MSDS 6372 Project 1

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Introduction

With big data on the rise, there is a greater interest in wanting to use statistical tools to predict home value and find out what factors are the most significant for a home buyer when buying a home. The obvious factors such as square feet and number of bathrooms may not actually be the most important factors when determining a sale price. Using a sample of home sales from Ames, Iowa, between 2006 and 2010, we explore the relationships between the various factors that affect sale price to determine both an intuitively simple model as well as a more complex and predictive model.

Data Description

The data comes from a Kaggle tournament taken from Ames Iowa. Dean De Cock, who compiled the dataset obtained the data directly from Ames City Assessor's Office. While there were over 100 variables in the initial dataset, the dataset used for this analysis features 79 different explanatory variables that required no special knowledge or previous calculations. The variables range from including information on "condition" and "roof type" to "size of living area".

A breakdown of just a few of the many notable variables:

- **`LotArea`** - Lot size in square feet
- **`SaleCondition`** - The type of sale (normal, foreclosure, etc)
- **`ScreenPorch`** - Screen porch area in square feet
- **`MasVnrArea`** - Masonry veneer area in square feet
- **`Condition1`** - Proximity to main road or railroad
- **`BldgType`** - Type of dwelling
- **`BsmtFinSF1`** - Type 1 finished square feet
- **`BsmtExposure`** - Walkout or garden level basement walls
- **`2ndFlrSF`** - Square feet of second floor
- **`GrLivArea`** - Above grade (ground) living area square feet
- **`RoofMatl`** - Roof material
- **`MSSubClass`**- Type of dwelling involved in the sale.

A complete list and explanation of all the variables looked at for this analysis are available in the appendix and Kaggle.com.

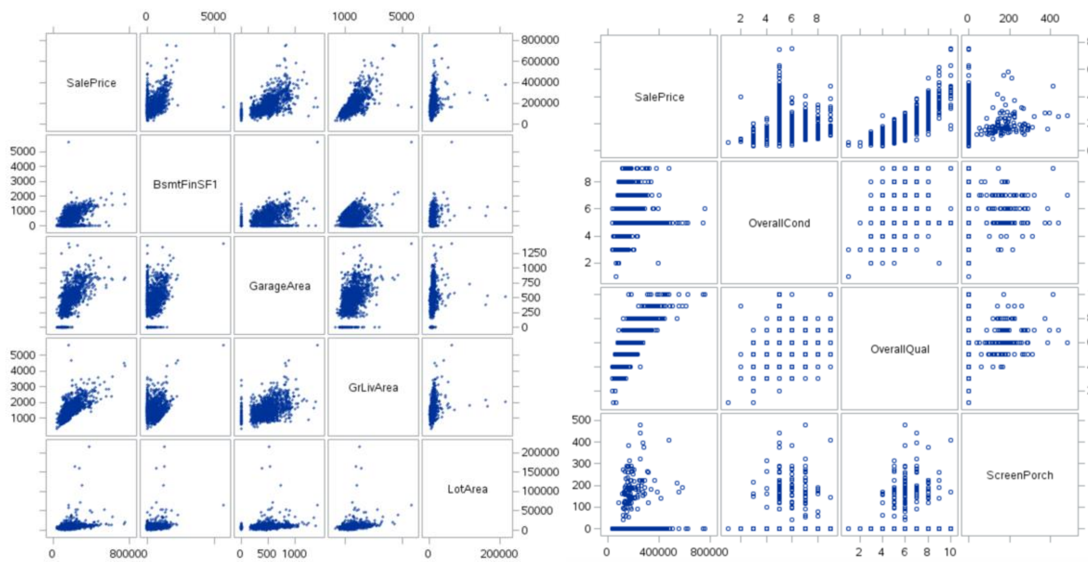
Exploratory Analysis

Before we begin with data exploration and look for correlation, we performed a deep dive into the data. Our objectives were to look for missing values, identify outliers, and design strategies to clean and address these issues. Using SAS scripts, we found over 80 missing values within the dataset. Our first order was to fill in the values based on the variable explanations provided by the Kaggle project. Wherever applicable, we used "NA", 0, or "None" where appropriate. In situations where "NA" has a specific meaning, we used "NT" as the identifier. In cases where the value is not obvious, we perform record-level reconciliation to evaluate the appropriate response. For example, the observation with `ID` *#1916* has a missing value in `Utilities`. Examining other observations with the same `Neighborhood` and similar characteristics such as `SalePrice`, `Street`, and `Alley`, we determined the most appropriate value for that record should be "AllPub".

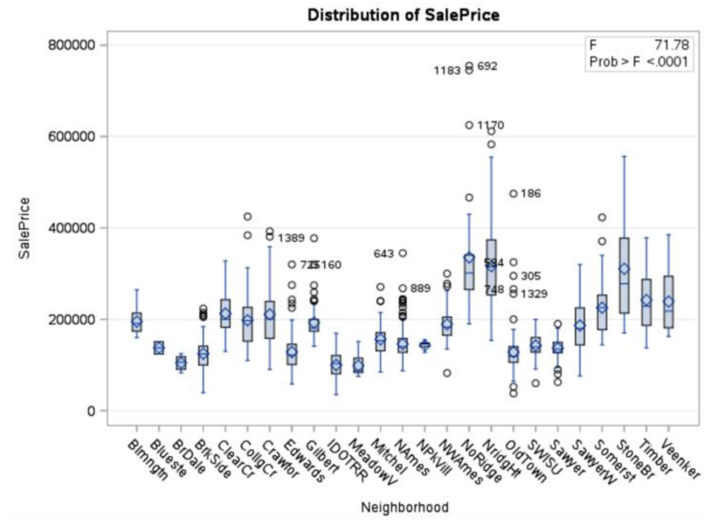
Through this process, we also identified other errors in the dataset. The observation with `ID` *#1299* has 4692 SqFt on the first level and 950 SqFt on the second level. However, it only has a total above ground area of 1426.9 SqFt. Due to this inconsistency beteen the `SalePrice`, `Neighborhood`, and `LotArea` explanatory variables, we were not able to determine which of the variables has the incorrect value thus we removed it from the train set.

In addition, we made sure that levels for factors in both the train and test set aligned. We identified that the observation with `ID` *#1556* (test set) has a `KitchenQual` value of "NA", which is not a recognized level in the train set. Using the same technique mentioned above, we assigned the specific value of "TA", a more appropriate identifier. A detailed list of changes is provided with the SAS code in the appendix and includes things like changing the spelling of the values that were different from the description like "Duplx" vs. "Duplex" for the `BldgType` variable. In all, heavy emphasis was placed on data wrangling prior to the start of the full statistical analysis.

After we had mostly exhausted all our data cleansing examinations, we began the actual data exploration to help construct a good model. The first step was reviewing the scatter plots. From the plots, we were able to immediately identify some correlations among different variables. There are also signs of large outliers and possibly covariation. As expected, the size of the living area above ground (`GrLivArea`) has a strong correlation with sale price (Pearson's "r" correlation ≈ 0.73). You can see in the scatter plots below that there appears to be a high correlation to `SalePrice` between many variables.

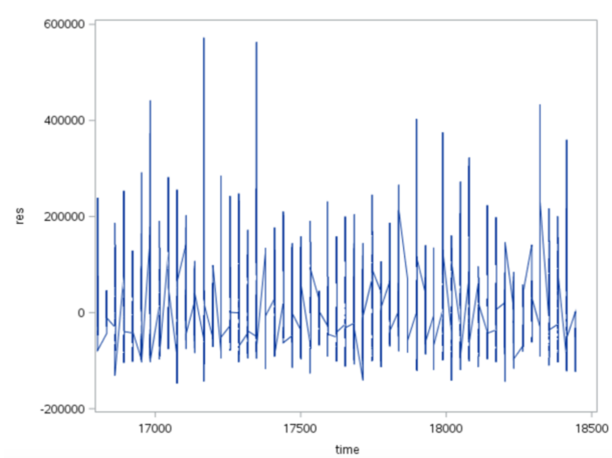


With `Neighborhood`, we theorized that there would be interesting interactions with other variables. We spent time analyzing its effect on `SalePrice`. As suspected, the location of the house has a large effect on the price of the home. One way to see this correlation is to simply look at the `SalePrice` vs. `Neighborhood`. The box-plots below show the variation in the price for each neighborhood.

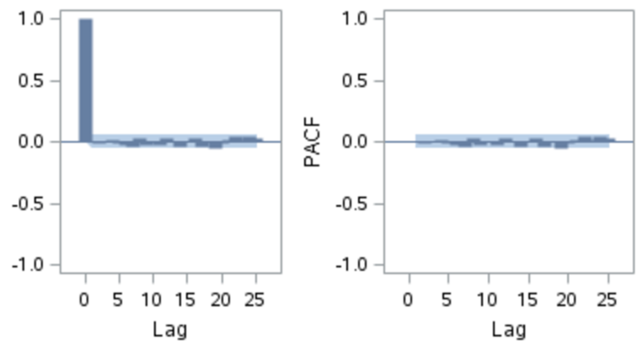


Serial Correlation

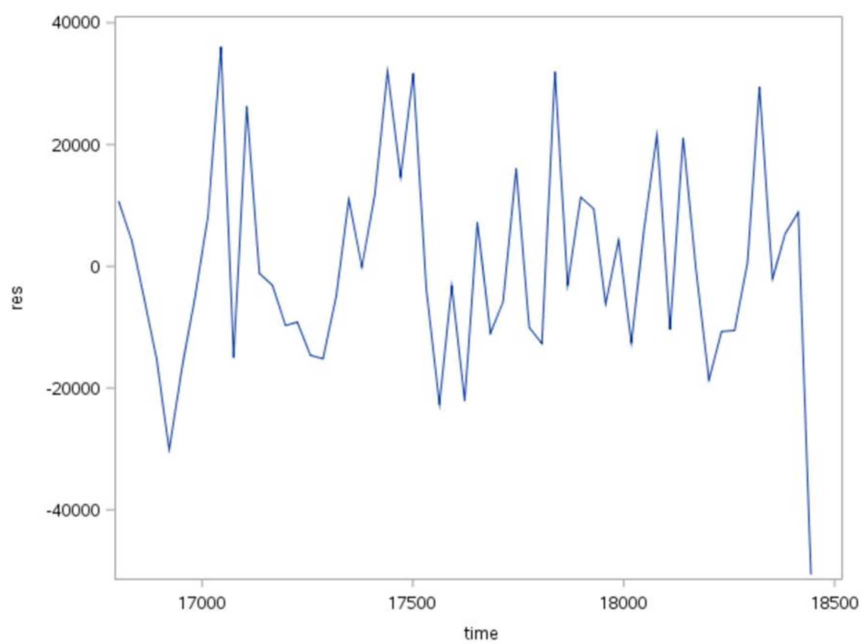
An analysis was done to determine if a serial correlation exists in our dataset using the month and year of the sale. A plot of the data shows no evidence of a serial correlation. Because we have 1460 observations in the train set, we are able to use a standard autocorrelation analysis to determine if this is just white noise.



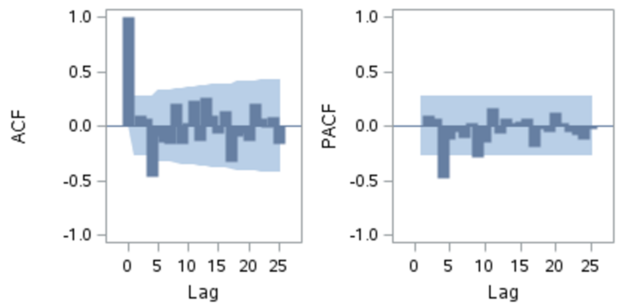
Looking at the ACF/PACF output (below) in the autocorrelation analysis, we see no evidence of a serial correlation. A Durbin-Watson statistic of 1.9994 supports this claim.



Further exploration will require us to consider if grouping the observations by the month and year sold in combination will prove a serial correlation for the means of each of these groups.



There is not overwhelming evidence for a positive correlation from a plot of residual vs. time (above), but we will use autocorrelation to make sure. Although much more evidence exists here, than above, we it is difficult to make a convincing argument for a first order autocorrelation.



A Durbin-Watson statistic of 1.81 and a Yule-Walker' Total R^2 of 0.09 seems to strongly suggest there is not a measurable serial correlation.

Analysis: Question 1

When searching for variables that most simply and powerfully model the sale price of a home, we compare various selection techniques: forward, backward, stepwise, and LASSO using cross validation. Because we are looking for a parsimonious model we chose to focus on variables produced by forward and stepwise selection methods. Using intuition and criterion compares, we then carefully examined the variables presented to us and removed variables that either overly-complicated the model or did not contribute to the model in a significant enough way. This is a subjective process, but ultimately does leave us with one "full model" which seems to do a good job of explaining a large portion of the variation in sale price with just 6 explanatory variables (4 categorical) and a total of 58 parameters. This gives us Model 1:

$$\text{SalePrice1} = \beta_0 + \beta_i\text{GrLivArea} + \beta_i\text{LotArea} + \beta_{ij}\text{MSSubClass} + \beta_{ij}\text{Neighborhood} + \beta_{ij}\text{OverallCond} + \beta_{ij}\text{OverallQual}$$

Where the parameter estimates are β_0, the intercept, with β_i and β_{ij} as corresponding parameter estimates for the variables and their levels. For instance, i corresponds to the variable; while j corresponds to the variable level. Each variable and variable level will have a different parameter estimate β_i or β_{ij}. Examples and tables of the values are provided below.

