**MSDS 6372 Project 1**

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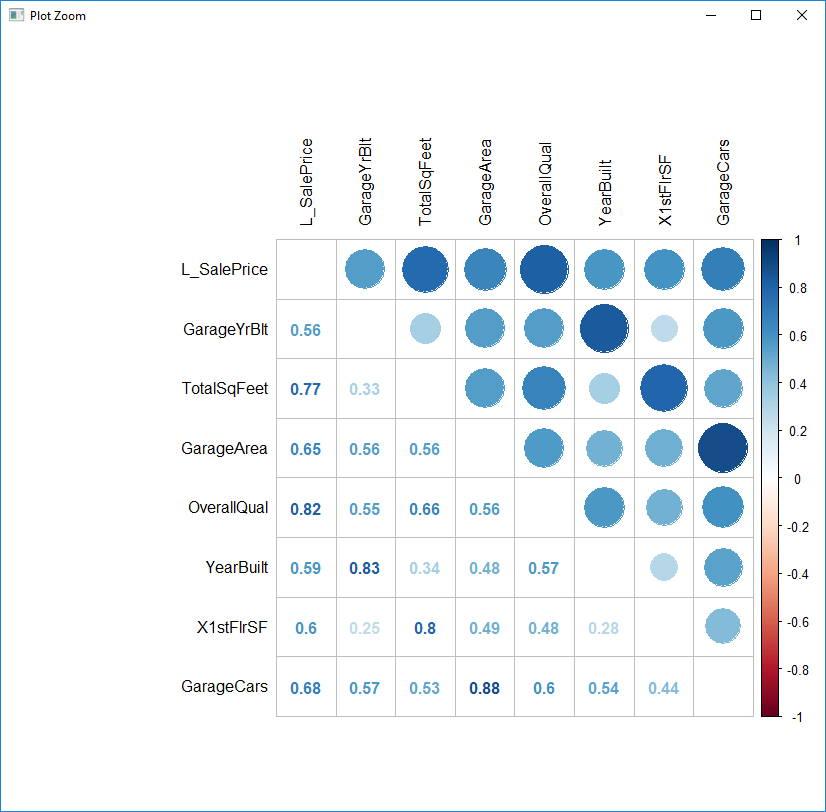
1. **Introduction**

With the large number of houses available on the market it is difficult to have a professional go through a home and come up with a reasonable price for a home. Our goal is create a few models that will allow houses to be quickly and accurately priced. To accomplish this goal, we have worked on some detailed EDA and many different modeling techniques to identify an algorithm that performs better with a train/test sets RMSE-score. Two of our models will be complex with the third being easy to explain in order to allow people to quickly see what the most important things are that relate to the SalePrice of their home.

1. **Data Description**

This dataset is from the Ames area of Idaho and contains 1460 observations with 79 explanatory variables and one response variable called “SalePrice”. Each one of these explanatory variables describes nearly every aspect of the residential homes in that area. For more information about the dataset go to Kaggle’s website (https://www.kaggle.com/c/house-prices-advanced-regression-techniques).

1. **Exploratory Analysis**



[**CHART 3.1**]

The initial examination of the data resulted in finding approximately 19 columns have missing data. We examined each of these and fixed those with logical values (EX: with Fence being NA, it is assumed that there is no fence). Next we removed columns that had factors that had problems with their levels (EX: Utilities had two levels, 1459 of the rows were of one level and the final row was of the other level). Examining a scatterplot of the variables lead us to take a log transform the response variable. Removal of columns that had too much missing data and the consolidation of redundant columns were next. We examined the correlation plots [CHART 3.1] and removed a few highly correlated columns that were describing similar attributes. At this point the data was clean so we moved on to the model building analysis.

