Principal Component and Regression Approach: Identification of the factors contributing the Sale Price of Residential Properties

Prepared for
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1. Introduction

This paper demonstrates the use of Principal Component Analysis as the tool for an exploratory data analysis and feature extraction using the residential property dataset for the City of Ames, Iowa. The main objective of this study is to identify important features that contributes to the high the sale price and find the model with a predictive power. The regression model will be obtained by using a set of significant principal components and categorical predictors. We also employ stepwise model selection approach to fit the model using optimal subset of predictors. It has been always an area of interest among real Estate Business, property owners and researchers to identify which factors contribute to the Sale price of residential property and model for the prediction of the Sale price. The study on well-known Boston housing dataset is one of such example. This project is also an attempt to answers these questions. But, the approach used during this study is slightly different than normal regression setting as dataset used in this study is high dimensional. Therefore, we will first use the feature extraction method to reduce the dimensionality of the data and then use the regression technique to find the model.

1.1 Description of Dataset

The dataset used in during the study contains 2390 observations which constitutes 23 nominal, 23 ordinal, 14 discrete and 20 continuous variables. The original source of the dataset traced back to City of Ames Assessor office which keep the track of Real estate properties in Ames. The author[1] has done significant amount of work by separating the extraneous variables with has a little impact on sales prices of the properties. I decided to exclude the discrete predictors from my study. The Dataset description is as follows . Further information about the dataset can be found in [1].

1.1.1 Continuous Variables

1. LotArea = Lot size in square feet
2. MasVnrArea = Masonry veneer area in square feet
3. BsmtFin SF 1 =Type 1 finished square feet
4. BsmtFin SF 2 =Type 2 finished square feet
5. Bsmt Unf SF = Unfinished square feet of basement area
6. Total Bsmt SF = Total square feet of basement area
7. 1st Flr SF = First Floor square feet
8. 2nd Flr SF = Second floor square feet
9. Low Qual Fin SF = Low quality finished square feet (all floors)
10. GrLivArea = Above grade (ground) living area square feet
11. Garage Area = Size of garage in square feet
12. Wood Deck SF = Wood deck area in square feet
13. Open Porch SF = Open porch area in square feet
14. Enclosed Porch = Enclosed porch area in square feet
15. 3-Ssn Porch= Three season porch area in square feet
16. Screen Porch= Screen porch area in square feet
17. Pool Area = Pool area in square feet
18. Misc Val = $Value of miscellaneous feature
19. SalePrice= Sale price $$

1.1.2 Categorical Variables Presents in the dataset

1. LotShape (Ordinal): General shape of property
2. Utilities (Ordinal): Type of utilities available

3. LandSlope (Ordinal): Slope of property
4. OverallQual (Ordinal): Rates the overall material and finish of the house
5. OverallCond (Ordinal): Rates the overall condition of the house
6. ExterQual (Ordinal): Evaluates the quality of the material on the exterior
7. ExterCond (Ordinal): Evaluates the present condition of the material on the exterior
8. BsmtQual (Ordinal): Evaluates the height of the basement
9. BsmtCond (Ordinal): Evaluates the general condition of the basement
10. BsmtExposure(Ordinal): Refers to walkout or garden level walls
11. BsmtFinType 1(Ordinal): Rating of basement finished area
12. BsmtFinType 2(Ordinal): Rating of basement finished area (if multiple types)
13. HeatingQC (Ordinal): Heating quality and condition
14. Electrical (Ordinal): Electrical system
15. KitchenQual (Ordinal): Kitchen quality
16. Functional (Ordinal): Home functionality (Assume typical unless deductions are warranted)
17. FireplaceQu (Ordinal): Fireplace quality
18. Garage Finish (Ordinal) : Interior finish of the garage
19. Garage Qual (Ordinal): Garage quality
20. Garage Cond (Ordinal): Garage condition
21. Paved Drive (Ordinal): Paved driveway
22. Pool QC (Ordinal): Pool quality
23. Fence (Ordinal): Fence quality
24. PID : Parcel Identification Number
25. MSSubCls : Identifies the type of dwelling involved in the Sale
26. MSZoning (Nominal): Identifies the general zoning classification of the sale. (7 levels)
27. Street (Nominal): Type of road access to property(Grave and Paved)
28. Alley (Nominal): Type of alley access to property (Gravel, PAve, No Access)
29. LandContour (Nominal): Flatness of the property(4 levels)
30. LotConfig (Nominal): Lot configuration
31. Neighborhood (Nominal): Physical locations within Ames city limits (map available)
32. Condition1 (Nominal): Proximity to various conditions
33. Condition2 (Nominal): Proximity to various conditions (if more than one is present)
34. BldgType (Nominal): Type of dwelling
35. HouseStyle (Nominal): Style of dwelling
36. RoofStyle (Nominal): Type of roof
37. RoofMatl (Nominal): Roof material
38. Exterior1 (Nominal): Exterior covering on house
39. Exterior2 (Nominal): Exterior covering on house (if more than one material)
40. MasVnrType (Nominal): Masonry veneer type
41. Foundation (Nominal): Type of foundation
42. Heating (Nominal): Type of heating
43. CentralAir (Nominal): Central air conditioning
44. GarageType (Nominal): Garage location
45. Misc Feature (Nominal): Miscellaneous feature not covered in other categories
46. SaleType (Nominal): Type of sale
47. Sale Condition (Nominal): Condition of sale
48. garage unit

1.2 Dealing with Missing Values in Continuous variable

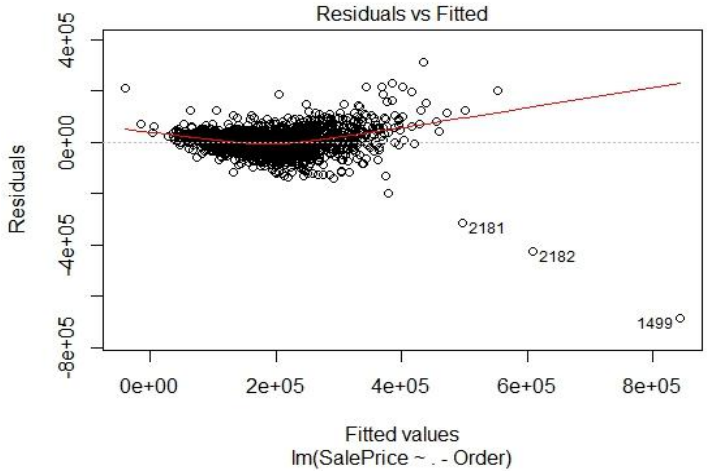
The summary of Ames dataset is as given Appendix: A and data description in the paper[1] indicates that many residential properties do not have a Pool, fence and Other miscellaneous features. The 'NA' values in the dataset for the mentioned variables represent no such feature applicable to the corresponding residential property[1]. Square feet area for such feature is entered as 'zero' in the given dataset. Therefore, it is reasonable to exclude

these variables from this study. The 'NA' s also observed for the variable 'Lot frontage' which indicates linear feet of the street connected to a property. the p-value for it is less than p-cutoff[Appendix B] and also discussed in section 3.1 and 3.2. I chose to exclude categorical variables Alley, Fence, FireplaceQC variables as over 1500 houses have NAs which either represents a missing or not applicable values.

The categorical variables that describe additional information about the garage and basement are missing for few residential properties. Features related to garage and basement are also excluded from the study as we have continuous variables that can describe the importance of such features. Variable 'Masonry veneer' indicates 23 missing values and results in appendix B indicates its p-value is less than 0.05. Variables in the set A = (BsmtFinSF1, BsmtFinSF2, BsmtUnfSF1, TotalBSmtSF, GarageArea) and Masonry Veneer replaced with their corresponding mean values to avoid removal of these records while applying Principal Component Analysis(PCA) and multiple linear regression modelling. This analysis does not consider the discrete variables for the sake of simplicity of the model. Thus, we will consider 54 variables (19 continuous and 35 categorical) for the further study.