Exploring that perhaps the size of the living area of the house is more expensive depending on the neighborhood, we include an interaction term for

`Neighborhood*GrLivArea`. This increases the number of parameters to 82 and gives us Model 2:

$$\begin{aligned}\texttt{SalePrice2} = {} & \beta_0 + \beta_i\texttt{GrLivArea} + \beta_i\texttt{LotArea} + \beta_{ij}\texttt{MSSubClass} \\ & + \beta_{ij}\texttt{Neighborhood} + \beta_{ij}\texttt{OverallCond} + \beta_{ij}\texttt{OverallQual} \\ & + \beta_{ij}\texttt{Neighborhood*GrLivArea}\end{aligned}$$

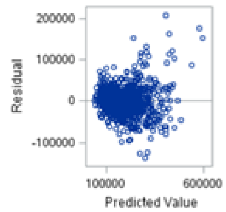
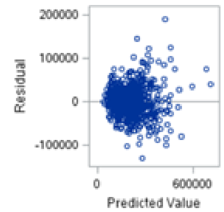
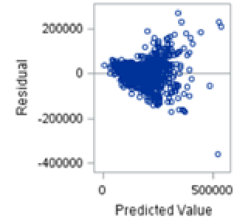
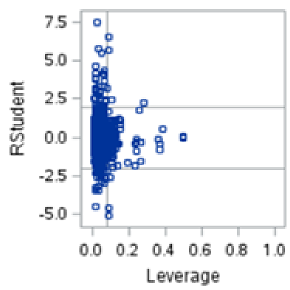
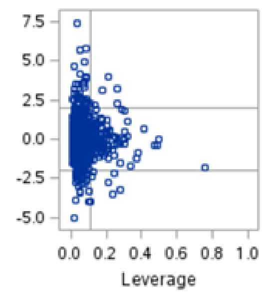
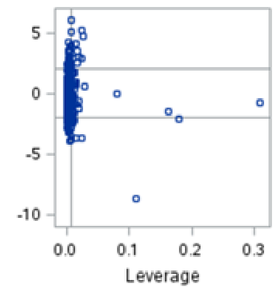
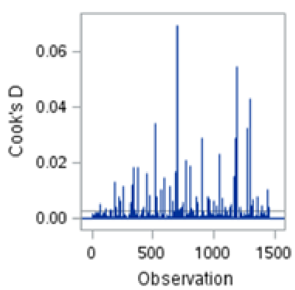
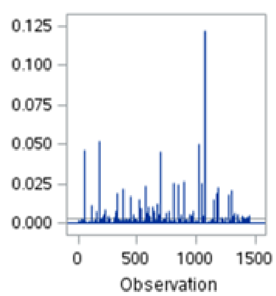
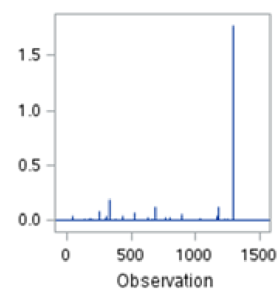
Taking a different approach, we look at an oversimplified model which includes no categorical variables, but only continuous variables. With only 5 parameters, this seems by far the easiest model to interpret but, as we will see, performs poorly compared to the other models. This gives us Model 3:

$$\begin{aligned}\texttt{SalePrice3} = {} & \beta_0 + \beta_i\texttt{FullBath} + \beta_i\texttt{GrLivArea} + \beta_i\texttt{LotArea} \\ & + \beta_i\texttt{TotalBsmtSF}\end{aligned}$$

Table 1 below provides a statistical comparison of the 3 models. The residual plots show similar patterns among the 3 model and provide little indication of which is better. All models seem to have a few outliers. One could argue that the first two models have the most "well formed" cluster around the 0 residual line.

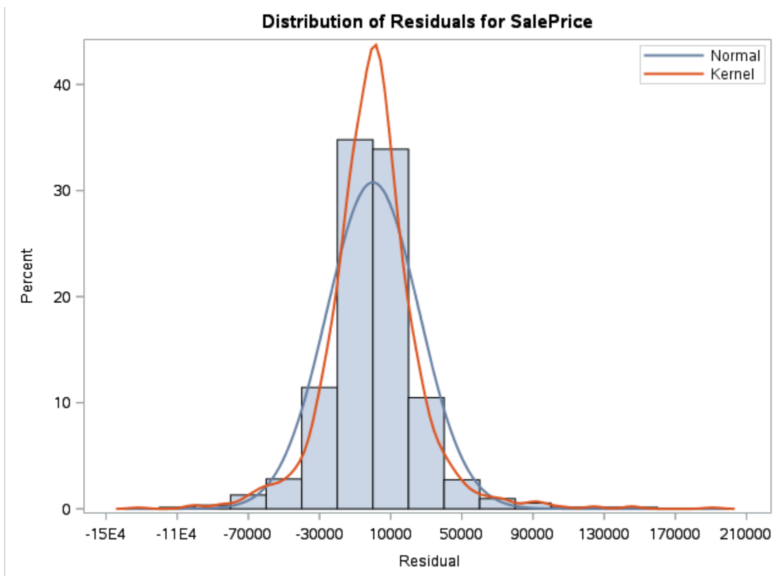
Looking at the Cook's D and RStudent plots from SAS, we can see that the first model appears to have the least number of influential outliers. The last model, in particular, has one observation which seems to be very influential and may need to be reviewed.

To explore whether multicollinearity is an issue for these models, we look at the tolerance values from SAS' PROC GLM output. Since tolerance = 1 / VIF, and VIF > 10 is generally considered to be an issue, we instead look for tolerance < 0.1. There were no multicollinearity issues detected in Model 1 and 3. In Model 2, we found isolated collinearity issues in the interaction term `Neighborhood*GrLivArea`. This is not surprising since Model 2 has Neighborhood now in two parts of the model. This sort of collinearity is expected and generally not a large issue.[1]

Table 1	Model Statistical comparison		
	Model 1	Model 2	Model 3
R-Squared	0.8747	0.8935	0.6782
Adj. R-Squared	0.8697	0.8873	0.6773
Coeff. of Variance	15.853	14.7406	24.9425
			
Studentized Residual			
Cooks'D			
AIC	31490	31350	32761
BIC	30035	29889	31301
CV PRESS	1.275728E12	1.180003E12	3.035844E12

Comparing our three models, Model 2 provides the best fit and makes the most sense. Although there was some concern about multicollinearity, the impact is small (24 interaction terms with average tolerance of 0.5). Model 2 provides a straightforward and easily interpretable picture of the significant factors that influence the final sale price of a home in Ames, Iowa.

In regards to our assumptions, the histogram of residuals (below) shows no evidence against equal spread, additionally we can assume independence of observations and a linear relationship between the explanatory variables and sale price.



It should be noted that LASSO and external cross validation techniques were used to help choose our models. However, LASSO proved difficult and unwieldy while a manual external cross validation turned out to be a very powerful technique that we used to fine tune our predictive model in question 2.

Interpretation of our final model:

SalePrice = 65170.95 + (54.58)GrLivArea + (0.68)LotArea
+ β_{ij}Neighborhood + β_{ij}OverallCond + β_{ij}OverallQual
+ β_{ij}Neighborhood*GrLivArea

In order to use this model, the user must have the information on the above variables. It is straightforward for continuous variables such as GrLivArea and LotArea. However, for the categorical variables, specific coefficients must be used (see Appendix I for a full list of parameter estimates, p-values, and confidence intervals). For example, assuming a house for sale with the following criteria:

```
GrLivArea = 2500 Sqft
LotArea = 5000 Sqft
MSSubClass = "50"
OverallCond = "7"
OverallQual = "6"
Neighborhood = "Gilbert"
```

The estimated `SalePrice = 65170.95 + 54.58*(2500) + 0.6753*(5000)`

```
        + (-9428.53) + (-31049.29) + (10926.21) + (12281.08)
        + 22.33*(2500)
                                                = $243,551.92
```

with a 95% confidence interval is ($100,727.90, $383,328.66)

The specific references for each categorical variable that were used for this specific example are MSSubClass (ref = "20"), Neighborhood (ref = "NAmes"), OverallCond (ref = "5"), OverallQual (ref = "5"). These references were chosen because the median sale price for these levels fell roughly in the middle of their respective categories.

The most important things about this model are its simplicity and parsimony. Out of the original 79 variables it was determined that only 6 were necessary to obtain an adjusted R^2 of almost 0.89. By itself `GrLivArea` produces an adjusted R^2 of 0.54, while the interaction of `GrLivArea` and `Neighborhood` alone in the model produce an adjusted R^2 of 0.78. In the final analysis, these variables were chosen because they form a model that fits the data nearly as well as the final model in question 2 with half the number of variables. This model helps to show to interested parties (such as real estate agents and prospective home buyers/sellers) the most significant factors that impact the sale price of a home. The coolest part is this model makes sense. Location and size of the house have always been thought to be the key price indicators when selling or buying a home. Add in the size of the house lot, the type of building (`MSSubClass)`, and the overall condition and quality of the home, and you can account for nearly 95% of the home's price.

Analysis: Question 2

For prediction, our first goal was to find a model that would minimize adjusted R^2. This led us to use a backward elimination of parameters, giving us a model with an adjusted R^2 of 0.95 (which includes 78 explanatory variables and 573 parameters). The complete model will not be included for brevity, but this will be considered to be Model 1 for prediction.

Unfortunately, Model 1 performed terribly when submitted in Kaggle. In fact, we were not even able to submit to Kaggle by itself as there were so many missing observations so we had to trim it down to get a score (thus the NA in the Kaggle submission summary for Model 1 below). We found that Model 1 was grossly overfitting the data. We continued to try different selection processes; LASSO, stepwise, forward, etc. It turns out that forward selection seemed to give us an initial model with the highest adjusted R^2 and overall best Kaggle score. We continued through this process but we were finding that the criterion from our own data (Adjusted R^2, AIC, etc.) seem to always overvalue our model when compared to what we got on Kaggle.

To compensate for the first model deficiency, we experimented with grouping within variables. The idea is to minimize the influence of some of the outliers while preserving the correlation effect with the sale price. Reducing the number of levels for a category will also increase the degrees of freedom. Special care was taken to preserve the significance of each level by looking carefully at how significant the difference was between each level within a category. For example, a comparison using a *pdiff* or Bonferroni adjustment was run on `Neighborhood` and similar categories to look at the significant differences between levels with respect to `SalePrice`. These noted differences, along with side-by-side box-plot comparisons helped to regroup most of the categorical variables into new variables with fewer levels. This was done to both numerical and character categorical variables. After the levels within a category were combined, the new groupings were tested using an external cross validation on the original train dataset. The most notable variables that were regrouped are `Neighborhood, Condition1, BldgType, GarageType, BsmtExposure, BsmtQual, RoofMatl, SaleCondition`, and `Functional`.

The `Neighborhood` variable, which has 25 levels, was particularly difficult to regroup. It was found through trial and error using our external cross validation technique that `Neighborhood` could be grouped into a new variable that had only 12 levels and increase our prediction metrics significantly! In fact, this particular regrouping decrease our Kaggle score by nearly 10%. Through this trial and error process, we were able to identify the other new variables that help to improve the model for best prediction.

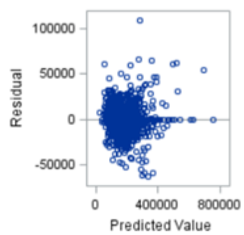
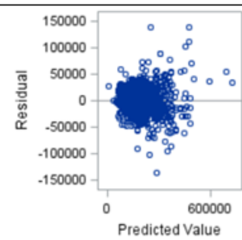
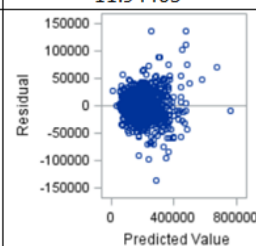
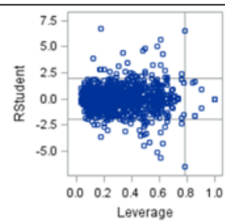
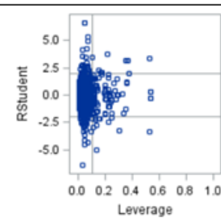
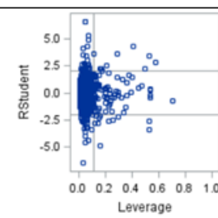
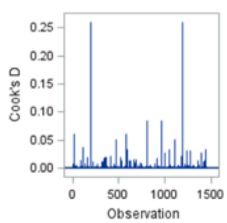
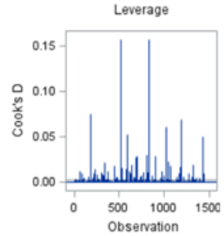
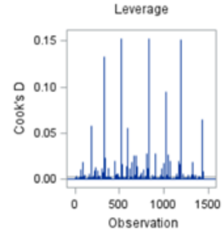
The manual external cross validation technique, mentioned above, was chosen because it used the same metric that the Kaggle website uses to check submitted predictions: Root Mean Squared Logarithmic Error or RMSLE. The cross validation set was created using the original train set. A random number was assigned to each observation in the train set and then the dataset was split in half using these random numbers to create a new train and test set. The data was then fit using proc glm and the new train set to make predictions for the new test set. These predictions were then used to calculate the RMSLE described on the Kaggle website, which in essence is a method for calculating the average total logarithmic difference between the predicted value and actual values. This technique was also used to refine our final model.