1. **Objective 1**
2. **Problem Restatement**

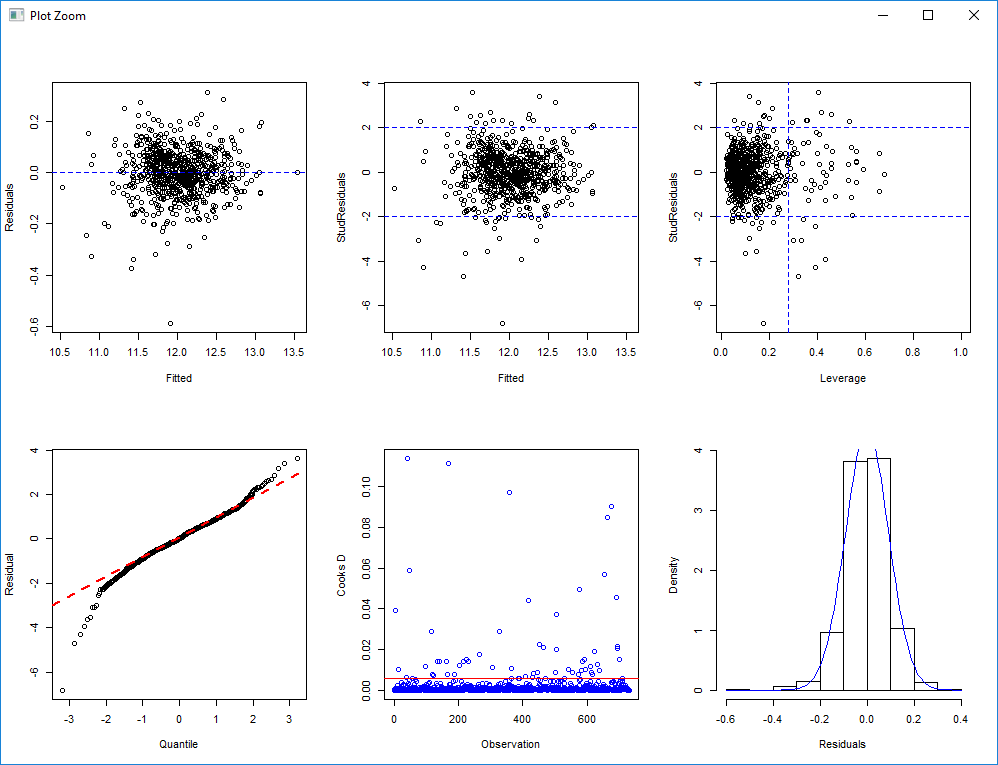
…and the overall approach to solve it

1. **Build and Fit Models**

For our analysis we built three different models. Two of them were built with automatic selection algorithms: stepwise and lasso. The other model is custom and was designed to be easily interpretable.

**Stepwise**

For the creation of the stepwise model we removed a few categorical parameters that did not have enough of certain levels to do testing upon them. Also we included the interaction terms: Neighborhood\*LotArea, Neighborhood\*GarageCars, TotalSqFeet\*FullBath, TotalSqFeet \*GarageCars, TotalSqFeet \*BedroomAbvGr, and Neighborhood\*OverallCond. When doing the selection we also ran into an issue with the categorical variables BsmtQual/BsmtExposure being correlated and GarageQual/GarageCond being correlated. We removed BsmtQual and GarageCond to fix this. In the end, the stepwise model selected 33 of the variables and 1 interaction. Those variables are: MSZoning, LotArea, Street, LandContour, LandSlope, Neighborhood, Condition1, BldgType, OverallQual, OverallCond, YearBuilt, RoofMatl, ExterQual, Foundation, BsmtExposure, BsmtFinSF1, BsmtFinSF2, BsmtUnfSF, CentralAir, LowQualFinSF, AllFullBath, AllHalfBaths, KitchenAbvGr, KitchenQual, FireplaceQu, GarageCars, GarageQual, WoodDeckSF, OpenPorchSF, ScreenPorch, MiscVal, SaleCondition, TotalSqFeet, and one the interaction term GarageCars\*TotalSqFeet. The initial model seemed to have a small problem with normality with an outlier. We ran it again without that outlier and looked at the results. Normality and constant variance were slightly better, but the Adjusted R-Squared value was slightly worse. We decided to leave the point in and continue with our analysis.