1.3 Identification of Outliers

The residual Vs fitted graph for lm() model fitted by regressing all the continuous predictor against Sale Price shows the possible presence of 3 outliers. Houses represented by these records have partial sale conditions and have above grade living area greater than 4500 square feet. Although the value R^2 remains same after removal of these records I chose to exclude to these records to avoid it's impact on the Principal components. Author [1] in this article also suggested to exclude these variables as these houses represents the partial Sale condition which do not necessarily reflects the actual market Sale Price and two of them shows questionable Sale Prices.



2. Methodology

2.1 Usability of Studied Approaches

Ames Housing Dataset is a very rich data set. It contains the combination of both quantitative and qualitative variables that explains various attributes of the residential properties. As per my analysis, one can use the combination of Principal component Analysis, Multiple Linear regression to identify the factors contributing to the Sale Prices. For this analysis, I chose to use the PCA, Multiple linear regression and Stepwise (Forward and

backward) feature selection method to find the best model that predict the Sale prices of residential properties. PCA used as the tool for the exploratory data analysis and dimensionality reduction for all the continuous features of Residential properties. The scatter plot in section 2.2 and analysis of correlation matrix point that some of these variables are highly correlated with each other. The statistical study indicates that such predictor hampers the accuracy of a final model. Moreover, PCA proved useful to reduce the dimensionality of this dataset. The newly transformed variables are the linear combination of the original variables which are uncorrelated.

Multiple linear regression is applied to this dataset as many variables such that GrLivArea, GargaeArea show a strong linear relationship with the response Sale Price. This can be shown from the scatter plot presented in subsection 2.2.1. I decided to use Forward Stepwise and Backward Stepwise selection method of feature selection. Best Subset Selection method cannot be applied here as we have a relatively larger value of p. For p=54, we would have 2p possibilities which are computationally not practical. Forward Stepwise Selection approach is an efficient technique to deal with this issue. It starts with null model and keep adding the predictors one at a time[2]. I used the step() function which select the best model based on the Akaike Information Criteria(AIC) with a minimum information loss.

Later sections explain step by step process of modeling, results at each step and finally discusses the final model, statistical inference based on it and then tries to answers the research questions. First, I will describe the use principal component analysis as a tool for exploratory data analysis and its results. In the later section, I will use multiple regression models to identify significant variables using variable selection method. Finally, I will discuss model derived using Variable selection method (Forward and Backward) and iterative removal of insignificant predictors to improve the model

2.2 Specifications of the Final model

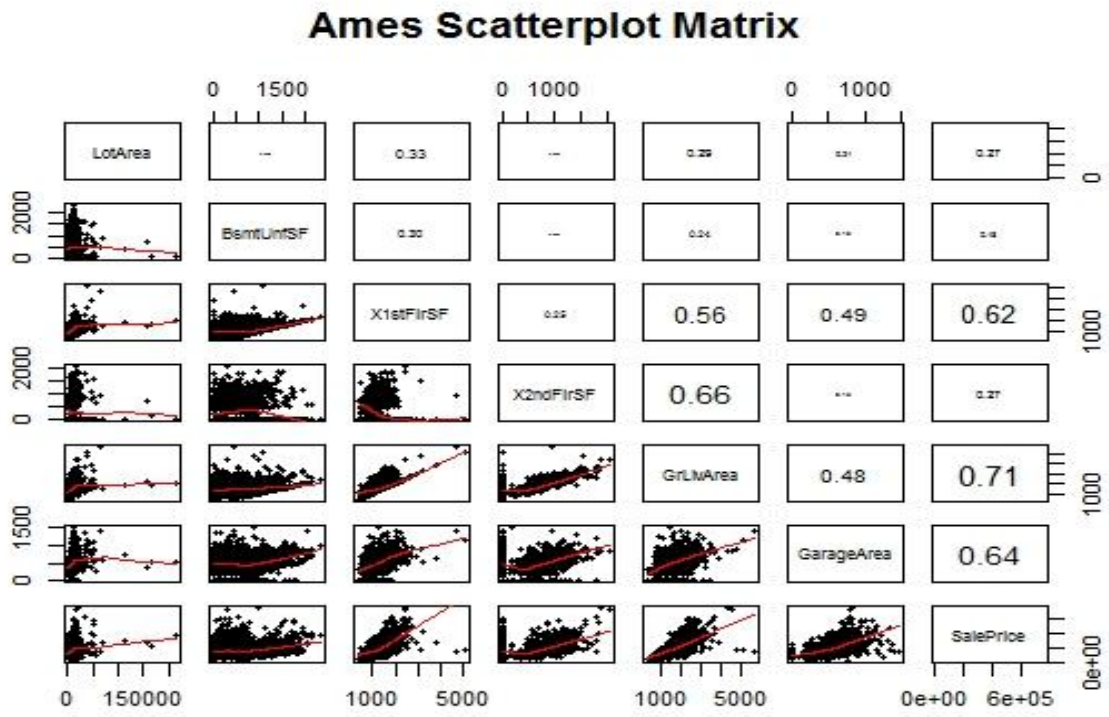
2.2.1 Exploration of continuous data using pair-wise scatter plots

As the first step to analysis, I used the pair wise scatter plot of the few continuous variables is as shown in below "the Ames Scatter Plot matrix" and the correlation matrix to roughly identify the pattern in the dataset. The below scatter plot shows variables GrLivAr, x1stFlr, x2Flr are highly correlated with each other. Garage Area and LivArea have a perfect linear relationship with the Sale price.

2.2.2 Assumption and Specification for final Model

We assume the linear relationship between the predictors variables and Response variable to find the regression model that can predict the Sale price of residential properties. Important categorical variables which describe the neighborhood, house style and amenities in the residential properties also included in the study. Any Selection method to find the a model with an optimal set of variables does not always guarantee estimation of accurate model prediction.

The Scatter plot matrix for few set of predictors is as follows:



3. Results

3.1 Full Regression Model Using Continuous Predictors

The model is fitted using all 18 continuous predictors as it is without any transformation and consideration of missing values in the dataset. As per me, this model helped me get the sense of important features which I can include in the final model. The output F-Statics = 391.2 clearly shows many of these variables are related to the response variable. The NA values for the TotalBsmtSF and GrLivArea indicates multilinearity problem. 509 observations are deleted due to missing values which significantly reduces the sample size and can affect our analysis. As discussed in section 1.3,
we removed outliers which indicate unusual Sale price of these residential properties. After removal of the outliers, R2 value increased from 73% to 79% and Residual Standard Error also decreased. Hence, I decided to remove these outliers for my final working dataset. Appendix[B]

Results of full model before removing the outliers:

```
Residual standard error: 43090 on 2403 degrees of freedom
Multiple R-squared:  0.7346,       Adjusted R-squared:  0.7327
F-statistic: 391.2 on 17 and 2403 DF,  p-value: < 2.2e-16
```

Results of full model After removing the outliers:

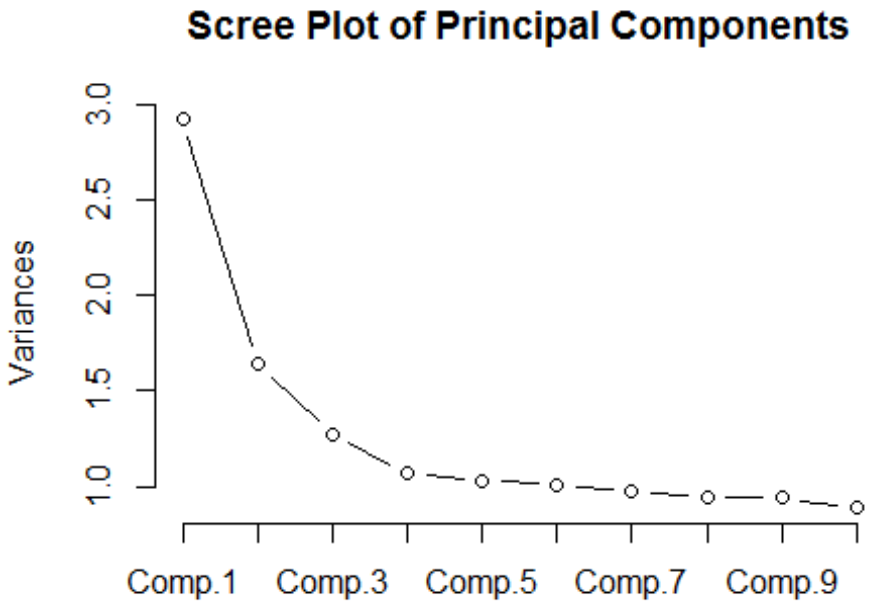
```
Residual standard error: 37580 on 2398 degrees of freedom
Multiple R-squared:  0.7904,       Adjusted R-squared:  0.789
F-statistic: 532.1 on 17 and 2398 DF,  p-value: < 2.2e-16
```