Model 2 was the first model we selected using this external cross validation technique and RMSLE. It produced a model with 18 variables. Model 2 includes the grouping of several new categorical variables (`OverallCondGroup`, `OverallQualGroup`, `NeighborhoodGroup`), which seemed to greatly help with overfitting. Also, an interaction term `GrLivArea*Neighborhood` was seen to help as well.

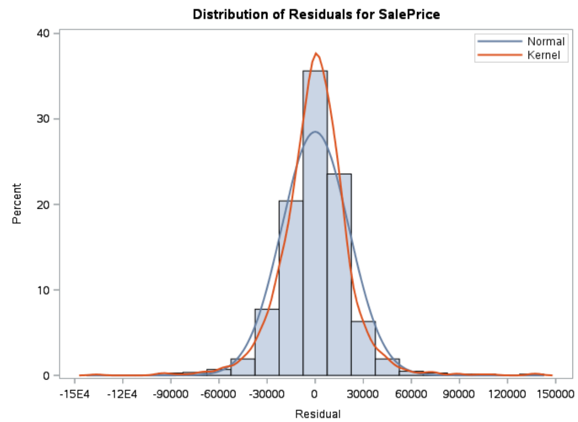
After several more iterations of adding, removing, and grouping variables by hand, the final model was uncovered which gave us our best to date Kaggle score. The only difference between this new Model 3 and the previous Model 2 is that the new model includes the newly grouped variable `Condition1Group` as well as the interaction term `GrLivArea*RoofMatl`. The following is the final model used:

$$\begin{aligned}\text{SalePrice} = {} & \beta_0 + \beta_i\text{2ndFlrSF} + \beta_i\text{MasVnrArea} + \beta_i\text{3SsnPorch} + \beta_i\text{BsmtFinSF1} \\ & + \beta_i\text{GarageArea} + \beta_i\text{LotArea} + \beta_i\text{ScreenPorch} + \beta_{ij}\text{BldgType} \\ & + \beta_{ij}\text{BsmtExposure} + \beta_{ij}\text{BsmtQual} + \beta_{ij}\text{Condition1Group} \\ & + \beta_{ij}\text{Condition2} + \beta_{ij}\text{KitchenQual} + \beta_{ij}\text{RoofMatl} + \beta_{ij}\text{SaleCondition} \\ & + \beta_{ij}\text{NeighborhoodGroup} + \beta_{ij}\text{OverallCondGroup} + \beta_{ij}\text{OverallQualGroup} \\ & + \beta_{ij}\text{GrLivArea*NeighborhoodGroup} + \beta_{ij}\text{GrLivArea*RoofMatl}\end{aligned}$$

Table 2 below provides a statistical comparison of the 3 models. The residual plots show similar patterns among the 3 model. All models seem to have a few outliers. One could argue that the last two models have the most “well formed” cluster around the 0 residual line. Looking at the Cook’s D and RStudent plots from SAS, we can see that there may be a few issues with outliers. However, since the objective is prediction some of these outliers may be remove later and then the model checked with cross validation to determine if the prediction metrics are better.

Table 2	Model Statistical comparison For Question 2		
	Model 1	Model 2	Model 3
R-Squared	0.9206	0.9229	0.9272
Adj. R-Squared	0.9157	0.9176	0.9236
Coeff. of Variance	10.02468	12.06299	11.94465
Residual			
Studentized Residual			
Cooks’D			
AIC	30879	30787	30721
BIC	29360	29324	29263
CV PRESS	1.025297E12	9.047722E11	9.054827E11

Similar to Question 1, the histogram of residuals (below) shows no evidence against equal spread, additionally we can assume independence of observations and a linear relationship between the explanatory variables and sale price.



The Kaggle submission summary:

Model 1: Kaggle score = NA. No Kaggle score was produced for this model. Because there were over 50 variables in this model there were simply too many mismatches between the levels of the training and test data sets. However, our first submission to Kaggle using Model 2 from Question 1 produced a Kaggle score of 0.16010.

Model 2: Kaggle score = 0.13722. This model was our first big improvement of our Kaggle score after we started using external cross validation.

Model 3: Kaggle score = 0.13474. This model was the last big improvement using the new level regrouping technique along with external cross validation.

For several days, Model 3 was our best Kaggle submission and nothing else we tried seemed to improve our Kaggle score. The very last thing that we did was to pull out all the stops to get the best Kaggle score we could. We were ruthless in this regard and have tried several last ditch and some perhaps highly questionable techniques. If we had more time for this project we would rewrite certain parts of this report with updated models.

In what we call our final Kaggle score minimization project, we were finally able to see some further reduction in our Kaggle score by using a log transformation on several of the continuous variables as well as on `SalePrice`. Using a log transformation on the prediction variable was a bit tricky but an exponential transformation was done after the prediction to transform it back to a form that could be submitted to Kaggle. After that the only thing left to do was to clean up any observations that had high Cook's D values. In this last effort, we simply started deleting the observations with the largest Cook's D values until our cross validation prediction metrics bottomed out. In the end this dirty trick improved our final Kaggle score from 0.13474 to 0.12611.

The Kaggle submission summary continued:

Final Model: Kaggle score = 0.12611. As discussed directly above this score was obtained using a log transformation of most of the continuous variables as well as removing most of highest Cook's D observation. Our goal was to try anything that could reduce the score. And as you can see this final push illustrates that complicated models with a large diversity of data and variables will have many outliers that can play a significant role in prediction accuracy.

If we spent more time on this project, we would do a couple of other things. The first would be to use several different seeds for our external cross validation RMSLE checks. We would write some code to use at least 10 different seeds one after the other to have a metric that was not overly depended on one random train and test set. This would allow us to fine tune our model on a more diverse set. Right now, we are basically squeezing a damp cloth for that one final drip of water. Finally, we would run more proc glmselect methods on the log transformed model.

Conclusion/Discussion

In this project, we have built two models using a specific design and technique. For Model 1 in Question 1, our goal was parsimony and to create a model that made sense and could be easily interpreted and understood by a realtor or home buyer/seller. Instead of just using a variable selection technique, we looked for variables that were intuitive and that common knowledge told us should impact any given sale price of a home. However, we went one step further and decided to introduce an interaction term to enhance the predictability without adding much complexity. With an adjusted R^2 of 0.8873, it suggested that 89% of the sale price variation has been captured by the model. This demonstrates a strong correlation, and allows anyone to predict an individual house sale price with only 8 easy-to-obtain parameters, from the table in appendix I, and as shown in the example in the interpretation section of Question 1. The shortcoming however is the confidence interval. With 95% confidence, the range of the possible values is much larger than desired. This is largely driven by the range of home price in the city Ames, IA.

For question two, we explored many of the techniques that we have learned. Multiple selection techniques were used and compared. Interaction terms were tested based on assumptions. We tested out transformation techniques such as applying a logarithm to certain variables. We also performed grouping of variables to narrow the band, thus possibly reducing the influence of some outliers. At the very end, we settled on a model that gave us the best Kaggle score = 0.12611.

The Appendix has our final model and the SAS code that was used to produce our best Kaggle score.

1689	▾164	RiccardoEsclapon		0.12609	1	4mo
1690	▾164	testing471		0.12609	3	1mo
1691	new	daresnick		0.12611	28	3m
1692	▾165	HardyLittlewood		0.12612	5	1mo
1693	▾165	CelsoA		0.12615	8	4mo