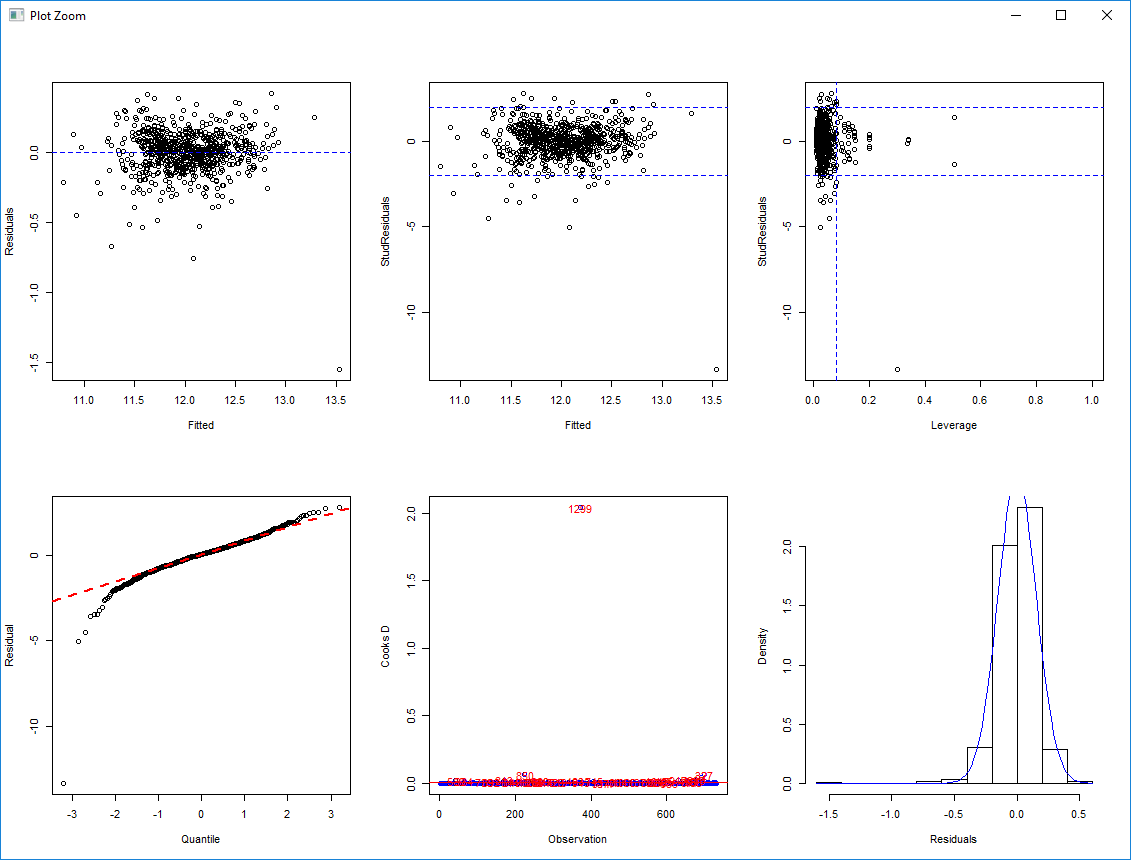


**[CHART 4.b.1]**

Checking the VIF’s resulted in the values all being between 1.06 and 6.9 which indicated no multicollinearity. The residual plot indicates that except for a few outliers (which we decided to keep in the initial stage of analyzing this model) there is constant variance. The data is a bit non-normally distributed with a small tail at the beginning. This is fine because (as seen in the histogram) there few outliers. We will assume independence, although due to the nature of house pricing this is in suspect. As mentioned earlier, there are a few minor outliers. However because these outliers are minor and out of 1480 total, their influence is low so we included this point.

**Custom**

The custom model was to be one that is simple to understand and interpret. For this model we took the variables that were the most significantly correlated with L\_SalePrice and also a few sensible ones. The model consists of OverallQual, TotalSqFeet, GarageCars, AllFullBath, Neighborhood, and OverallCond. The initial model had a severely outlying value. After analyzing the row there is no error in that recording so we proceeded to do the test without it to see the result. Without the point normality and the adjusted r-squared appeared worse but Cook’s D and Leverage was be better. Because this is just a single point out of 1480, its influence is low so we continued our analysis with the point included.