3.2 Full regression model with no NA's

I replaced NA's for the predictor set [MasVnrArea, BsmtFinSF1, BsmtFinSF2, BsmtUnfSF, TotalBsmtSF, GarageArea] with their corresponding mean values as discussed in section 1.3. The values of R2 is decreased slightly but RSE is improved. The result of VIF() function clearly indicates a severe multi-linearity problem with this model.

3.3 Principal Component Analysis (PCA)

Multi-linearity often causes intricacy while using the regression technique to find the model. PCA is a very good tool to deal with this constraints. We chose 16 continuous variables for the PCA excluding Sale Price (response variable) and X1stFlrSF and X1stFlrSF(due to singularity issue). The build in R function princcomp() is used to perform the principal component analysis. The results of PCA is shown in the Appendix D. Below Scree plot of principal components depicts the proportion of variance explained by the first 10 principal components. I chose to use first 9 principal components as it describes 73% percentage variation in the data for our large dataset. According to me, including additional principal components can cause the overfitting problem in our final regression model.



PCA scores are calculated by linear combination loading vectors and original variables. The loading vector gives the direction of variation in the data in data[appendix D]

3.4 Variable Selection

At this step my working dataset now contains 2925 observation with 9 continuous (Principal components scores) and 29 categorical variables and Response variable SalePrice. I started with the simplest model with no predictors and model with all predictor variables to select the best subset of variables. Several automated

variable selection methods will be performed to find the final model. I used R's step() function to build the linear model using the forward selection and backward selection approach.

Null Model = lm(SalePrice ~ ., data = finalWorkingSet)
Full model = lm(SalePrice ~ 1, data = finalWorkingSet)

The summary of final working set is as shown in appendix E. The performance measures used during this approach is based on sum of squared error as I want to find the regression model.

$$\sum_{i=1}^{n}(\text{Yiobserved} - \text{Ymean})^2 = \sum_{i=1}^{n}(\text{Yobserved} - \text{Yfitted})^2 + \sum_{i=1}^{n}(\text{Yifitted} - \text{Ymean})^2 +$$

i.e. SST = SSE + SSR

R^2 which is ratio of sum of square residual to total sum of squares (SST) total. Step() function uses the AIC (Akaike Infomation Criteria) which is based on SSE to find the best subset model.

AICp = nlog(SSEp) – nlong(n) + 2p

n = no of observation
p= no of predictors

3.5 Stepwise forward Selection

Here we start with null model and keep removing the predictors one by one in the model. The final model derived as result of many automated selection techniques is as follows:

forward = lm(formula = SalePrice ~ Comp.1 + Neighborhood + KitchenQual +ExterQual + HouseStyle + BldgType + MasVnrType + SaleCondition +Exterior1st + Functional + Foundation + Comp.8 + Comp.2 + Condition1 + HeatingQC + LandSlope + RoofMatl + LandContour +Street + Comp.5 + Comp.3 + LotConfig + ExterCond + Condition2 +RoofStyle + Comp.7 + Utilities + Comp.4 + SaleType, data = finalWorkingSet)

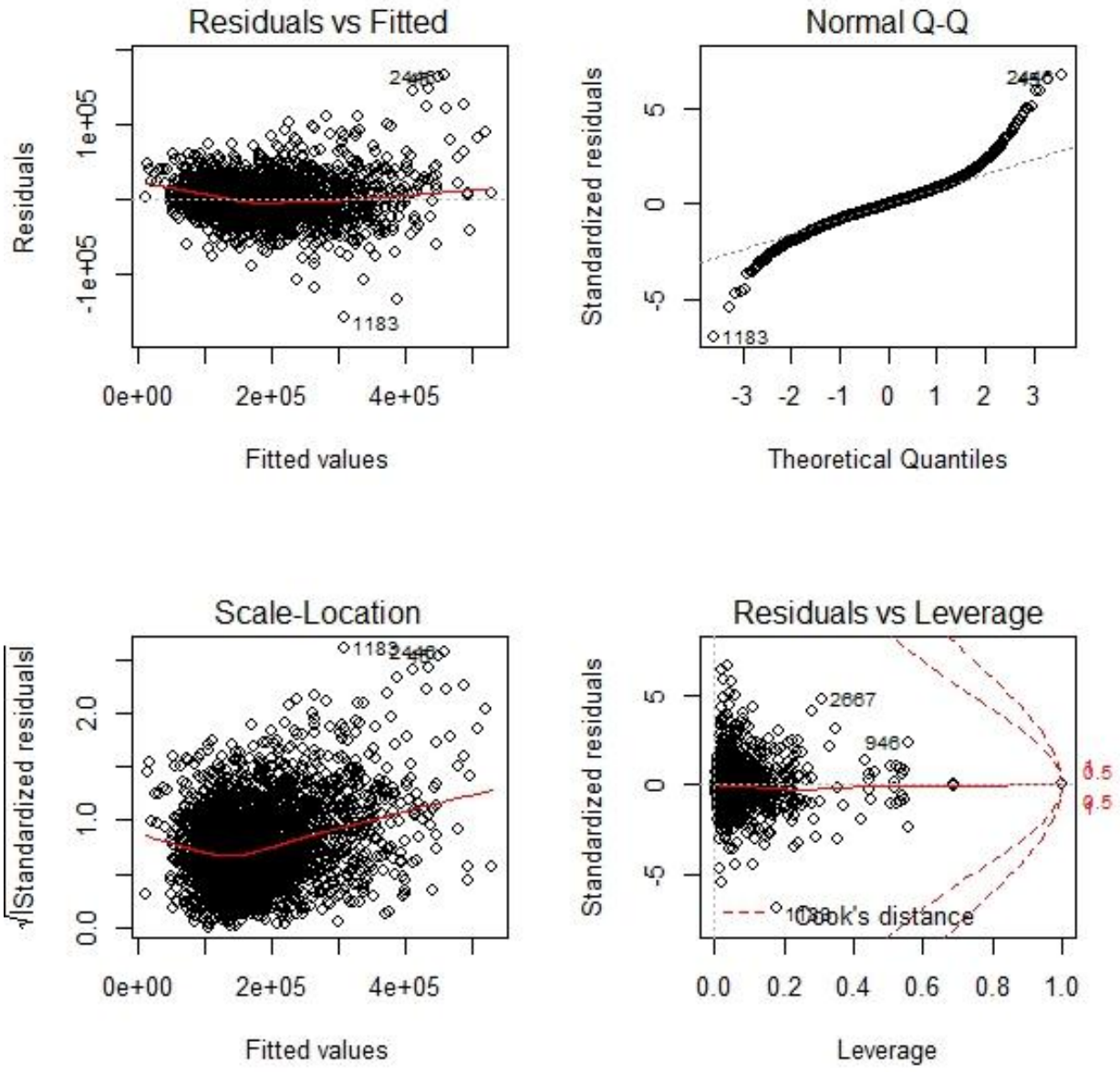
3.6 Stepwise Backward Selection

Here we start with full model and keep adding the predictors one by one in the model. The fitted model during this step is as shown below:

backward = lm(formula = SalePrice ~ Comp.1 + Comp.2 + Comp.3 + Comp.4 +Comp.5 + Comp.7 + Comp.8 + Street + LandContour + Utilities +LotConfig + LandSlope + Neighborhood + Condition1 + Condition2 + BldgType + HouseStyle + RoofStyle + RoofMatl + Exterior1st + MasVnrType + ExterQual + ExterCond + Foundation + HeatingQC + KitchenQual + Functional + SaleType + SaleCondition, data = finalWorkingSet)