Appendix I Kaggle Submission SAS code

Copy and paste this code directly into SAS. Make sure to change the two datafile= lines at the beginning of the code as well as the outfile= line at the very end of the code. Look for two proc import statements and at the end a proc export statement. We have also attached a .sas file that has this code. (Kagglescorerunfinal1a.sas) If you prefer, you can just run it in SAS after you have made the directory file changes.

```
/* To run this file you need to set the correct datafile= lines in the two
proc import statements directly below as well
the outfile= line at the very end of this code. Change these directories and
file names to the appropriate ones for your machine.*/
/* This code produces a Kaggle score of 0.12611 */
/* Happy Kaggle submission! */

/*
** Data files taken from www.kaggle.com/c/house-prices-advanced-regression-
techniques/data
** Running this will likely say that the imports have failed...
** ...Be sure you update the path with your own path...
** ...Otherwise, there will be some errors will SAS trying to turn "NA" into
a number
*/

/* Replace with your own file path */
proc import datafile='C:\Users\hp\Desktop\SMU\Exp Stats II\Homework and
projects\Project 1\test.csv' dbms=csv out=test replace;
delimiter = ",";
getnames=yes;
guessingrows=1460;
run;

*proc print data=test; run;

/* Replace with your own file path */
proc import datafile='C:\Users\hp\Desktop\SMU\Exp Stats II\Homework and
projects\Project 1\train.csv' dbms=csv out=train replace;
delimiter = ",";
getnames=yes;
guessingrows=1461;
run;

*proc print data=train; run;


/* Below is code to clean the data */
```

```
data test;
  set test;
  if MasVnrType = "NA" then MasVnrType = "None";
  if MasVnrArea = "NA" then MasVnrArea = 0;
  if MSZoning = "NA" then MSZoning = .;
  if Functional = "NA" then Functional = .;
  if BsmtHalfBath = "NA" then BsmtHalfBath = .;
  if BsmtFullBath = "NA" then BsmtFullBath = .;
  if Utilities = "NA" then Utilities = .;
  if SaleType = "NA" then SaleType = .;
  if GarageArea = "NA" then GarageArea = 0;
  if GarageCars = "NA" then GarageCars = 0;
  if TotalBsmtSF = "NA" then TotalBsmtSF = 0;
  if BsmtUnfSF = "NA" then BsmtUnfSF = 0;
  if BsmtFinSF2 = "NA" then BsmtFinSF2 = 0;
  if BsmtFinSF1 = "NA" then BsmtFinSF1 = 0;
  if Exterior2nd = "NA" then Exterior2nd = .;
  if Exterior1st = "NA" then Exterior1st = .;
  if LotFrontage = "NA" then LotFrontage = "0";
  if GarageYrBlt = "NA" then GarageYrBlt = "0";
  /* Fill missing data */
  if ID=1556 then KitchenQual = 'TA';
  /*if ID=1620 then TBD*/
  if ID=1692 then MasVnrType= 'None';
  if ID=1692 then MasVnrArea = 0;
  if ID=1707 then MasVnrType= 'None';
  if ID=1707 then MasVnrArea = 0;
  /*if ID=1829 then TBD*/
  /*if ID=1862 then TBD*/
  /*if ID=1863 then TBD*/
  /*if ID=1864 then TBD*/
  if ID=1883 then MasVnrType= 'None';
  if ID=1883 then MasVnrArea = 0;
  if ID=1916 then MSZoning='RL';
  if ID=1916 then Utilities='AllPub';
  if ID=1946 then Utilities='AllPub';
  if ID=1993 then MasVnrType= 'None';
  if ID=1993 then MasVnrArea = 0;
  if ID=2005 then MasVnrType= 'None';
  if ID=2005 then MasVnrArea = 0;
  if ID=2042 then MasVnrType= 'None';
  if ID=2042 then MasVnrArea = 0;
  if ID=2121 then BsmtFinSF2= 0;
  if ID=2121 then BsmtUnfSF = 0;
  if ID=2121 then TotalBsmtSF = 0;
  if ID=2121 then BsmtFinSF1 = 0;
  if ID=2121 then BsmtFullBath = 0;
  if ID=2121 then BsmtHalfBath = 0;
  if ID=2189 then BsmtFullBath = 0;
  if ID=2189 then BsmtHalfBath = 0;
```

```
  if ID=2217 then MSZoning='RL';
  if ID=2217 then Functional ='Typ';
  if ID=2251 then MSZoning='RL';
  if ID=2312 then MasVnrType= 'None';
  if ID=2312 then MasVnrArea = 0;
  if ID=2326 then MasVnrType= 'None';
  if ID=2326 then MasVnrArea = 0;
  if ID=2341 then MasVnrType= 'None';
  if ID=2341 then MasVnrArea = 0;
  if ID=2350 then MasVnrType= 'None';
  if ID=2350 then MasVnrArea = 0;
  if ID=2369 then MasVnrType= 'None';
  if ID=2369 then MasVnrArea = 0;
  if ID=2474 then Functional ='Typ';
  if ID=2577 then GarageCars =0;
  if ID=2577 then GarageArea =0;
  if ID=2593 then MasVnrType= 'None';
  if ID=2593 then MasVnrArea = 0;
  if ID=2611 then MasVnrType= 'BrkFace';
  if ID=2658 then MasVnrType= 'None';
  if ID=2658 then MasVnrArea = 0;
  if ID=2687 then MasVnrType= 'None';
  if ID=2687 then MasVnrArea = 0;
  /*If ID=2711 then TBD*/
  if ID=2863 then MasVnrType= 'None';
  if ID=2863 then MasVnrArea = 0;
  if ID=2905 then MSZoning='RL';
run;

data train;
  set train;
  if MasVnrType = "NA" then MasVnrType = ".";
  if MasVnrArea = "NA" then MasVnrArea = ".";
  if Electrical = "NA" then Electrical = ".";
  if LotFrontage = "NA" then LotFrontage = "0";
  if GarageYrBlt = "NA" then GarageYrBlt = "0";

  /* Fill missing data */
  if ID=1299 then GrLivArea = 1426.9;
  if ID=1299 then LotArea= 9833.2;
  if ID=1183 then LotArea= 23404.7;
  if ID=524 then GrLivArea = 1574.536;
  if ID=524 then LotArea = 10107.7;
  if ID=1424 then MSSubClass= '60';
  if ID=1424 then OverallCond = '5';
  if ID=1424 then OverallQual = '8';
  if ID=692 then OverallCond = '5';
run;

/***** Turn all 'NA' values into the SAS-Safe '.' *****/
```

```
data test;
  set test;
  array change _character_;
  do over change;
  if change='NA' then change='NT';
  end;
run;


data train;
  set train;
  array change _character_;
  do over change;
  if change='NA' then change='NT';
  end;
run;


/******** cast columns to numbers (that were lost in proc import) ********/
data test;
   set test;

   LotFrontage1 = input(LotFrontage, 8.);
       attrib LotFrontage1  format= BEST12. informat=BEST32.;
   MasVnrArea1 = input(MasVnrArea, 8.);
       attrib MasVnrArea1  format= BEST12. informat=BEST32.;
   GarageYrBlt1 = input(GarageYrBlt, 8.);
       attrib GarageYrBlt1  format= BEST12. informat=BEST32.;
   BsmtFinSF11 = input(BsmtFinSF1, 8.);
       attrib BsmtFinSF11  format= BEST12. informat=BEST32.;
   BsmtFinSF21 = input(BsmtFinSF2, 8.);
     attrib BsmtFinSF21 format= BEST12. informat=BEST32.;
   BsmtUnfSF1 = input(BsmtUnfSF, 8.);
     attrib BsmtUnfSF1 format= BEST12. informat=BEST32.;
   TotalBsmtSF1 = input(TotalBsmtSF, 8.);
     attrib TotalBsmtSF1 format= BEST12. informat=BEST32.;
   BsmtFullBath1 = input(BsmtFullBath, 8.);
     attrib BsmtFullBath1 format= BEST12. informat=BEST32.;
   BsmtHalfBath1 = input(BsmtHalfBath, 8.);
     attrib BsmtHalfBath1 format= BEST12. informat=BEST32.;
   GarageCars1 = input(GarageCars, 8.);
     attrib GarageCars1 format= BEST12. informat=BEST32.;
   GarageArea1 = input(GarageArea, 8.);
     attrib GarageArea1 format= BEST12. informat=BEST32.;

   drop BsmtFinSF1;
   drop BsmtFinSF2;
   drop BsmtUnfSF;
   drop TotalBsmtSF;
   drop BsmtFullBath;
   drop BsmtHalfBath;
```

```
   drop GarageCars;
   drop GarageArea;
   drop LotFrontage;
   drop MasVnrArea;
   drop GarageYrBlt;

   rename BsmtFinSF11 = BsmtFinSF1;
   rename BsmtFinSF21 = BsmtFinSF2;
   rename BsmtUnfSF1 = BsmtUnfSF;
   rename TotalBsmtSF1 = TotalBsmtSF;
   rename BsmtFullBath1 = BsmtFullBath;
   rename BsmtHalfBath1 = BsmtHalfBath;
   rename GarageCars1 = GarageCars;
   rename GarageArea1 = GarageArea;
   rename LotFrontage1= LotFrontage;
   rename MasVnrArea1 = MasVnrArea;
   rename GarageYrBlt1 = GarageYrBlt;
run;


data train;
   set train;

   LotFrontage1 = input(LotFrontage, 8.);
        attrib LotFrontage1  format= BEST12. informat=BEST32.;
   MasVnrArea1 = input(MasVnrArea, 8.);
      attrib MasVnrArea1  format= BEST12. informat=BEST32.;
   GarageYrBlt1 = input(GarageYrBlt, 8.);
      attrib GarageYrBlt1  format= BEST12. informat=BEST32.;

   drop LotFrontage;
   drop MasVnrArea;
   drop GarageYrBlt;

   rename LotFrontage1= LotFrontage;
   rename MasVnrArea1 = MasVnrArea;
   rename GarageYrBlt1 = GarageYrBlt;
run;


/* I created 3 new categorical variables based on existig values.   */

Data Train;
Set train;
TotalBath = BsmtFullBath+BsmtHalfBath+FullBath;
if YearRemodAdd<2007 then YearRemodAddGROUP = "OLD";
if YearRemodAdd>=2007 then YearRemodAddGROUP = "NEW";
if GrLivArea<1000 then GrLivAreaGroup = "Small1";
If GrLivArea>=1000 and GrLivArea< 1500 then GrLivAreaGroup = "Small2";
If GrLivArea>=1500 and GrLivArea< 2000 then GrLivAreaGroup = "Med1";
If GrLivArea>=2000 and GrLivArea< 2500 then GrLivAreaGroup = "Med2";
```

```
If GrLivArea>=2500 and GrLivArea< 3000 then GrLivAreaGroup = "Large1";
If GrLivArea>=3000then GrLivAreaGroup = "Large2";
If Neighborhood ="Blmngtn" then NeighborhoodGroup =  "G01";
If Neighborhood ="Blueste" then NeighborhoodGroup =  "G02";
If Neighborhood ="BrDale" then NeighborhoodGroup =  "G03";
If Neighborhood ="BrkSide" then NeighborhoodGroup =  "G04";
If Neighborhood ="ClearCr" then NeighborhoodGroup =  "G01";
If Neighborhood ="CollgCr" then NeighborhoodGroup =  "G01";
If Neighborhood ="Crawfor" then NeighborhoodGroup =  "G01";
If Neighborhood ="Edwards" then NeighborhoodGroup =  "G02";
If Neighborhood ="Gilbert" then NeighborhoodGroup =  "G05";
If Neighborhood ="IDOTRR" then NeighborhoodGroup =  "G03";
If Neighborhood ="MeadowV" then NeighborhoodGroup =  "G03";
If Neighborhood ="Mitchel" then NeighborhoodGroup =  "G06";
If Neighborhood ="NAmes" then NeighborhoodGroup =  "G06";
If Neighborhood ="NPkVill" then NeighborhoodGroup =  "G02";
If Neighborhood ="NWAmes" then NeighborhoodGroup =  "G07";
If Neighborhood ="NoRidge" then NeighborhoodGroup =  "G12";
If Neighborhood ="NridgHt" then NeighborhoodGroup =  "G08";
If Neighborhood ="OldTown" then NeighborhoodGroup =  "G09";
If Neighborhood ="SWISU" then NeighborhoodGroup =  "G02";
If Neighborhood ="Sawyer" then NeighborhoodGroup =  "G02";
If Neighborhood ="SawyerW" then NeighborhoodGroup =  "G10";
If Neighborhood ="Somerst" then NeighborhoodGroup =  "G11";
If Neighborhood ="StoneBr" then NeighborhoodGroup =  "G08";
If Neighborhood ="Timber" then NeighborhoodGroup =  "G11";
If Neighborhood ="Veenker" then NeighborhoodGroup =  "G11";
run;

Data test;
Set test;
TotalBath = BsmtFullBath+BsmtHalfBath+FullBath;
if YearRemodAdd<2007 then YearRemodAddGROUP = "OLD";
if YearRemodAdd>=2007 then YearRemodAddGROUP = "NEW";
if GrLivArea<1000 then GrLivAreaGroup = "Small1";
If GrLivArea>=1000 and GrLivArea< 1500 then GrLivAreaGroup = "Small2";
If GrLivArea>=1500 and GrLivArea< 2000 then GrLivAreaGroup = "Med1";
If GrLivArea>=2000 and GrLivArea< 2500 then GrLivAreaGroup = "Med2";
If GrLivArea>=2500 and GrLivArea< 3000 then GrLivAreaGroup = "Large1";
If GrLivArea>=3000then GrLivAreaGroup = "Large2";
If Neighborhood ="Blmngtn" then NeighborhoodGroup =  "G01";
If Neighborhood ="Blueste" then NeighborhoodGroup =  "G02";
If Neighborhood ="BrDale" then NeighborhoodGroup =  "G03";
If Neighborhood ="BrkSide" then NeighborhoodGroup =  "G04";
If Neighborhood ="ClearCr" then NeighborhoodGroup =  "G01";
If Neighborhood ="CollgCr" then NeighborhoodGroup =  "G01";
If Neighborhood ="Crawfor" then NeighborhoodGroup =  "G01";
If Neighborhood ="Edwards" then NeighborhoodGroup =  "G02";
If Neighborhood ="Gilbert" then NeighborhoodGroup =  "G05";
If Neighborhood ="IDOTRR" then NeighborhoodGroup =  "G03";
If Neighborhood ="MeadowV" then NeighborhoodGroup =  "G03";
```

```
If Neighborhood ="Mitchel" then NeighborhoodGroup =  "G06";
If Neighborhood ="NAmes" then NeighborhoodGroup =  "G06";
If Neighborhood ="NPkVill" then NeighborhoodGroup =  "G02";
If Neighborhood ="NWAmes" then NeighborhoodGroup =  "G07";
If Neighborhood ="NoRidge" then NeighborhoodGroup =  "G12";
If Neighborhood ="NridgHt" then NeighborhoodGroup =  "G08";
If Neighborhood ="OldTown" then NeighborhoodGroup =  "G09";
If Neighborhood ="SWISU" then NeighborhoodGroup =  "G02";
If Neighborhood ="Sawyer" then NeighborhoodGroup =  "G02";
If Neighborhood ="SawyerW" then NeighborhoodGroup =  "G10";
If Neighborhood ="Somerst" then NeighborhoodGroup =  "G11";
If Neighborhood ="StoneBr" then NeighborhoodGroup =  "G08";
If Neighborhood ="Timber" then NeighborhoodGroup =  "G11";
If Neighborhood ="Veenker" then NeighborhoodGroup =  "G11";
run;

/***** Include boolean values *****/
data train;
set train;
if EnclosedPorch > 0 or ScreenPorch > 0 or OpenPorchSF > 0 or _3SsnPorch > 0
      then porch = 1;
      else porch = 0;
run;

data test;
set test;
if EnclosedPorch > 0 or ScreenPorch > 0 or OpenPorchSF > 0 or _3SsnPorch > 0
      then porch = 1;
      else porch = 0;
/* Blueste neighborhood does not a house with a porch in train data */
if Neighborhood = 'Blueste' then porch = 0;
run;


data train;
set train;
if OverallQual = 1 then OverallQualGroup = 12;
if OverallQual = 2 then OverallQualGroup = 12;
if OverallQual = 3 then OverallQualGroup = 3;
if OverallQual = 4 then OverallQualGroup = 4;
if OverallQual = 5 then OverallQualGroup = 5;
if OverallQual = 6 then OverallQualGroup = 6;
if OverallQual = 7 then OverallQualGroup = 7;