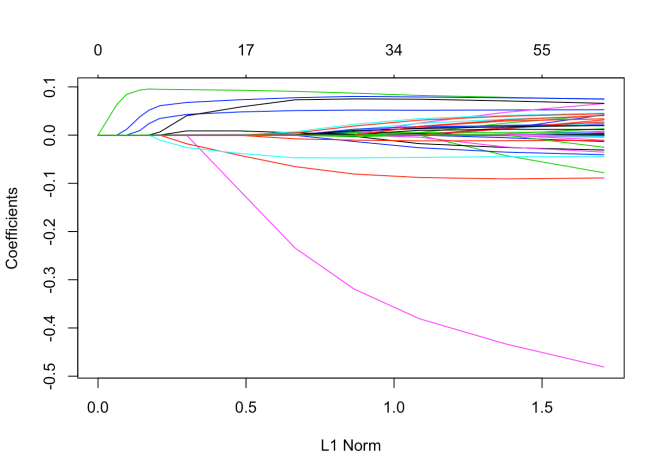


**[CHART 4.b.2]**

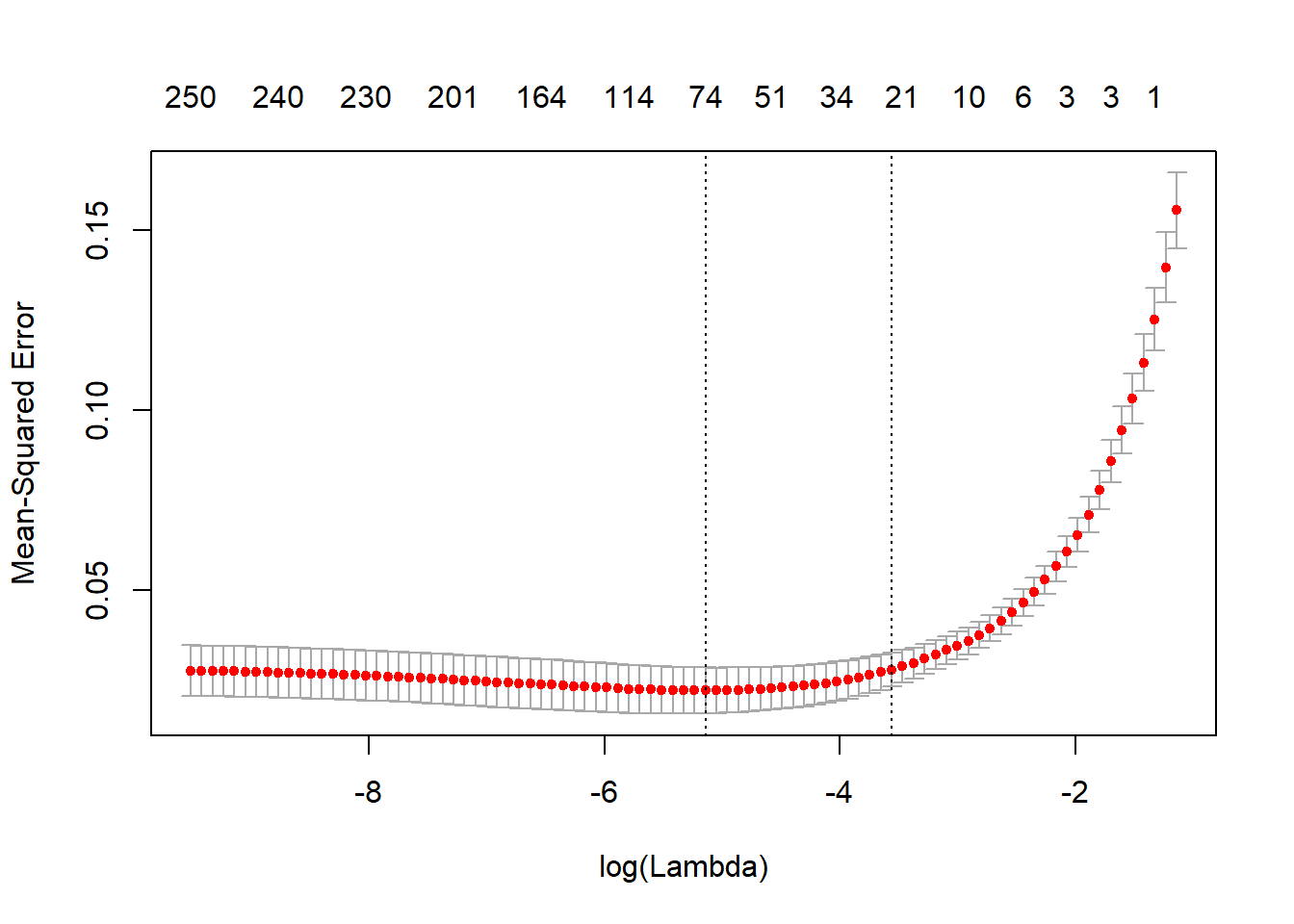
The VIF’s are very low and nearly identical with the values ranging from 1.06 to 2.0. This indicates that there is no multicollinearity present. The residual plot indicates that except for a few outliers (which we decided to keep in the initial stage of analyzing this model) there is constant variance. The data is nearly normally distributed, with a bit of a tail at the beginning. This is fine because (as seen in the histogram) there few outliers. We will assume independence, although due to the nature of house pricing this is in suspect. As mentioned earlier, there is one major outlier. However this is just one point out of 1480, its influence is low so we continued our analysis with the point included.