We got a model with the same optimal subset of predictors using both Forward and backward selection methods . The additional detail about the summary of both model present in appendix E and F respectively. The Residual Standard error for this model 25230 and R^2 is 90%. Below residual-fitted graph does not show any strong pattern which is a good estimate for the selection of final model.

```
## Residual standard error: 25230 on 2780 degrees of freedom
## Multiple R-squared:  0.902,  Adjusted R-squared:  0.8969
## F-statistic: 177.6 on 144 and 2780 DF,  p-value: < 2.2e-16
```



3.7 Further model improvements

In this step, I tried to improve the model interpretability by removing the insignificant categorical predictors such as LotConfig, RoofStyle, ExterCond, Condition2, Exterior1st step by step. Removal of these predictors from the model decreased our R^2 by approximately 2%. Finally, I chose to combine the level of categorical variables: Functional, HeatingQC, Condition1 and KitchenQual based on their ranking to further increase the interpretability of the final

model. The bar plot for these variables is as shown Appendix H distribution clearly shows we can combine the level for these variables.

3.8 Final Model

The model calculated using multiple linear regression method takes the form
$Y = \beta_0X_1 + \beta_0X_1 + \beta_0X_1 + \beta_0X_1 + \ldots\ldots. + \beta_0X_1 + €$. The β_i represents the coefficients for the predictors
Our final model obtained is as follows:
Note: coefficient for the categorical variables are not shown in below model for the readability purpose. The

SalePrice = **220403**.2+ **27323.1**Comp.1 + Neighborhood - 2495.5KitchenQualPo + ExterQual + HouseStyle + BldgType + MasVnrType + SaleCondition + Functional + Foundation + 932.5Comp.8 + **3224.5Comp**.2 + 6435.0Condition1 -11033.3HeatingQCPo + LandSlope + RoofMatl + LandContour + 31203.3StreetPave + 2086.5Comp.5 -2396.4Comp.3 + 114.7Comp.7 + Utilities -1392.4Comp.4 , data = WS_combLevel)

Summary of model is as shown below:

```
summary(finalmodel)

##
## Call:
## lm(formula = SalePrice ~ Comp.1 + Neighborhood + KitchenQual +
##     ExterQual + HouseStyle + BldgType + MasVnrType + SaleCondition +
##     Functional + Foundation + Comp.8 + Comp.2 + Condition1 +
##     HeatingQC + LandSlope + RoofMatl + LandContour + Street +
##     Comp.5 + Comp.3 + Comp.7 + Utilities + Comp.4, data = WS_combLevel)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -167993  -14104    -642   13157  169007
##
## Coefficients:
##                        Estimate Std. Error t value Pr(>|t|)
## (Intercept)           220403.2    13459.3  16.376  < 2e-16 ***
## Comp.1                -27323.1      503.9 -54.219  < 2e-16 ***
## NeighborhoodBlueste   -15074.7    10565.4  -1.427 0.153747
## NeighborhoodBrDale    -34436.4     8130.8  -4.235 2.35e-05 ***
## NeighborhoodBrkSide   -38928.0     6639.5  -5.863 5.07e-09 ***
## NeighborhoodClearCr   -31326.2     7433.7  -4.214 2.59e-05 ***
## NeighborhoodCollgCr   -34613.8     5864.7  -5.902 4.01e-09 ***
## NeighborhoodCrawfor   -11311.3     6511.4  -1.737 0.082469 .
## NeighborhoodEdwards   -43553.2     6209.8  -7.014 2.89e-12 ***
## NeighborhoodGilbert   -32226.6     6151.5  -5.239 1.73e-07 ***
## NeighborhoodGreens      4939.6    11343.0   0.435 0.663249
## NeighborhoodGrnHill   115072.0    19992.1   5.756 9.54e-09 ***
## NeighborhoodIDOTRR    -50700.5     6735.8  -7.527 6.92e-14 ***
## NeighborhoodLandmrk   -23976.9    28071.7  -0.854 0.393105
## NeighborhoodMeadowV   -36019.8     7527.3  -4.785 1.80e-06 ***
## NeighborhoodMitchel   -45547.7     6383.8  -7.135 1.22e-12 ***
```

```
## NeighborhoodNAmes     -43469.3     6056.3  -7.178 9.02e-13 ***
## NeighborhoodNoRidge     1999.6     6666.2   0.300 0.764225
## NeighborhoodNPkVill   -11715.1     8291.2  -1.413 0.157777
## NeighborhoodNridgHt     3608.5     6016.9   0.600 0.548734
## NeighborhoodNWAmes    -39047.4     6346.4  -6.153 8.69e-10 ***
## NeighborhoodOldTown   -50904.3     6274.9  -8.112 7.31e-16 ***
## NeighborhoodSawyer    -41892.7     6353.2  -6.594 5.09e-11 ***
## NeighborhoodSawyerW   -38611.9     6159.4  -6.269 4.19e-10 ***
## NeighborhoodSomerst   -19058.2     5849.6  -3.258 0.001135 **
## NeighborhoodStoneBr    33132.5     6751.1   4.908 9.74e-07 ***
## NeighborhoodSWISU     -45780.5     7303.0  -6.269 4.19e-10 ***
## NeighborhoodTimber    -24000.7     6586.4  -3.644 0.000273 ***
## NeighborhoodVeenker   -20838.2     8031.1  -2.595 0.009517 **
## KitchenQualPo          -2495.5     3492.4  -0.715 0.474951
## ExterQualFa           -75269.6     6351.2 -11.851  < 2e-16 ***
## ExterQualGd           -56478.9     3274.6 -17.247  < 2e-16 ***
## ExterQualTA           -73736.9     3660.7 -20.143  < 2e-16 ***
## HouseStyle1.5Unf       -1561.9     6562.3  -0.238 0.811893
## HouseStyle1Story       -7456.1     2002.7  -3.723 0.000201 ***
## HouseStyle2.5Fin        7732.8    10865.9   0.712 0.476735
## HouseStyle2.5Unf       13565.7     5939.3   2.284 0.022441 *
## HouseStyle2Story        8654.5     2120.5   4.081 4.60e-05 ***
## HouseStyleSFoyer        2998.9     3755.6   0.799 0.424632
## HouseStyleSLvl          3131.8     3174.6   0.987 0.323965
## BldgType2fmCon        -17101.3     3686.0  -4.639 3.65e-06 ***
## BldgTypeDuplex        -15819.1     3026.8  -5.226 1.85e-07 ***
## BldgTypeTwnhs         -30414.1     3959.4  -7.682 2.15e-14 ***
## BldgTypeTwnhsE        -25590.7     2465.9 -10.378  < 2e-16 ***
## MasVnrTypeBrkCmn      -16852.7     8061.6  -2.091 0.036661 *
## MasVnrTypeBrkFace      -9788.5     5917.6  -1.654 0.098213 .
## MasVnrTypeCBlock     -106605.5    28091.4  -3.795 0.000151 ***
## MasVnrTypeNone         -1450.4     5870.3  -0.247 0.804866
## MasVnrTypeStone         1170.4     6051.1   0.193 0.846642
## SaleConditionAdjLand   12517.6     8379.8   1.494 0.135343
## SaleConditionAlloca    16292.1     6371.0   2.557 0.010602 *
## SaleConditionFamily     4666.2     4521.2   1.032 0.302133
## SaleConditionNormal    12506.0     2112.5   5.920 3.60e-09 ***
## SaleConditionPartial   27389.7     2969.8   9.223  < 2e-16 ***
## FunctionalTyp          14908.3     2132.6   6.991 3.39e-12 ***
## FoundationCBlock        -175.0     2175.0  -0.080 0.935870
## FoundationPConc        10023.1     2382.0   4.208 2.66e-05 ***
## FoundationSlab         25205.1     4696.0   5.367 8.63e-08 ***
## FoundationStone         5184.1     8525.1   0.608 0.543171
## FoundationWood         -1831.1    12599.7  -0.145 0.884465
## Comp.8                   932.5      564.6   1.652 0.098701 .
## Comp.2                  3224.5      457.5   7.048 2.27e-12 ***
## Condition1Norm          6435.0     1551.0   4.149 3.44e-05 ***
## HeatingQCPo           -11033.3     2983.8  -3.698 0.000222 ***
## LandSlopeMod            7556.2     3078.1   2.455 0.014156 *
## LandSlopeSev          -28070.0     8239.7  -3.407 0.000667 ***
```

```
## RoofMatlMembran       109014.1    28548.2   3.819 0.000137 ***
## RoofMatlMetal          33200.1    28736.8   1.155 0.248058
## RoofMatlRoll          -30606.2    27532.8  -1.112 0.266392
## RoofMatlTar&Grv         9861.6     6044.1   1.632 0.102873
## RoofMatlWdShake        10708.3     9259.7   1.156 0.247597
## RoofMatlWdShngl        57410.0    11634.3   4.935 8.50e-07 ***
## LandContourHLS          8773.9     3899.5   2.250 0.024523 *
## LandContourLow        -17203.7     4994.1  -3.445 0.000580 ***
## LandContourLvl         -1643.2     2878.3  -0.571 0.568108
## StreetPave             31203.3     8698.0   3.587 0.000340 ***
## Comp.5                  2086.5      522.2   3.995 6.62e-05 ***
## Comp.3                 -2396.4      515.3  -4.651 3.46e-06 ***
## Comp.7                   114.7      539.0   0.213 0.831494
## UtilitiesNoSeWa       -62480.9    27747.3  -2.252 0.024412 *
## UtilitiesNoSewr       -12332.2    19961.2  -0.618 0.536750
## Comp.4                 -1392.4      502.1  -2.773 0.005591 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 27240 on 2843 degrees of freedom
## Multiple R-squared:  0.8831, Adjusted R-squared:  0.8798
## F-statistic: 265.2 on 81 and 2843 DF,  p-value: < 2.2e-16
```