if OverallQual = 8 then OverallQualGroup = 8;
if OverallQual = 9 then OverallQualGroup = 9;
if OverallQual = 10 then OverallQualGroup = 10;
run;


data test;
set test;
```

```
if OverallQual = 1 then OverallQualGroup = 12;
if OverallQual = 2 then OverallQualGroup = 12;
if OverallQual = 3 then OverallQualGroup = 3;
if OverallQual = 4 then OverallQualGroup = 4;
if OverallQual = 5 then OverallQualGroup = 5;
if OverallQual = 6 then OverallQualGroup = 6;
if OverallQual = 7 then OverallQualGroup = 7;
if OverallQual = 8 then OverallQualGroup = 8;
if OverallQual = 9 then OverallQualGroup = 9;
if OverallQual = 10 then OverallQualGroup = 10;
run;


data train;
set train;
if OverallCond = 1 then OverallCondGroup = 12;
if OverallCond = 2 then OverallCondGroup = 12;
if OverallCond = 3 then OverallCondGroup = 34;
if OverallCond = 4 then OverallCondGroup = 34;
if OverallCond = 5 then OverallCondGroup = 5;
if OverallCond = 6 then OverallCondGroup = 6;
if OverallCond = 7 then OverallCondGroup = 78;
if OverallCond = 8 then OverallCondGroup = 78;
if OverallCond = 9 then OverallCondGroup = 9;
if OverallCond = 10 then OverallCondGroup = 9;
run;

data test;
set test;
if OverallCond = 1 then OverallCondGroup = 12;
if OverallCond = 2 then OverallCondGroup = 12;
if OverallCond = 3 then OverallCondGroup = 34;
if OverallCond = 4 then OverallCondGroup = 34;
if OverallCond = 5 then OverallCondGroup = 5;
if OverallCond = 6 then OverallCondGroup = 6;
if OverallCond = 7 then OverallCondGroup = 78;
if OverallCond = 8 then OverallCondGroup = 78;
if OverallCond = 9 then OverallCondGroup = 9;
if OverallCond = 10 then OverallCondGroup = 9;
run;


/* group condition1 values by similar mean|observations|variation */
data train;
set train;
if Condition1 = 'Artery' then Condition1Group = 'Small';
if Condition1 = 'Feedr' then Condition1Group = 'Small';
if Condition1 = 'RRAe' then Condition1Group = 'Small';

if Condition1 = 'PosA' then Condition1Group = 'Large';
if Condition1 = 'PosN' then Condition1Group = 'Large';
```

```
if Condition1 = 'RRNe' then Condition1Group = 'Large';
if Condition1 = 'RRAn' then Condition1Group = 'Large';
if Condition1 = 'RRNn' then Condition1Group = 'Large';

if Condition1 = 'Norm' then Condition1Group = 'Norm';
run;

data test;
set test;
if Condition1 = 'Artery' then Condition1Group = 'Small';
if Condition1 = 'Feedr' then Condition1Group = 'Small';
if Condition1 = 'RRAe' then Condition1Group = 'Small';

if Condition1 = 'PosA' then Condition1Group = 'Large';
if Condition1 = 'PosN' then Condition1Group = 'Large';
if Condition1 = 'RRNe' then Condition1Group = 'Large';
if Condition1 = 'RRAn' then Condition1Group = 'Large';
if Condition1 = 'RRNn' then Condition1Group = 'Large';

if Condition1 = 'Norm' then Condition1Group = 'Norm';
run;


data train;
set train;
If BldgType in ("1Fam","TwnhsI") then BldgTypeGroup="Single";
If BldgType in ("2FmCon","Duplx","TwnhsE","Twnhs","Duplex","2fmCon") then
BldgTypeGroup="Multi";
run;

data test;
set test;
If BldgType in ("1Fam","TwnhsI") then BldgTypeGroup="Single";
If BldgType in ("2FmCon","Duplx","TwnhsE","Twnhs","Duplex","2fmCon") then
BldgTypeGroup="Multi";
run;


data train;
set train;
If GarageType in ("BuiltIn","Attchd") then GarageTypeGroup = "Good";
else GarageTypeGroup = "Bad";
Run;

data test;
set test;
If GarageType in ("BuiltIn","Attchd") then GarageTypeGroup = "Good";
else GarageTypeGroup = "Bad";
Run;
```

```
data train;
set train;
if BsmtExposure = "Av" then BsmtExposureGroup = "Av";
if BsmtExposure = "Gd" then BsmtExposureGroup = "Gd";
if BsmtExposure = "Mn" then BsmtExposureGroup = "Gd";
if BsmtExposure = "NT" then BsmtExposureGroup = "Av";
if BsmtExposure = "No" then BsmtExposureGroup = "Av";
run;

data test;
set test;
if BsmtExposure = "Av" then BsmtExposureGroup = "Av";
if BsmtExposure = "Gd" then BsmtExposureGroup = "Gd";
if BsmtExposure = "Mn" then BsmtExposureGroup = "Gd";
if BsmtExposure = "NT" then BsmtExposureGroup = "Av";
if BsmtExposure = "No" then BsmtExposureGroup = "Av";
run;


data train;
set train;
if BsmtQual = "Ex" then BsmtQualGroup = "Ex";
if BsmtQual = "Fa" then BsmtQualGroup = "FN";
if BsmtQual = "Gd" then BsmtQualGroup = "Gd";
if BsmtQual = "NT" then BsmtQualGroup = "FN";
if BsmtQual = "TA" then BsmtQualGroup = "TA";
run;

data test;
set test;
if BsmtQual = "Ex" then BsmtQualGroup = "Ex";
if BsmtQual = "Fa" then BsmtQualGroup = "FN";
if BsmtQual = "Gd" then BsmtQualGroup = "Gd";
if BsmtQual = "NT" then BsmtQualGroup = "FN";
if BsmtQual = "TA" then BsmtQualGroup = "TA";
run;


data train;
set train;
if KitchenQual = "Ex" then KitchenQualGroup = "Ex";
if KitchenQual = "Fa" then KitchenQualGroup = "Gd";
if KitchenQual = "Gd" then KitchenQualGroup = "Gd";
if KitchenQual = "TA" then KitchenQualGroup = "TA";
run;

data test;
set test;
if KitchenQual = "Ex" then KitchenQualGroup = "Ex";
if KitchenQual = "Fa" then KitchenQualGroup = "Gd";
if KitchenQual = "Gd" then KitchenQualGroup = "Gd";
```

```
if KitchenQual = "TA" then KitchenQualGroup = "TA";
run;



data train;
set train;
if RoofMatl = "ClyTile" then RoofMatlGroup = "ClyTile";
if RoofMatl = "CompShg" then RoofMatlGroup = "CompShg";
if RoofMatl = "Membran" then RoofMatlGroup = "WdShake";
if RoofMatl = "Metal" then RoofMatlGroup = "Metal";
if RoofMatl = "Roll" then RoofMatlGroup = "Roll";
if RoofMatl = 'Tar&Grv' then RoofMatlGroup = 'Tar&Grv';
if RoofMatl = "WdShake" then RoofMatlGroup = "WdShake";
if RoofMatl = "WdShngl" then RoofMatlGroup = "WdShngl";
run;

data test;
set test;
if RoofMatl = "ClyTile" then RoofMatlGroup = "ClyTile";
if RoofMatl = "CompShg" then RoofMatlGroup = "CompShg";
if RoofMatl = "Membran" then RoofMatlGroup = "WdShake";
if RoofMatl = "Metal" then RoofMatlGroup = "Metal";
if RoofMatl = "Roll" then RoofMatlGroup = "Roll";
if RoofMatl = 'Tar&Grv' then RoofMatlGroup = 'Tar&Grv';
if RoofMatl = "WdShake" then RoofMatlGroup = "WdShake";
if RoofMatl = "WdShngl" then RoofMatlGroup = "WdShngl";
run;


data train;
set train;
if SaleCondition = "Abnorml" then SaleConditionGroup = "Abnorml";
if SaleCondition = "AdjLand" then SaleConditionGroup = "AdjLand";
if SaleCondition = "Alloca" then SaleConditionGroup = "Family";
if SaleCondition = "Family" then SaleConditionGroup = "Family";
if SaleCondition = "Normal" then SaleConditionGroup = "Normal";
if SaleCondition = "Partial" then SaleConditionGroup = "Partial";
run;

data test;
set test;
if SaleCondition = "Abnorml" then SaleConditionGroup = "Abnorml";
if SaleCondition = "AdjLand" then SaleConditionGroup = "AdjLand";
if SaleCondition = "Alloca" then SaleConditionGroup = "Family";
if SaleCondition = "Family" then SaleConditionGroup = "Family";
if SaleCondition = "Normal" then SaleConditionGroup = "Normal";
if SaleCondition = "Partial" then SaleConditionGroup = "Partial";
run;
```

```
data train;
set train;
if ExterCond = "Ex" then ExterCondGroup = "Gd";
if ExterCond = "Fa" then ExterCondGroup = "Fa";
if ExterCond = "Gd" then ExterCondGroup = "Gd";
if ExterCond = "Po" then ExterCondGroup = "Po";
if ExterCond = "TA" then ExterCondGroup = "TA";
run;

data test;
set test;
if ExterCond = "Ex" then ExterCondGroup = "Gd";
if ExterCond = "Fa" then ExterCondGroup = "Fa";
if ExterCond = "Gd" then ExterCondGroup = "Gd";
if ExterCond = "Po" then ExterCondGroup = "Po";
if ExterCond = "TA" then ExterCondGroup = "TA";
run;


data train;
set train;
if Functional = "Maj1" then FunctionalGroup = "Mod";
if Functional = "Maj2" then FunctionalGroup = "Maj2";
if Functional = "Min1" then FunctionalGroup = "Min1";
if Functional = "Min2" then FunctionalGroup = "Min1";
if Functional = "Mod" then FunctionalGroup = "Mod";
if Functional = "Sev" then FunctionalGroup = "Sev";
if Functional = "Typ" then FunctionalGroup = "Typ";
run;

data test;
set test;
if Functional = "Maj1" then FunctionalGroup = "Mod";
if Functional = "Maj2" then FunctionalGroup = "Maj2";
if Functional = "Min1" then FunctionalGroup = "Min1";
if Functional = "Min2" then FunctionalGroup = "Min1";
if Functional = "Mod" then FunctionalGroup = "Mod";
if Functional = "Sev" then FunctionalGroup = "Sev";
if Functional = "Typ" then FunctionalGroup = "Typ";
run;


data train;
Set train;
If ID=301 then MasVnrType = "Brkface";
If ID=1335 then MasVnrType = "Brkface";
If ID=625 then MasVnrType = "Brkface";
If ID=1301 then MasVnrType = "Brkface";
If ID=1670 then MasVnrType = "Brkface";
If MasVnrArea = 1 then  MasVnrArea = 0;
If MasVnrArea = 0 then MasVnrType ="None";
```

```
*if MasVnrType = "."  then MasVnrArea = 0;
if MasVnrType = "." then MasVnrType = "None";
if Electrical = "." then Electrical =  "SBrkr";
*If ID=524 then _2ndFlrSF = 769;
*If ID=1299 then _2ndFlrSF = 475;
*if Id=530 then LotArea = 11650;
Run;

data test;
Set test;
If ID=301 then MasVnrType = "Brkface";
If ID=1335 then MasVnrType = "Brkface";
If ID=625 then MasVnrType = "Brkface";
If ID=1301 then MasVnrType = "Brkface";
If ID=1670 then MasVnrType = "Brkface";
If MasVnrArea = 1 then  MasVnrArea = 0;
If MasVnrArea = 0 then MasVnrType ="None";
*if MasVnrType = "."  then MasVnrArea = 0;
if MasVnrType = "." then MasVnrType = "None";
if Electrical = "." then Electrical = "SBrkr";
*If ID=524 then _2ndFlrSF = 769;
*If ID=1299 then _2ndFlrSF = 475;
*if Id=530 then LotArea = 11650;
Run;

data train;
Set train;
logSalePrice = log(SalePrice + 1);
log_2ndFlrSF = log(_2ndFlrSF + 1);
logMasVnrArea = log(MasVnrArea + 1);
log_3SsnPorch = log(_3SsnPorch + 1);
logBsmtFinSF1 = log(BsmtFinSF1 + 1);
logGarageArea = log(GarageArea + 1);
logLotArea = log(LotArea + 1);
logScreenPorch = log(ScreenPorch + 1);
logGrLivArea = log(GrLivArea + 1);
run;


data test;
Set test;
log_2ndFlrSF = log(_2ndFlrSF + 1);
logMasVnrArea = log(MasVnrArea + 1);
log_3SsnPorch = log(_3SsnPorch + 1);
logBsmtFinSF1 = log(BsmtFinSF1 + 1);
logGarageArea = log(GarageArea + 1);
logLotArea = log(LotArea + 1);
logScreenPorch = log(ScreenPorch + 1);
logGrLivArea = log(GrLivArea + 1);
run;
```

```
data train;
Set train;
If ID=89 then delete;
If ID=813 then delete;
If ID=524 then delete;
If ID=826 then delete;
If ID=589 then delete;
If ID=1424 then delete;
If ID=969 then delete;
If ID=186 then delete;
If ID=633 then delete;
If ID=325 then delete;
If ID=534 then delete;
If ID=496 then delete;
If ID=31 then delete;
If ID=1025 then delete;
If ID=667 then delete;
If ID=917 then delete;
If ID=1001 then delete;
If ID=711 then delete;
If ID=1325 then delete;
If ID=590 then delete;
run;


data test;
Set test;
If ID=1706 then Condition2 = "Norm";
If ID=1947 then Condition2 = "Norm";
*If ID=2111 then Condition2 = "Norm";
*If ID=2239 then Condition2 = "Norm";
*If ID=2456 then Condition2 = "Norm";
run;

data train;
Set train;
If ID=278 then delete;
If ID=706 then delete;
If ID=411 then delete;
If ID=739 then delete;
If ID=689 then delete;
If ID=1063 then delete;
If ID=1381 then delete;
If ID=975 then delete;
If ID=480 then delete;
If ID=379 then delete;
If ID=692 then delete;
If ID=1062 then delete;
If ID=609 then delete;
```

```
If ID=1045 then delete;
*If ID=1187 then delete;
*If ID=10 then delete;
*If ID=630 then delete;
*If ID=54 then delete;
run;


/* The code below creats the submission file to Kaggle */

data logtrain;
set train;
drop SalePrice;
run;


data loghousing;
set logtrain test;
run;


/*This is the final model */
/* kaggle=0.12611, adjrsquared = 0.93, e = 0.10086  */
proc glm data = loghousing plots=all;
class

      BldgType BsmtExposure BsmtQual Condition1Group KitchenQual
SaleCondition NeighborhoodGroup RoofMatl

      OverallCondGroup OverallQualGroup;

      model logSalePrice = log_2ndFlrSF
            BsmtFinSF1 GarageArea logLotArea ScreenPorch
            BldgType BsmtExposure BsmtQual Condition1Group KitchenQual
            SaleCondition NeighborhoodGroup
            OverallCondGroup OverallQualGroup
            logGrLivArea*NeighborhoodGroup
            RoofMatl*logGrLivArea;
      output out = predictions predicted = prediction;
run; quit;

data predictions;
set predictions;
prediction = exp(prediction) - 1;
run;


/* the predictions for test data */
data finalprediction;
set predictions;
if Id > 1460;
```

```
SalePrice = prediction;
keep Id SalePrice;
run;



/* Be sure to change the outfile to your own file location */
/* The outfile "submission.csv" will be used in submission to kaggle */
proc export data=finalprediction outfile='C:\Users\hp\Desktop\SMU\Exp Stats
II\Homework and projects\Project 1\Submissions\submissionfinal.csv' replace
dbms=csv; run;


/* If this comes out with nothing then you should be able to submit cleanly.
*/
title 'Observations with Missing Values';
data finalpredictionMissing;
set finalprediction;
if SalePrice = .;
run;
proc print data=finalpredictionMissing;
run;

data finalprediction;
set predictions;
if Id > 1460;
SalePrice = prediction;
run;
```