**Lasso**

Since we are dealing with high-dimensional data set, we have used the shrinkage model Lasso to obtain the model with the least effect of predictors variance and colinearity. Lasso penalizes the model coefficient estimates, using Lambda tuning parameter, to reduce their variance which result in a better model fitting. Lasso's GLM-NET performs 10-fold CV to determine an optimal penalty parameter. The coefficients are easy to extract and making predictions are straight forward.

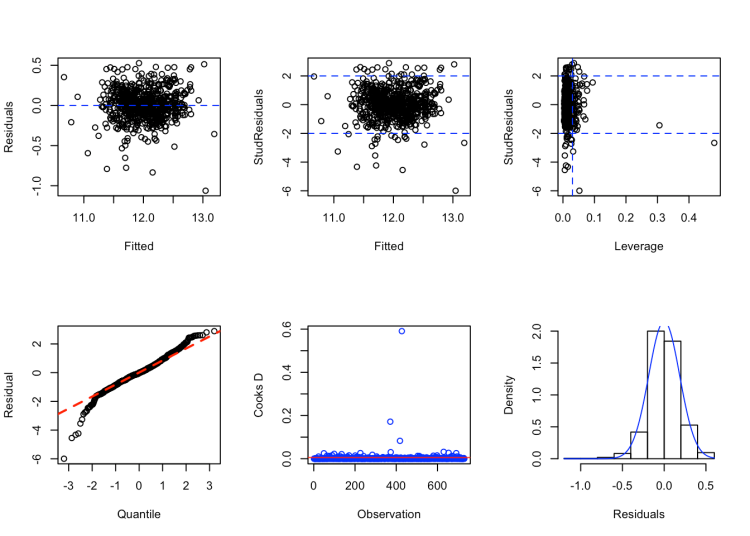


**[CHART 4.b.3]**



**[CHART 4.b.4]**

We can see from the coefficient plot **[CHART 4.b.3]** that depending on the choice of tuning parameter, some of the coefficients will be exactly equal to zero. We performed cross validation and examined the test error. The number of non-zero coefficients that the Lasso Regression picked is 56 **[CHART 4.b.4]**. From this list of coefficients we selected the top ten variables that were the most significantly correlated with L\_SalePrice and ran a LM model on those. The model consists of MSSubClass, LotArea, OverallQual, OverallCond, YearBuilt, YearRemodAdd, X2ndFlrSF, BedroomAbvGr, KitchenAbvGr, GarageCars.

**[CHART 4.b.5]**

On this model the VIF’s are very low and nearly identical (between 1.06 and 2.0), which indicates that there is no multicollinearity. The residual plot indicates that except for a few outliers (which we decided to keep in the initial stage of analyzing this model) there is constant variance. The data is nearly normally distributed, with a bit of a tail at the beginning. This is fine because (as seen in the histogram) there are few outliers. We will assume independence, although due to the nature of house pricing this is in suspect. As mentioned earlier there is one major and one minor outlier. However this is out of 1480 total rows which makes its influence low. Because of this so we continued our analysis with the points included.

1. **Comparing Models**

|  |  |  |
| --- | --- | --- |
|  | **RMSE** | **Adj-R2** |
| **Stepwise** | 36687 | 0.813 |
| **Lasso** | 40740 | 0.76 |
| **Custom** | 31489 | 0.86 |

**[CHART 4.c.1]**

For each of the models we generated an adjusted r-squared (Adj-R2) and the root mean squared error (RMSE) values. On the left [CHART 4.c.1] are those results. As you can see the Custom model performed best (RMSE: 31489). This is most likely due to our domain knowledge.

1. **Parameter Interpretation**

Interpretation

Confidence Intervals

1. **Conclusion**

Conclusions, insights, concerns, what to do better next time?

*Do better*: deal with zero inflation aka create dummy variables

1. **Objective 2**
2. **Goal of 2way ANOVA**

State what route you are going to take 2way ANOVA or Time series and summarize the goal.

1. **Analysis of 2way ANOVA**
2. **Conclusion/Discussion Required**

The conclusion should reprise the questions and conclusions of objective 2.

1. **Appendix**

Contains code and extra charts