The coefficient of comp.1 is 27323.1 As the comp.1 is the linear combination of predictors and Eigenvector. By analyzing the result of loading vectors in appendix D, we can write:

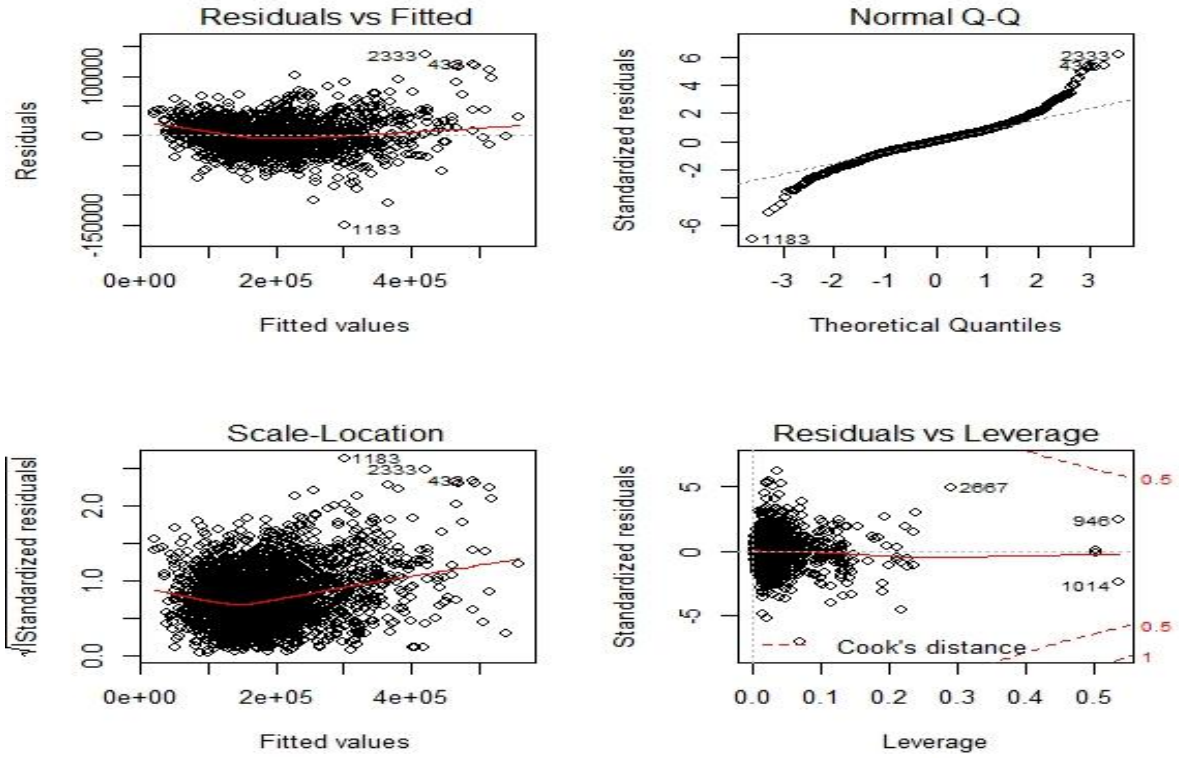
Comp.1 = 0.358 MasVnrArea -0.301BsmtFinSF1 -0.460 TotalBSmtSF -0.418 GrLivArea -0.432 GarageArea.

We can show this linear equation between original variable using comp.1 to connect the original variable back to Sale price. The above result indicates that Sale price of residential properties decreases when the square feet area for the TotalBsmt, GrLivArea, and Garage Area decreased by 1 Unit by $5000 as comp.1 explains 18% of the cumulative variation in these variables. Maximum variance explained comp.2 is due to predictor BsmtUnfSF and BsmtFinSF1. Hence, We can write:

Comp2 = -702BsmtUnfSF + 0.530 BsmtFinSF1.

The proportion of variance explained by Comp.2 is 10%. Therefore, increase in 1 Unit in Comp.2 results in an increase of Sale price by $323. It means as Bsmt unfinished area decreases or BsmtFinSF1 increase by one unit Sale price increase. The Same way another result can be interpreted. Residential property Sale prices increase when the properties are near to the city centers and famous locations. The Sale price of residential properties decreases when they are in Old town. In the same fashion, other significant factors can be analyzed using the value of regression coefficient for the predictor variables.

The plot of residual-fitted as shown below:



Discussion & Conclusions

Our primary purpose of this study is to use the model for making a prediction of the sale price, identify a factor which contributes to the Sale price of properties. The predictors in the final model indicate contributing factor and regression coefficient shows the strength of this relationship. The residential properties with greater above grade living area, miscellaneous features such as elevator, WooD Deck Surface, garage, a good neighborhood tend to the good market Sale price. As a part of this project, we also use inferential study of final model to identify the pattern in the dataset. The final model discussed in the section 3.8 can be used to calculate the Sale Price by substituting values for the predictors in the model. As per my analysis, when we get the different model using different selection methods it is beneficial to use same performance measure to choose the best model out of one. In the regression setting, we can use R2 to select the best model when we encounter such situation. One can use the feature extraction methods such as PCA, Factor analysis to reduce the number of variables. The results of the study support this statement. We also solved the multi-linearity issue and found the new set of variables which are uncorrelated with each other using PCA which later included as predictors in our final model.

