 3. Select Models

I used a multitude of criteria to select the best model. Overall, I relied on the Kaggle testing and scoring tool as my main means of section. The best score was received by Model 5 which was a score of 41973.798. It also had some of the best AIC/BIC scores and also the best R-squared score. I attached a table below with summary stats from the OLS outputs.

	Model 1	Model 2	Model 3	Model 4	**Model 5**
R sq.	0.808	0.802	0.802	0.794	**0.896**
AIC	4.85E+04	4.85E+04	3.85E+04	3.86E+04	**3.75E+04**
BIC	4.88E+04	4.87E+04	3.86E+04	3.86E+04	**3.77E+04**

Section 4. Model Formula

For the model I choose some of the variables will have to be referred back to the coefficient table for the output. For example ,which neighborhood a person lived in. I used the OLS output for model 5 to get the formula based on coefficients. First, I had to start with the intercept coefficient and work down from there.

p_salesprice = -834100 + or - the neighborhood coefficient value multiplied + (1677.5519 * qualityindex) + (55.5622*totalsqftcalc) – (8.2319*totalbsmtsf) + (39.6388*garagearea) + (32.0698*bsmtunfsf) + (415.4386*yearbuilt)

Section 5. Scored Data File

This was submitted to canvas with extra files.

Conclusion

This exercise was an excellent opportunity to blend together all of the techniques learned so far in the class to build a successful model. There was significant improvement from the first assignment to the most recent one in model predictive capabilities. By using different techniques like a correlation matrix or other tools from sklearn, I was able to build a more accurate predictive model. A seven variable model called Model 5 ended up being the best choice for this project. The continous variables seemed to be the most accurate predictors for the model with the the help of some ordinal values. A good data cleaning up front helped to make sure the model was able to perform as well. In this case, I got rid of the erroneous zoning attributes that didn't make sense for the model along with outliars in lotarea, salesprice, sale condition and totalsqftcalc. I would be curious to see what my model what do in real life if given the change to apply the same model to recently sold houses today in that market. Overall, this model should be accurate based on the train and test data. I used a QQ plot and other visuals as well to verify the results and eliminate outliers.