Appendix II Parameter table estimates for Question 1 Model 2.

Below is a table with all the parameter estimates for Model 2 of Question 1.

Parameter	Estimate		Standard Error	t Value	Pr > |t|	95% Confidence Limits	
Intercept	65170.952	B	6300.7675	10.34	<.0001	52810.818	77531.0854
GrLivArea	54.5817	B	4.6756	11.67	<.0001	45.4097	63.7537
LotArea	0.6753		0.0826	8.18	<.0001	0.5133	0.8373
MSSubClass 30	-21609.83	B	4610.1809	-4.69	<.0001	-30653.565	-12566.101
MSSubClass 40	-13168.65	B	13638.196	-0.97	0.3344	-39922.517	13585.2261
MSSubClass 45	-19121.37	B	8364.8658	-2.29	0.0224	-35530.613	-2712.1165
MSSubClass 50	-31049.29	B	3394.1512	-9.15	<.0001	-37707.55	-24391.025
MSSubClass 60	-25442.42	B	2729.7374	-9.32	<.0001	-30797.306	-20087.526
MSSubClass 70	-39664.04	B	4790.0548	-8.28	<.0001	-49060.627	-30267.45
MSSubClass 75	-37615.87	B	8252.6464	-4.56	<.0001	-53804.982	-21426.764
MSSubClass 80	-7998.147	B	3864.3994	-2.07	0.0387	-15578.89	-417.4054
MSSubClass 85	5325.6338	B	6217.7771	0.86	0.3919	-6871.6987	17522.9664
MSSubClass 90	-29566.88	B	4273.951	-6.92	<.0001	-37951.035	-21182.727
MSSubClass 120	-91.9547	B	4187.7209	-0.02	0.9825	-8306.9523	8123.0429
MSSubClass 160	-44026.37	B	5659.1982	-7.78	<.0001	-55127.947	-32924.796
MSSubClass 180	-6729.019	B	12167.52	-0.55	0.5803	-30597.885	17139.8467
MSSubClass 190	-33706.59	B	5777.3211	-5.83	<.0001	-45039.887	-22373.295
MSSubClass 20	0	B	.	.	.	.	.
Neighborhood Blmngtn	-84770.98	B	69561.851	-1.22	0.2232	-221229.56	51687.5938
Neighborhood Blueste	-15710.74	B	161950.67	-0.1	0.9227	-333407.26	301985.771
Neighborhood BrDale	-20015.18	B	52366.646	-0.38	0.7024	-122742.15	82711.7905
Neighborhood BrkSide	-29205.99	B	14879.215	-1.96	0.0499	-58394.352	-17.6255
Neighborhood ClearCr	42614.131	B	21606.843	1.97	0.0488	228.2676	84999.9941
Neighborhood CollgCr	-26037.87	B	10189.732	-2.56	0.0107	-46026.939	-6048.8084
Neighborhood Crawfor	8153.6641	B	14734.771	0.55	0.5801	-20751.345	37058.6737
Neighborhood Edwards	-11539.27	B	12354.078	-0.93	0.3504	-35774.101	12695.5686
Neighborhood Gilbert	-9428.527	B	18245.214	-0.52	0.6054	-45219.927	26362.8723
Neighborhood IDOTRR	-21962.1	B	20838.126	-1.05	0.2921	-62839.979	18915.783
Neighborhood MeadowV	-11038.72	B	22838.394	-0.48	0.6289	-55840.504	33763.0571

Neighborhood Mitchel	-11122.67	B	15159.6	-0.73	0.4633	-40861.056	18615.7248
Neighborhood NPkVill	-72713.51	B	53263.466	-1.37	0.1724	-177199.76	31772.743
Neighborhood NWAmes	-14445.45	B	14970.772	-0.96	0.3348	-43813.414	14922.5237
Neighborhood NoRidge	-142926.2	B	20697.395	-6.91	<.0001	-183527.99	-102324.37
Neighborhood NridgHt	-75304.85	B	17204.163	-4.38	<.0001	-109054.03	-41555.666
Neighborhood OldTown	-2360.728	B	9931.5102	-0.24	0.8121	-21843.243	17121.7865
Neighborhood SWISU	13801.377	B	19001.648	0.73	0.4678	-23473.909	51076.6633
Neighborhood Sawyer	3305.6301	B	13029.693	0.25	0.7998	-22254.55	28865.8103
Neighborhood SawyerW	-31082.9	B	13343.466	-2.33	0.02	-57258.601	-4907.192
Neighborhood Somerst	-19747.08	B	19102.401	-1.03	0.3014	-57220.013	17725.8505
Neighborhood StoneBr	-87620.23	B	21206.69	-4.13	<.0001	-129221.11	-46019.339
Neighborhood Timber	-16032.56	B	21143.979	-0.76	0.4484	-57510.434	25445.3047
Neighborhood Veenker	-53478.91	B	42941.411	-1.25	0.2132	-137716.52	30758.6944
Neighborhood NAmes	0	B	.	.	.	.	.
OverallCond 1	-29128.16	B	40414.852	-0.72	0.4712	-108409.45	50153.1278
OverallCond 2	-16001.2	B	12610.425	-1.27	0.2047	-40738.906	8736.5083
OverallCond 3	-23895.5	B	6123.4269	-3.9	<.0001	-35907.75	-11883.257
OverallCond 4	-8726.718	B	4090.9764	-2.13	0.0331	-16751.933	-701.5025
OverallCond 6	5579.9104	B	2252.6285	2.48	0.0134	1160.9584	9998.8624
OverallCond 7	10926.208	B	2451.4075	4.46	<.0001	6117.314	15735.1024
OverallCond 8	15262.858	B	3608.1331	4.23	<.0001	8184.8303	22340.8857
OverallCond 9	29565.69	B	6290.0729	4.7	<.0001	17226.536	41904.8439
OverallCond 5	0	B	.	.	.	.	.
OverallQual 1	-4146.427	B	29356.39	-0.14	0.8877	-61734.475	53441.6204
OverallQual 2	-15241.22	B	17446.017	-0.87	0.3825	-49464.846	18982.4023
OverallQual 3	-11958.42	B	6571.2345	-1.82	0.069	-24849.12	932.2903
OverallQual 4	-4465.712	B	3068.4785	-1.46	0.1458	-10485.106	1553.6827
OverallQual 6	12281.078	B	2234.4662	5.5	<.0001	7897.7551	16664.4017
OverallQual 7	29562.069	B	2834.0354	10.43	<.0001	24002.579	35121.5597
OverallQual 8	54546.033	B	3773.9671	14.45	<.0001	47142.69	61949.3746
OverallQual 9	107741.02	B	5850.0971	18.42	<.0001	96264.964	119217.083
OverallQual 10	137103.53	B	7896.5339	17.36	<.0001	121613	152594.055
OverallQual 5	0	B	.	.	.	.	.
GrLivArea*Neighborho Blmngtn	70.2775	B	48.5317	1.45	0.1478	-24.9264	165.4814
GrLivArea*Neighborho Blueste	26.6447	B	115.4316	0.23	0.8175	-199.796	253.0855
GrLivArea*Neighborho BrDale	26.0535	B	45.0018	0.58	0.5627	-62.2259	114.3328
GrLivArea*Neighborho BrkSide	29.2515	B	11.2736	2.59	0.0096	7.1362	51.3668

GrLivArea*Neighborho ClearCr	-8.1447	B	12.072	-0.67	0.5	-31.8262	15.5367
GrLivArea*Neighborho CollgCr	35.6866	B	7.1016	5.03	<.0001	21.7555	49.6177
GrLivArea*Neighborho Crawfor	15.5523	B	8.4528	1.84	0.066	-1.0296	32.1341
GrLivArea*Neighborho Edwards	6.7965	B	9.1182	0.75	0.4562	-11.0906	24.6836
GrLivArea*Neighborho Gilbert	22.33	B	11.2236	1.99	0.0468	0.3128	44.3472
GrLivArea*Neighborho IDOTRR	11.1825	B	17.3461	0.64	0.5192	-22.8451	45.2102
GrLivArea*Neighborho MeadowV	8.4602	B	17.5999	0.48	0.6308	-26.0653	42.9857
GrLivArea*Neighborho Mitchel	17.0544	B	11.2441	1.52	0.1296	-5.0029	39.1118
GrLivArea*Neighborho NPkVill	70.8368	B	42.1404	1.68	0.093	-11.8295	153.5031
GrLivArea*Neighborho NWAmes	13.9915	B	8.8859	1.57	0.1156	-3.4398	31.4229
GrLivArea*Neighborho NoRidge	91.9615	B	8.8859	10.35	<.0001	74.5301	109.3929
GrLivArea*Neighborho NridgHt	78.4985	B	9.4401	8.32	<.0001	59.98	97.017
GrLivArea*Neighborho OldTown	-6.131	B	6.6734	-0.92	0.3584	-19.2221	6.96
GrLivArea*Neighborho SWISU	-10.3308	B	10.3802	-1	0.3198	-30.6934	10.0319
GrLivArea*Neighborho Sawyer	-3.1257	B	10.155	-0.31	0.7583	-23.0467	16.7952
GrLivArea*Neighborho SawyerW	32.8645	B	8.3873	3.92	<.0001	16.4113	49.3177
GrLivArea*Neighborho Somerst	41.2805	B	11.7235	3.52	0.0004	18.2827	64.2784
GrLivArea*Neighborho StoneBr	88.5111	B	11.0406	8.02	<.0001	66.8529	110.1692
GrLivArea*Neighborho Timber	28.4211	B	12.1917	2.33	0.0199	4.5048	52.3373
GrLivArea*Neighborho Veenker	63.4592	B	27.4776	2.31	0.0211	9.5568	117.3616
GrLivArea*Neighborho NAmes	0	B	.	.	.	.	.

Appendix III

Model SAS scripts

Since these models can be very large we simply copy the SAS code for proc glm for each of the models discussed in Question 2.