Statistical Inference: residual Vs fitted graph in section 3.8 shows a very little pattern in residuals for the dataset used in this study which indicates there is no severe problem with this model. The confidence interval for all regression coefficient is as shown in Appendix J. It shows the 97.5%confidendence interval for β0 [1828851.28, 225999.9542]. Similarly, results of comp.1 indicate the Sale price of residential properties decreases approximately by dollar 30,346 to 28819 when there is the decrease in square feet area of GrlivArea or GarageArea.

```
#confint(finalmodel)
                              2.5 %      97.5 %
(Intercept)           182851.2857 225999.9542
Comp.1                -30346.6980 -28819.8951
```

Observing the Variance inflation Factor (VIF) values in Appendix K indicates the absence of collinearity issues in the model which point out the quality of good model. Thus, we conclude the it good model for prediction Sale price. There is always a scope to improve the model estimate further. The model performance can be improved if we include Discrete variables in our model. Additionally we can use other alternative techniques for dealing with the missing values to use large sample set. I think, there is always possibility of overfitting the model. Hence, care should be taken while improving the model further.

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Appendix :

Mid-Term Project : PCA and Multiple Linear Regression

Smita Sukhadeve

Appendix & Program Code

A: Dataset summary

```
ames0 = read.csv("http://people.usm.maine.edu/cpeng/datasets/amescsv.csv")
# dimension of the dataset
dim(ames0)
```

```
## [1] 2930   82
```

```
# Summary of the Dataset
summary(ames0)
```

```
##      Order             PID               MSSubCls         MSZoning
##  Min.   :   1.0   Min.   :5.263e+08   Min.   : 20.00   A (agr):   2
##  1st Qu.: 733.2   1st Qu.:5.285e+08   1st Qu.: 20.00   C (all):  25
##  Median :1465.5   Median :5.355e+08   Median : 50.00   FV     : 139
##  Mean   :1465.5   Mean   :7.145e+08   Mean   : 57.39   I (all):   2
##  3rd Qu.:2197.8   3rd Qu.:9.072e+08   3rd Qu.: 70.00   RH     :  27
##  Max.   :2930.0   Max.   :1.007e+09   Max.   :190.00   RL     :2273
##                                                        RM     : 462
##   LotFrontage        LotArea        Street      Alley      LotShape
##  Min.   : 21.00   Min.   :  1300   Grvl:  12   Grvl: 120   IR1: 979
##  1st Qu.: 58.00   1st Qu.:  7440   Pave:2918   Pave:  78   IR2:  76
##  Median : 68.00   Median :  9436               NA's:2732   IR3:  16
##  Mean   : 69.22   Mean   : 10148                           Reg:1859
##  3rd Qu.: 80.00   3rd Qu.: 11555
##  Max.   :313.00   Max.   :215245
##  NA's   :490
##  LandContour  Utilities      LotConfig    LandSlope   Neighborhood
##  Bnk: 117    AllPub:2927   Corner : 511   Gtl:2789   NAmes  : 443
##  HLS: 120    NoSeWa:   1   CulDSac: 180   Mod: 125   CollgCr: 267
##  Low:  60    NoSewr:   2   FR2    :  85   Sev:  16   OldTown: 239
##  Lvl:2633                  FR3    :  14              Edwards: 194
##                            Inside :2140              Somerst: 182
##                                                      NridgHt: 166
##                                                      (Other):1439
##    Condition1     Condition2     BldgType      HouseStyle
##  Norm   :2522   Norm   :2900   1Fam  :2425   1Story :1481
##  Feedr  : 164   Feedr  :  13   2fmCon:  62   2Story : 873
##  Artery :  92   Artery :   5   Duplex: 109   1.5Fin : 314
##  RRAn   :  50   PosA   :   4   Twnhs : 101   SLvl   : 128
##  PosN   :  39   PosN   :   4   TwnhsE: 233   SFoyer :  83
##  RRAe   :  28   RRNn   :   2                 2.5Unf :  24
```

```
##  (Other):  35   (Other):   2                 (Other):  27
##   OverallQual      OverallCond      YearBuilt     YearRemodAdd
##  Min.   : 1.000   Min.   :1.000   Min.   :1872   Min.   :1950
##  1st Qu.: 5.000   1st Qu.:5.000   1st Qu.:1954   1st Qu.:1965
##  Median : 6.000   Median :5.000   Median :1973   Median :1993
##  Mean   : 6.095   Mean   :5.563   Mean   :1971   Mean   :1984
##  3rd Qu.: 7.000   3rd Qu.:6.000   3rd Qu.:2001   3rd Qu.:2004
##  Max.   :10.000   Max.   :9.000   Max.   :2010   Max.   :2010
##
##    RoofStyle       RoofMatl     Exterior1st    Exterior2nd
##  Flat   :  20   CompShg:2887   VinylSd:1026   VinylSd:1015
##  Gable  :2321   Tar&Grv:  23   MetalSd: 450   MetalSd: 447
##  Gambrel:  22   WdShake:   9   HdBoard: 442   HdBoard: 406
##  Hip    : 551   WdShngl:   7   Wd Sdng: 420   Wd Sdng: 397
##  Mansard:  11   ClyTile:   1   Plywood: 221   Plywood: 274
##  Shed   :   5   Membran:   1   CemntBd: 126   CmentBd: 126
##                 (Other):   2   (Other): 245   (Other): 265
##    MasVnrType     MasVnrArea     ExterQual ExterCond  Foundation
##         :  23   Min.   :   0.0   Ex: 107   Ex:  12   BrkTil: 311
##  BrkCmn :  25   1st Qu.:   0.0   Fa:  35   Fa:  67   CBlock:1244
##  BrkFace: 880   Median :   0.0   Gd: 989   Gd: 299   PConc :1310
##  CBlock :   1   Mean   : 101.9   TA:1799   Po:   3   Slab  :  49
##  None   :1752   3rd Qu.: 164.0             TA:2549   Stone :  11
##  Stone  : 249   Max.   :1600.0                       Wood  :   5
##                 NA's   :23
##  BsmtQual    BsmtCond    BsmtExposure  BsmtFinType1   BsmtFinSF1
##      :   1       :   1       :   4    GLQ    :859   Min.   :   0.0
##  Ex  : 258   Ex  :   3   Av  : 418    Unf    :851   1st Qu.:   0.0
##  Fa  :  88   Fa  : 104   Gd  : 284    ALQ    :429   Median : 370.0
##  Gd  :1219   Gd  : 122   Mn  : 239    Rec    :288   Mean   : 442.6
##  Po  :   2   Po  :   5   No  :1906    BLQ    :269   3rd Qu.: 734.0
##  TA  :1283   TA  :2616   NA's:  79    (Other):155   Max.   :5644.0
##  NA's:  79   NA's:  79                NA's   : 79   NA's   :1
##   BsmtFinType2    BsmtFinSF2        BsmtUnfSF       TotalBsmtSF
##  Unf    :2499   Min.   :   0.00   Min.   :   0.0   Min.   :   0
##  Rec    : 106   1st Qu.:   0.00   1st Qu.: 219.0   1st Qu.: 793
##  LwQ    :  89   Median :   0.00   Median : 466.0   Median : 990
##  BLQ    :  68   Mean   :  49.72   Mean   : 559.3   Mean   :1052
##  ALQ    :  53   3rd Qu.:   0.00   3rd Qu.: 802.0   3rd Qu.:1302
##  (Other):  36   Max.   :1526.00   Max.   :2336.0   Max.   :6110
##  NA's   :  79   NA's   :1         NA's   :1        NA's   :1
##   Heating     HeatingQC CentralAir Electrical     X1stFlrSF
##  Floor:   1   Ex:1495   N: 196          :   1   Min.   : 334.0
##  GasA :2885   Fa:  92   Y:2734     FuseA: 188   1st Qu.: 876.2
##  GasW :  27   Gd: 476              FuseF:  50   Median :1084.0
##  Grav :   9   Po:   3              FuseP:   8   Mean   :1159.6
##  OthW :   2   TA: 864              Mix  :   1   3rd Qu.:1384.0
##  Wall :   6                        SBrkr:2682   Max.   :5095.0
##
##    X2ndFlrSF       LowQualFinSF        GrLivArea     BsmtFullBath
```

```
##  Min.   :   0.0   Min.   :   0.000   Min.   : 334   Min.   :0.0000
##  1st Qu.:   0.0   1st Qu.:   0.000   1st Qu.:1126   1st Qu.:0.0000
##  Median :   0.0   Median :   0.000   Median :1442   Median :0.0000
##  Mean   : 335.5   Mean   :   4.677   Mean   :1500   Mean   :0.4314
##  3rd Qu.: 703.8   3rd Qu.:   0.000   3rd Qu.:1743   3rd Qu.:1.0000
##  Max.   :2065.0   Max.   :1064.000   Max.   :5642   Max.   :3.0000
##                                                    NA's   :2
##   BsmtHalfBath        FullBath        HalfBath       BedroomAbvGr
##  Min.   :0.00000   Min.   :0.000   Min.   :0.0000   Min.   :0.000
##  1st Qu.:0.00000   1st Qu.:1.000   1st Qu.:0.0000   1st Qu.:2.000
##  Median :0.00000   Median :2.000   Median :0.0000   Median :3.000
##  Mean   :0.06113   Mean   :1.567   Mean   :0.3795   Mean   :2.854
##  3rd Qu.:0.00000   3rd Qu.:2.000   3rd Qu.:1.0000   3rd Qu.:3.000
##  Max.   :2.00000   Max.   :4.000   Max.   :2.0000   Max.   :8.000
##  NA's   :2
##   KitchenAbvGr   KitchenQual  TotRmsAbvGrd      Functional
##  Min.   :0.000   Ex: 205     Min.   : 2.000   Typ    :2728
##  1st Qu.:1.000   Fa:  70     1st Qu.: 5.000   Min2   :  70
##  Median :1.000   Gd:1160     Median : 6.000   Min1   :  65
##  Mean   :1.044   Po:   1     Mean   : 6.443   Mod    :  35
##  3rd Qu.:1.000   TA:1494     3rd Qu.: 7.000   Maj1   :  19
##  Max.   :3.000               Max.   :15.000   Maj2   :   9
##                                               (Other):   4
##    Fireplaces     FireplaceQu   GarageType    GarageYrBlt   GarageFinish
##  Min.   :0.0000   Ex  :  43   2Types :  23   Min.   :1895       :   2
##  1st Qu.:0.0000   Fa  :  75   Attchd :1731   1st Qu.:1960   Fin : 728
##  Median :1.0000   Gd  : 744   Basment:  36   Median :1979   RFn : 812
##  Mean   :0.5993   Po  :  46   BuiltIn: 186   Mean   :1978   Unf :1231
##  3rd Qu.:1.0000   TA  : 600   CarPort:  15   3rd Qu.:2002   NA's: 157
##  Max.   :4.0000   NA's:1422   Detchd : 782   Max.   :2207
##                               NA's   : 157   NA's   :159
##    GarageCars      GarageArea     GarageQual  GarageCond  PavedDrive
##  Min.   :0.000   Min.   :   0.0       :   1       :   1   N: 216
##  1st Qu.:1.000   1st Qu.: 320.0   Ex  :   3   Ex  :   3   P:  62
##  Median :2.000   Median : 480.0   Fa  : 124   Fa  :  74   Y:2652
##  Mean   :1.767   Mean   : 472.8   Gd  :  24   Gd  :  15
##  3rd Qu.:2.000   3rd Qu.: 576.0   Po  :   5   Po  :  14
##  Max.   :5.000   Max.   :1488.0   TA  :2615   TA  :2665
##  NA's   :1       NA's   :1        NA's: 158   NA's: 158
##    WoodDeckSF       OpenPorchSF     EnclosedPorch       X3SsnPorch
##  Min.   :   0.00   Min.   :  0.00   Min.   :   0.00   Min.   :  0.000
##  1st Qu.:   0.00   1st Qu.:  0.00   1st Qu.:   0.00   1st Qu.:  0.000
##  Median :   0.00   Median : 27.00   Median :   0.00   Median :  0.000
##  Mean   :  93.75   Mean   : 47.53   Mean   :  23.01   Mean   :  2.592
##  3rd Qu.: 168.00   3rd Qu.: 70.00   3rd Qu.:   0.00   3rd Qu.:  0.000
##  Max.   :1424.00   Max.   :742.00   Max.   :1012.00   Max.   :508.000
##
##   ScreenPorch     PoolArea        PoolQC       Fence      MiscFeature
##  Min.   :  0   Min.   :  0.000   Ex  :   4   GdPrv: 118   Elev:   1
##  1st Qu.:  0   1st Qu.:  0.000   Fa  :   2   GdWo : 112   Gar2:   5
```

```
##  Median :  0   Median :  0.000   Gd  :   4   MnPrv: 330   Othr:   4
##  Mean   : 16   Mean   :  2.243   TA  :   3   MnWw :  12   Shed:  95
##  3rd Qu.:  0   3rd Qu.:  0.000   NA's:2917   NA's :2358   TenC:   1
##  Max.   :576   Max.   :800.000                            NA's:2824
##
##     MiscVal             MoSold           YrSold        SaleType
##  Min.   :    0.00   Min.   : 1.000   Min.   :2006   WD     :2536
##  1st Qu.:    0.00   1st Qu.: 4.000   1st Qu.:2007   New    : 239
##  Median :    0.00   Median : 6.000   Median :2008   COD    :  87
##  Mean   :   50.63   Mean   : 6.216   Mean   :2008   ConLD  :  26
##  3rd Qu.:    0.00   3rd Qu.: 8.000   3rd Qu.:2009   CWD    :  12
##  Max.   :17000.00   Max.   :12.000   Max.   :2010   ConLI  :   9
##                                                     (Other):  21
##  SaleCondition    SalePrice
##  Abnorml: 190   Min.   : 12789
##  AdjLand:  12   1st Qu.:129500
##  Alloca :  24   Median :160000
##  Family :  46   Mean   :180796
##  Normal :2413   3rd Qu.:213500
##  Partial: 245   Max.   :755000
##
```

Appendix B: Section 3.1 : Full Model With all continuous predictors

```
lm_allCont = lm(SalePrice ~.-Order, data = contVar.dat)
summary(lm_allCont)
```

```
##
## Call:
## lm(formula = SalePrice ~ . - Order, data = contVar.dat)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -683359  -19899     282   18904  309782
##
## Coefficients: (2 not defined because of singularities)
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)   -1.565e+04  3.638e+03  -4.302 1.76e-05 ***
## LotFrontage   -9.085e+01  4.683e+01  -1.940 0.052487 .
## LotArea        3.776e-01  1.624e-01   2.324 0.020184 *
## MasVnrArea     5.968e+01  5.797e+00  10.295  < 2e-16 ***
## BsmtFinSF1     5.736e+01  3.679e+00  15.593  < 2e-16 ***
## BsmtFinSF2     3.650e+01  6.331e+00   5.766 9.14e-09 ***
## BsmtUnfSF      3.921e+01  3.593e+00  10.913  < 2e-16 ***
## TotalBsmtSF           NA         NA      NA       NA
## X1stFlrSF      6.417e+01  4.272e+00  15.022  < 2e-16 ***
## X2ndFlrSF      6.518e+01  2.464e+00  26.452  < 2e-16 ***
## LowQualFinSF  -3.175e+00  1.822e+01  -0.174 0.861693
## GrLivArea             NA         NA      NA       NA
## GarageArea     8.932e+01  5.030e+00  17.756  < 2e-16 ***
```

```
## WoodDeckSF     5.850e+01  7.867e+00   7.437 1.43e-13 ***
## OpenPorchSF    4.471e+01  1.406e+01   3.180 0.001490 **
## EnclosedPorch -5.541e+01  1.412e+01  -3.924 8.97e-05 ***
## X3SsnPorch     3.117e+01  3.562e+01   0.875 0.381622
## ScreenPorch    5.321e+01  1.583e+01   3.362 0.000785 ***
## PoolArea      -8.633e+01  2.511e+01  -3.439 0.000594 ***
## MiscVal       -1.882e+01  1.776e+00 -10.600  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 43090 on 2403 degrees of freedom
##   (509 observations deleted due to missingness)
## Multiple R-squared:  0.7346, Adjusted R-squared:  0.7327
## F-statistic: 391.2 on 17 and 2403 DF,  p-value: < 2.2e-16
```