<table>
<tr><td>Q2
Model1</td><td><pre>/******* Model 1 (keep) - Backward elemination (adjrsquared = 0.9479, 573 parameters) *******/
proc glm data=housing plots=all;
Class
          MSSubClass MSZoning Alley LotShape LandContour LotConfig Neighborhood Condition1
          BldgType HouseStyle OverallQual OverallCond RoofStyle RoofMatl Exterior1st
          Exterior2nd MasVnrType MasVnrArea ExterQual ExterCond Foundation BsmtQual
          BsmtCond BsmtExposure BsmtFinType1 BsmtFinType2 HeatingQC HeatingQC Electrical
          KitchenQual FireplaceQu GarageType GarageFinish GarageQual GarageCond PavedDrive
          PoolQC Fence SaleType SaleCondition ;
model saleprice =
          BedroomAbvGr BsmtFinSF1 BsmtFinSF2 BsmtFullBath BsmtHalfBath BsmtUnfSF EnclosedPorch
          Fireplaces FullBath GarageArea GarageCars GarageYrBlt GrLivArea HalfBath Id KitchenAbvGr
          LotArea LotFrontage LowQualFinSF MSSubClass MasVnrArea MiscVal MoSold OpenPorchSF
          OverallCond OverallQual PoolArea ScreenPorch TotRmsAbvGrd WoodDeckSF YearBuilt
          YearRemodAdd YrSold _1stFlrSF _3SsnPorch MSZoning Alley LotShape LandContour
          LotConfig Neighborhood Condition1 BldgType HouseStyle RoofStyle RoofMatl Exterior1st
          Exterior2nd MasVnrType ExterQual ExterCond Foundation BsmtQual BsmtCond BsmtExposure
          BsmtFinType1 BsmtFinType2 HeatingQC Electrical KitchenQual FireplaceQu GarageType
          GarageFinish GarageQual GarageCond PavedDrive PoolQC Fence SaleType SaleCondition;
run; quit;</pre></td></tr>
<tr><td>Q2
Model2</td><td><pre>/******* Model 2 (keep) - Our own cross validation (kaggle = 0.13722, adjrsquared = 0.9245, e = 0.13297)
****
proc glm data = housing plots=all;
class
          BldgType BsmtExposure BsmtQual Condition2 KitchenQual RoofMatl SaleCondition
          NeighborhoodGroup OverallCondGroup OverallQualGroup ;
model saleprice =
                    _2ndFlrSF MasVnrArea _3SsnPorch BsmtFinSF1 GarageArea LotArea ScreenPorch
                    BldgType BsmtExposure BsmtQual Condition2 KitchenQual RoofMatl SaleCondition
                    NeighborhoodGroup OverallCondGroup OverallQualGroup GrLivArea*NeighborhoodGroup;
run; quit;</pre></td></tr>
<tr><td>Q2
Model3</td><td><pre>/******* Model 3 (keep) - (kaggle= 0.13474, adjrsquared = 0.9259, e = 0.13025) *******/
proc glm data = housing plots=all;
class
          BldgType BsmtExposure BsmtQual Condition1Group Condition2 KitchenQual RoofMatl
          SaleCondition NeighborhoodGroup OverallCondGroup OverallQualGroup;
model saleprice =
          _2ndFlrSF MasVnrArea _3SsnPorch BsmtFinSF1 GarageArea LotArea ScreenPorch
                    BldgType BsmtExposure BsmtQual Condition1Group Condition2 KitchenQual RoofMatl
                    SaleCondition NeighborhoodGroup OverallCondGroup OverallQualGroup
                    GrLivArea*NeighborhoodGroup GrLivArea*RoofMatl;
run; quit;</pre></td></tr>
</table>

Appendix IV

Other SAS scripts used.

Question 1

```
/* Model 1 (keep) - normal (without interaction) adj-r-squared=.8697, 58
params */
proc glm data = train plots = all;
class MSSubClass (ref = "20") OverallCond (ref = "5") OverallQual (ref = "5")
Neighborhood (ref = "NAmes");
model SalePrice = GrLivArea LotArea MSSubClass OverallCond OverallQual
Neighborhood  / solution tolerance clparm;
run; quit;

/* Model 2 (keep) - Full (with interaction) adj-r-squared=.8873, 82 params */
proc glm data = train plots = all;
class MSSubClass (ref = "20") OverallCond (ref = "5") OverallQual (ref = "5")
Neighborhood (ref = "NAmes");
model SalePrice = GrLivArea LotArea MSSubClass OverallCond OverallQual
Neighborhood GrLivArea*Neighborhood / solution tolerance clparm;
run; quit;

/* Model 3 (keep) - Simple (only continuous) adj-r-squared .6773, 5 params */
proc glm data = train plots=all;
model SalePrice = TotalBsmtSF FullBath GrLivArea LotArea / solution tolerance
clparm;
run; quit;

/* Model 4 (reject) - Just GrLivArea, Neighborhood and interaction adj-r-
squared=.7955, 50 params */
proc glm data = train plots = all;
class MSSubClass (ref = "20") OverallCond (ref = "5") OverallQual (ref = "5")
Neighborhood (ref = "NAmes");
model SalePrice = GrLivArea  GrLivArea*Neighborhood Neighborhood / solution
tolerance clparm;
run; quit;

/* Model 5 (reject) - Just GrLivArea, and Neighborhood interaction adj-r-
squared=.7828, 26 params */
proc glm data = train plots = all;
class MSSubClass (ref = "20") OverallCond (ref = "5") OverallQual (ref = "5")
Neighborhood (ref = "NAmes");
model SalePrice = GrLivArea  GrLivArea*Neighborhood / solution tolerance
clparm;
run; quit;

/* Model 6 (reject) - Full (with groups) adj-r-squared= .885 , 52 params */
proc glm data = train plots = all;
```

```
class MSSubClass (ref = "20") OverallCond (ref = "5") OverallQual (ref = "5")
Neighborhood (ref = "NAmes") NeighborhoodGroup OverallCondGroup
OverallQualGroup;
model SalePrice = GrLivArea LotArea MSSubClass OverallCondGroup
OverallQualGroup NeighborhoodGroup   GrLivArea*NeighborhoodGroup / solution
tolerance clparm;
run; quit;
```

Question 2

```
data housing;
set train test;
run;

/******* Model 3 (keep) - (kaggle= 0.13474, adjrsquared = 0.9259, e =
0.13025) *******/
/* Add GrLivArea*RoofMatl interaction */
proc glm data = housing plots=all;
class
      /* Character Categorical Variables */
      BldgType BsmtExposure BsmtQual Condition1Group Condition2 KitchenQual
RoofMatl SaleCondition NeighborhoodGroup

      /* Numerical Categorical Variables */
      OverallCondGroup OverallQualGroup;

      model saleprice = _2ndFlrSF MasVnrArea _3SsnPorch
            BsmtFinSF1 GarageArea LotArea ScreenPorch
            BldgType BsmtExposure BsmtQual Condition1Group Condition2
KitchenQual RoofMatl
            SaleCondition NeighborhoodGroup
            OverallCondGroup OverallQualGroup
            GrLivArea*NeighborhoodGroup
            GrLivArea*RoofMatl;

      output out = predictions predicted = prediction;

run; quit;

/* the predictions for test data */
data finalprediction;
set predictions;
if Id > 1460;
SalePrice = prediction;

keep Id SalePrice;
run;

/* Be sure to change the outfile to your own file location */
```

```
/* The outfile "submission.csv" will be used in submission to kaggle */
proc export data=finalprediction
outfile='/home/kjprice120/sasuser.v94/Project1/data/submission.csv' dbms=csv;
run;

title 'Observations with Missing Values';
data finalpredictionMissing;
set finalprediction;
if SalePrice = .;
run;
proc print data=finalpredictionMissing;
run;
```

Manual External Cross validation code

```
/* This code will be used to test models with another training and test set
*/
/* It calculates the Root Mean Squared Logarithmic Error for the test2 set */
/* Run this code after you have loaded and cleaned the data */

/* If you beat this score replace it with the better one kaggle= 0.13474,
adjrsquared = 0.9259, e = 0.13025 */

data trainrandom;
set train;
RandNumber = ranuni(11);
run;

data train2;
set trainrandom;
if RandNumber <= 1/2 then delete;
run;

data test2real;
set trainrandom;
SalePriceReal = saleprice;
if RandNumber > 1/2 then delete;
keep ID RandNumber SalePriceReal;
run;

data test2;
set trainrandom;
if RandNumber > 1/2 then delete;
SalePriceReal = SalePrice;
run;

data test2;
set test2;
```

```
drop SalePrice;
run;


data housing2;
set train2 test2;
run;


/* Place the model you want to use here */

/* kaggle= 0.13474, adjrsquared = 0.9259, e = 0.13025  */
/* Add RoofMatl*GrLivArea interaction */
proc glm data = housing2 plots=all;
class
      /* Character Categorical Variables */
      BldgType BsmtExposure BsmtQual Condition1Group Condition2 KitchenQual
RoofMatl SaleCondition NeighborhoodGroup

      /* Numerical Categorical Variables */
      OverallCondGroup OverallQualGroup;

      model saleprice = _2ndFlrSF MasVnrArea _3SsnPorch
            BsmtFinSF1 GarageArea LotArea ScreenPorch
            BldgType BsmtExposure BsmtQual Condition1Group Condition2
KitchenQual RoofMatl
            SaleCondition NeighborhoodGroup
            OverallCondGroup OverallQualGroup
            GrLivArea*NeighborhoodGroup
            RoofMatl*GrLivArea;

      output out = predictions predicted = prediction;
run; quit;


/* the predictions for test2 data */
data finalprediction2;
set predictions;
if RandNumber <= 1/2;
difference = (prediction - SalePriceReal)*(prediction - SalePriceReal);
logdiff = (log(prediction + 1) - log(SalePriceReal + 1))*(log(prediction + 1)
- log(SalePriceReal + 1));
keep RandNumber Id difference logdiff;
run;

data finalpredictionMissing2;
set finalprediction2;
if difference = .;
run;

title 'Rows with missing predictions';
```

```
proc print data=finalpredictionMissing2; run;

proc summary data = finalprediction2;
var logdiff;
output out = diffsummary mean=mean sum=sum n=n;
run;

data sqr;
set diffsummary;
e = sqrt(sum/(n));
keep e;
run;

title 'Root Mean Squared Logarithmic Error';
proc print data=sqr; run;
```

Automatic External Cross validation code

```
/* This code is designed to be run after data is loaded and cleaned. */

data trainrandom;
set train;
RandNumber = ranuni(11);
run;

data train3;
set trainrandom;
if RandNumber <= 1/2 then delete;
run;

data test3;
set trainrandom;
if RandNumber > 1/2 then delete;
run;

/* With Stepwise */
proc glmselect data = train3 testdata=test3
                        seed = 1 plots(stepAxis=number)=(criterionPanel
ASEPlot CRITERIONPANEL);
class
      /* Character Categorical Variables */
      BldgType BsmtExposure BsmtQual Condition2 KitchenQual RoofMatl
SaleCondition NeighborhoodGroup

      /* Numerical Categorical Variables */
      OverallCond OverallQual;
```

```
	/* model taken by using proc glmselect with stepwise selection  on KJ
model (kaggle = 0.14060, adjrsquared = 0.9162) */
	/* there are slight tolerance/VIF issues with OverallQual 4-8 and
OverallCond 5-6  */
	model saleprice =
		BsmtFinSF1 GarageArea LotArea ScreenPorch
		BldgType BsmtExposure BsmtQual Condition2 KitchenQual RoofMatl
SaleCondition NeighborhoodGroup
		OverallCond OverallQual
		GrLivArea*NeighborhoodGroup / selection= stepwise(choose=CV
stop=AIC) CVdetails;
run; quit;


/* With LASSO */
proc glmselect data = train3 testdata=test3
				seed = 1 plots(stepAxis=number)=(criterionPanel
ASEPlot CRITERIONPANEL);
class
	/* Character Categorical Variables */
	BldgType BsmtExposure BsmtQual Condition2 KitchenQual RoofMatl
SaleCondition NeighborhoodGroup

	/* Numerical Categorical Variables */
	OverallCond OverallQual;

	/* model taken by using proc glmselect with stepwise selection  on KJ
model (kaggle = 0.14060, adjrsquared = 0.9162) */
	/* there are slight tolerance/VIF issues with OverallQual 4-8 and
OverallCond 5-6  */
	model saleprice =
		BsmtFinSF1 GarageArea LotArea ScreenPorch
		BldgType BsmtExposure BsmtQual Condition2 KitchenQual RoofMatl
SaleCondition NeighborhoodGroup
		OverallCond OverallQual
		GrLivArea*NeighborhoodGroup / selection= LASSO(choose=CV
stop=AIC) CVdetails;
run; quit;
```

Appendix V

Screen shot of final Kaggle submissions

Submission and Description	Private Score	Public Score	Use for Final Score
submissionfinal.csv 36 minutes ago by daresnick *add submission details*		0.12611	☐
submission8e.csv an hour ago by daresnick *add submission details*		0.12611	☐
submission8d.csv an hour ago by daresnick *add submission details*		0.12678	☐
submission8c.csv an hour ago by daresnick *add submission details*		0.12701	☐
submission8a.csv an hour ago by daresnick *add submission details*		0.12678	☐
submission2w.csv 9 hours ago by daresnick *add submission details*		0.13089	☐
submission2w.csv 9 hours ago by daresnick		0.13089	☐

Appendix VI

Variable Description

The document below is just a copy of the file Kaggle has on there website.

https://www.kaggle.com/c/house-prices-advanced-regression-techniques/data

MSSubClass: Identifies the type of dwelling involved in the sale.

20	1-STORY 1946 & NEWER ALL STYLES
30	1-STORY 1945 & OLDER
40	1-STORY W/FINISHED ATTIC ALL AGES
45	1-1/2 STORY - UNFINISHED ALL AGES
50	1-1/2 STORY FINISHED ALL AGES
60	2-STORY 1946 & NEWER
70	2-STORY 1945 & OLDER
75	2-1/2 STORY ALL AGES
80	SPLIT OR MULTI-LEVEL
85	SPLIT FOYER
90	DUPLEX - ALL STYLES AND AGES
120	1-STORY PUD (Planned Unit Development) - 1946 & NEWER
150	1-1/2 STORY PUD - ALL AGES
160	2-STORY PUD - 1946 & NEWER
180	PUD - MULTILEVEL - INCL SPLIT LEV/FOYER
190	2 FAMILY CONVERSION - ALL STYLES AND AGES

MSZoning: Identifies the general zoning classification of the sale.

A	Agriculture
C	Commercial
FV	Floating Village Residential
I	Industrial
RH	Residential High Density
RL	Residential Low Density
RP	Residential Low Density Park
RM	Residential Medium Density

LotFrontage: Linear feet of street connected to property

LotArea: Lot size in square feet

Street: Type of road access to property

Grvl Gravel
Pave Paved

Alley: Type of alley access to property

Grvl Gravel
Pave Paved
NA No alley access

LotShape: General shape of property

Reg Regular
IR1 Slightly irregular
IR2 Moderately Irregular
IR3 Irregular

LandContour: Flatness of the property

Lvl Near Flat/Level
Bnk Banked - Quick and significant rise from street grade to building
HLS Hillside - Significant slope from side to side
Low Depression

Utilities: Type of utilities available

AllPub All public Utilities (E,G,W,& S)
NoSewr Electricity, Gas, and Water (Septic Tank)
NoSeWa Electricity and Gas Only
ELO Electricity only

LotConfig: Lot configuration

Inside Inside lot
Corner Corner lot
CulDSac Cul-de-sac
FR2 Frontage on 2 sides of property
FR3 Frontage on 3 sides of property

LandSlope: Slope of property

Gtl   Gentle slope
Mod   Moderate Slope
Sev   Severe Slope

Neighborhood: Physical locations within Ames city limits

Blmngtn Bloomington Heights
Blueste Bluestem
BrDale Briardale
BrkSide Brookside
ClearCr Clear Creek
CollgCr College Creek
Crawfor Crawford
Edwards Edwards
Gilbert Gilbert
IDOTRR Iowa DOT and Rail Road
MeadowV Meadow Village
Mitchel Mitchell
Names   North Ames
NoRidge Northridge
NPkVill Northpark Villa
NridgHt Northridge Heights
NWAmes Northwest Ames
OldTown Old Town
SWISU   South & West of Iowa State University
Sawyer Sawyer
SawyerW Sawyer West
Somerst Somerset
StoneBr Stone Brook
Timber Timberland
Veenker Veenker

Condition1: Proximity to various conditions

Artery Adjacent to arterial street
Feedr   Adjacent to feeder street
Norm Normal
RRNn Within 200' of North-South Railroad
RRAn Adjacent to North-South Railroad
PosN Near positive off-site feature--park, greenbelt, etc.
PosA Adjacent to postive off-site feature

RRNe Within 200' of East-West Railroad
RRAe Adjacent to East-West Railroad

Condition2: Proximity to various conditions (if more than one is present)

Artery Adjacent to arterial street
Feedr   Adjacent to feeder street
Norm Normal
RRNn Within 200' of North-South Railroad
RRAn Adjacent to North-South Railroad
PosN Near positive off-site feature--park, greenbelt, etc.
PosA Adjacent to postive off-site feature
RRNe Within 200' of East-West Railroad
RRAe Adjacent to East-West Railroad

BldgType: Type of dwelling

1Fam Single-family Detached
2FmCon Two-family Conversion; originally built as one-family dwelling
Duplx   Duplex
TwnhsE Townhouse End Unit
TwnhsI Townhouse Inside Unit

HouseStyle: Style of dwelling

1Story One story
1.5Fin One and one-half story: 2nd level finished
1.5Unf One and one-half story: 2nd level unfinished
2Story Two story
2.5Fin Two and one-half story: 2nd level finished
2.5Unf Two and one-half story: 2nd level unfinished
SFoyer Split Foyer
SLvl Split Level

OverallQual: Rates the overall material and finish of the house

10   Very Excellent
9   Excellent
8   Very Good
7   Good
6   Above Average
5   Average

4 Below Average
3 Fair
2 Poor
1 Very Poor

OverallCond: Rates the overall condition of the house

10 Very Excellent
9 Excellent
8 Very Good
7 Good
6 Above Average
5 Average
4 Below Average
3 Fair
2 Poor
1 Very Poor

YearBuilt: Original construction date

YearRemodAdd: Remodel date (same as construction date if no remodeling or additions)

RoofStyle: Type of roof

Flat Flat
Gable Gable
Gambrel Gabrel (Barn)
Hip Hip
Mansard Mansard
Shed Shed

RoofMatl: Roof material

ClyTile Clay or Tile
CompShg Standard (Composite) Shingle
Membran Membrane
Metal Metal
Roll Roll
Tar&Grv Gravel & Tar
WdShake Wood Shakes
WdShngl Wood Shingles

Exterior1st: Exterior covering on house

AsbShng Asbestos Shingles
AsphShn Asphalt Shingles
BrkComm Brick Common
BrkFace Brick Face
CBlock Cinder Block
CemntBd Cement Board
HdBoard Hard Board
ImStucc Imitation Stucco
MetalSd Metal Siding
Other   Other
Plywood Plywood
PreCast PreCast
Stone   Stone
Stucco Stucco
VinylSd Vinyl Siding
Wd Sdng Wood Siding
WdShing Wood Shingles

Exterior2nd: Exterior covering on house (if more than one material)

AsbShng Asbestos Shingles
AsphShn Asphalt Shingles
BrkComm Brick Common
BrkFace Brick Face
CBlock Cinder Block
CemntBd Cement Board
HdBoard Hard Board
ImStucc Imitation Stucco
MetalSd Metal Siding
Other   Other
Plywood Plywood
PreCast PreCast
Stone   Stone
Stucco Stucco
VinylSd Vinyl Siding
Wd Sdng Wood Siding
WdShing Wood Shingles

MasVnrType: Masonry veneer type

BrkCmn Brick Common
BrkFace Brick Face
CBlock Cinder Block
None None
Stone Stone

MasVnrArea: Masonry veneer area in square feet

ExterQual: Evaluates the quality of the material on the exterior

Ex Excellent
TA Average/Typical
Fa Fair
Po Poor

ExterCond: Evaluates the present condition of the material on the exterior

Ex Excellent
Gd Good
TA Average/Typical
Fa Fair
Po Poor

Foundation: Type of foundation

BrkTil Brick & Tile
CBlock Cinder Block
PConc Poured Contrete
Slab Slab
Stone Stone
Wood Wood

BsmtQual: Evaluates the height of the basement

Ex Excellent (100+ inches)
Gd Good (90-99 inches)
TA Typical (80-89 inches)
Fa Fair (70-79 inches)
Po Poor (<70 inches
NA No Basement

BsmtCond: Evaluates the general condition of the basement

Ex   Excellent
Gd   Good
TA   Typical - slight dampness allowed
Fa   Fair - dampness or some cracking or settling
Po   Poor - Severe cracking, settling, or wetness
NA   No Basement

BsmtExposure: Refers to walkout or garden level walls

Gd   Good Exposure
Av   Average Exposure (split levels or foyers typically score average or above)
Mn   Mimimum Exposure
No   No Exposure
NA   No Basement

BsmtFinType1: Rating of basement finished area

GLQ   Good Living Quarters
ALQ   Average Living Quarters
BLQ   Below Average Living Quarters
Rec   Average Rec Room
LwQ   Low Quality
Unf   Unfinshed
NA   No Basement

BsmtFinSF1: Type 1 finished square feet

BsmtFinType2: Rating of basement finished area (if multiple types)

GLQ   Good Living Quarters
ALQ   Average Living Quarters
BLQ   Below Average Living Quarters
Rec   Average Rec Room
LwQ   Low Quality
Unf   Unfinshed
NA   No Basement

BsmtFinSF2: Type 2 finished square feet

BsmtUnfSF: Unfinished square feet of basement area

TotalBsmtSF: Total square feet of basement area

Heating: Type of heating

Floor Floor Furnace
GasA Gas forced warm air furnace
GasW Gas hot water or steam heat
Grav Gravity furnace
OthW Hot water or steam heat other than gas
Wall Wall furnace

HeatingQC: Heating quality and condition

Ex Excellent
Gd Good
TA Average/Typical
Fa Fair
Po Poor

HeatingQC: Central air conditioning

N No
Y Yes

Electrical: Electrical system

SBrkr Standard Circuit Breakers & Romex
FuseA Fuse Box over 60 AMP and all Romex wiring (Average)
FuseF 60 AMP Fuse Box and mostly Romex wiring (Fair)
FuseP 60 AMP Fuse Box and mostly knob & tube wiring (poor)
Mix Mixed

1stFlrSF: First Floor square feet

2ndFlrSF: Second floor square feet

LowQualFinSF: Low quality finished square feet (all floors)

GrLivArea: Above grade (ground) living area square feet

BsmtFullBath: Basement full bathrooms

BsmtHalfBath: Basement half bathrooms

FullBath: Full bathrooms above grade

HalfBath: Half baths above grade

Bedroom: Bedrooms above grade (does NOT include basement bedrooms)

Kitchen: Kitchens above grade

KitchenQual: Kitchen quality

```
       Ex    Excellent
       Gd    Good
       TA    Typical/Average
       Fa    Fair
       Po    Poor
```

TotRmsAbvGrd: Total rooms above grade (does not include bathrooms)

Functional: Home functionality (Assume typical unless deductions are warranted)

```
       Typ   Typical Functionality
       Min1  Minor Deductions 1
       Min2  Minor Deductions 2
       Mod   Moderate Deductions
       Maj1  Major Deductions 1
       Maj2  Major Deductions 2
       Sev   Severely Damaged
       Sal   Salvage only
```

Fireplaces: Number of fireplaces

FireplaceQu: Fireplace quality

```
       Ex    Excellent - Exceptional Masonry Fireplace
```

Gd Good - Masonry Fireplace in main level
TA Average - Prefabricated Fireplace in main living area or Masonry Fireplace in basement
Fa Fair - Prefabricated Fireplace in basement
Po Poor - Ben Franklin Stove
NA No Fireplace

GarageType: Garage location

2Types More than one type of garage
Attchd Attached to home
Basment Basement Garage
BuiltIn Built-In (Garage part of house - typically has room above garage)
CarPort Car Port
Detchd Detached from home
NA No Garage

GarageYrBlt: Year garage was built

GarageFinish: Interior finish of the garage

Fin Finished
RFn Rough Finished
Unf Unfinished
NA No Garage

GarageCars: Size of garage in car capacity

GarageArea: Size of garage in square feet

GarageQual: Garage quality

Ex Excellent
Gd Good
TA Typical/Average
Fa Fair
Po Poor
NA No Garage

GarageCond: Garage condition

Ex	Excellent
Gd	Good
TA	Typical/Average
Fa	Fair
Po	Poor
NA	No Garage

PavedDrive: Paved driveway

Y	Paved
P	Partial Pavement
N	Dirt/Gravel

WoodDeckSF: Wood deck area in square feet

OpenPorchSF: Open porch area in square feet

EnclosedPorch: Enclosed porch area in square feet

3SsnPorch: Three season porch area in square feet

ScreenPorch: Screen porch area in square feet

PoolArea: Pool area in square feet

PoolQC: Pool quality

Ex	Excellent
Gd	Good
TA	Average/Typical
Fa	Fair
NA	No Pool

Fence: Fence quality

GdPrv	Good Privacy
MnPrv	Minimum Privacy
GdWo	Good Wood
MnWw	Minimum Wood/Wire
NA	No Fence

MiscFeature: Miscellaneous feature not covered in other categories

Elev	Elevator
Gar2	2nd Garage (if not described in garage section)
Othr	Other
Shed	Shed (over 100 SF)
TenC	Tennis Court
NA	None

MiscVal: $Value of miscellaneous feature

MoSold: Month Sold (MM)

YrSold: Year Sold (YYYY)

SaleType: Type of sale

WD 	Warranty Deed - Conventional
CWD	Warranty Deed - Cash
VWD	Warranty Deed - VA Loan
New	Home just constructed and sold
COD	Court Officer Deed/Estate
Con	Contract 15% Down payment regular terms
ConLw	Contract Low Down payment and low interest
ConLI	Contract Low Interest
ConLD	Contract Low Down
Oth	Other

SaleCondition: Condition of sale

Normal	Normal Sale
Abnorml	Abnormal Sale - trade, foreclosure, short sale
AdjLand	Adjoining Land Purchase
Alloca	Allocation - two linked properties with separate deeds, typically condo with a garage unit
Family	Sale between family members
Partial	Home was not completed when last assessed (associated with New Homes)