Section 1.2 - Removed Outliers from the Working Dataset

```
# Full model result after removing Outliers
workingSet2 = workingSet2[which(workingSet2$GrLivArea < 4000), ]
contVar.dat <- subset(workingSet2, select = continuous.var)
dim(contVar.dat)
```

```
## [1] 2925   21
```

```
lm_noOutlier = lm(SalePrice~ .-Order, data = contVar.dat)
summary(lm_noOutlier)
```

```
##
## Call:
## lm(formula = SalePrice ~ . - Order, data = contVar.dat)
## Residuals:
##     Min      1Q  Median      3Q     Max
## -209825  -19547    1119   20867  212241
##
## Residual standard error: 37580 on 2398 degrees of freedom
##   (509 observations deleted due to missingness)
## Multiple R-squared:  0.7904, Adjusted R-squared:  0.789
## F-statistic: 532.1 on 17 and 2398 DF,  p-value: < 2.2e-16
```

Appendix C : Section 3.2 - Full regression model using continuous predictors with NA's replaced with corresponding Mean values

```
#Replaced NAs by corresponding mean values for variables in blue
```

```
##         Order   LotFrontage       LotArea    MasVnrArea    BsmtFinSF1
##             0           490             0             0             0
##    BsmtFinSF2     BsmtUnfSF   TotalBsmtSF     X1stFlrSF     X2ndFlrSF
##             0             0             0             0             0
##  LowQualFinSF     GrLivArea    GarageArea    WoodDeckSF   OpenPorchSF
##             0             0             0             0             0
```

```
## EnclosedPorch    X3SsnPorch   ScreenPorch      PoolArea       MiscVal
##             0             0             0             0             0
##     SalePrice
##             0
```

```
#Fitting linear Model
lm_withNoNull = lm(contVar.dat$SalePrice ~.-Order, data = contVar.dat[,-2])
summary(lm_withNoNull )
```

```
##
## Call:
## lm(formula = contVar.dat$SalePrice ~ . - Order, data = contVar.dat[,
##     -2])
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -213378  -18984    1202   19791  218122
##
## Coefficients: (2 not defined because of singularities)
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)   -2.738e+04  2.703e+03 -10.127  < 2e-16 ***
## LotArea        2.205e-01  9.511e-02   2.318   0.0205 *
## MasVnrArea     5.344e+01  4.535e+00  11.782  < 2e-16 ***
## BsmtFinSF1     7.216e+01  2.977e+00  24.240  < 2e-16 ***
## BsmtFinSF2     4.374e+01  4.889e+00   8.946  < 2e-16 ***
## BsmtUnfSF      4.780e+01  2.862e+00  16.701  < 2e-16 ***
## TotalBsmtSF           NA         NA      NA       NA
## X1stFlrSF      6.418e+01  3.258e+00  19.700  < 2e-16 ***
## X2ndFlrSF      6.899e+01  1.937e+00  35.616  < 2e-16 ***
## LowQualFinSF  -4.375e+00  1.506e+01  -0.291   0.7714
## GrLivArea             NA         NA      NA       NA
## GarageArea     7.734e+01  4.049e+00  19.103  < 2e-16 ***
## WoodDeckSF     4.175e+01  5.957e+00   7.009 2.96e-12 ***
## OpenPorchSF    6.505e+01  1.113e+01   5.846 5.61e-09 ***
## EnclosedPorch -5.721e+01  1.116e+01  -5.128 3.13e-07 ***
## X3SsnPorch     1.285e+01  2.761e+01   0.466   0.6416
## ScreenPorch    2.664e+01  1.259e+01   2.115   0.0345 *
## PoolArea      -1.480e+01  2.143e+01  -0.690   0.4900
## MiscVal       -1.725e+00  1.470e+00  -1.174   0.2405
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 37420 on 2908 degrees of freedom
## Multiple R-squared:  0.7743, Adjusted R-squared:  0.7731
## F-statistic: 623.6 on 16 and 2908 DF,  p-value: < 2.2e-16
```

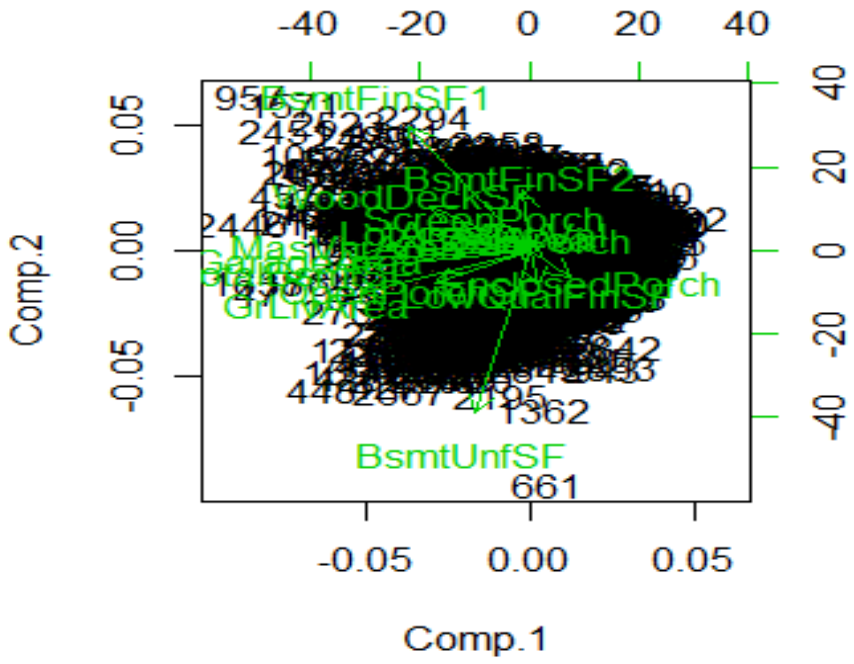
D: Result of Principal Component Analysis

```
# excluded SalePrice: Response variable and X1stFlrSF, X1stFlrSF
ames.pc = princomp(contVar.dat[, c(-1, -2, -21, -9, -10)], cor = TRUE)
summary(ames.pc, loadings = TRUE)

## Importance of components:
##                           Comp.1    Comp.2    Comp.3     Comp.4     Comp.5
## Standard deviation     1.7109750 1.2812616 1.1289493 1.03461167 1.01598803
## Proportion of Variance 0.1829647 0.1026020 0.0796579 0.06690133 0.06451448
## Cumulative Proportion  0.1829647 0.2855667 0.3652246 0.43212591 0.49664039
##                            Comp.6     Comp.7     Comp.8     Comp.9
## Standard deviation     1.00474754 0.98774499 0.97339698 0.96865569
## Proportion of Variance 0.06309485 0.06097751 0.05921886 0.05864337
## Cumulative Proportion  0.55973524 0.62071275 0.67993161 0.73857497
## Rest of the result excluded
## Loadings:
##               Comp.1 Comp.2 Comp.3 Comp.4 Comp.5 Comp.6 Comp.7 Comp.8
## LotArea       -0.231        -0.312                0.127 -0.235
## MasVnrArea    -0.358         0.172                       0.110
## BsmtFinSF1    -0.301  0.530  0.139         0.309         0.200
## BsmtFinSF2            0.257 -0.371        -0.546        -0.447
## BsmtUnfSF     -0.134 -0.702               -0.132        -0.119
## TotalBsmtSF   -0.460
## LowQualFinSF         -0.152 -0.357         0.345 -0.334         0.683
## GrLivArea     -0.418 -0.189 -0.183
## GarageArea    -0.432
## WoodDeckSF    -0.245  0.190 -0.120  0.424 -0.305         0.125  0.189
## OpenPorchSF   -0.235 -0.145        -0.272  0.103  0.133        -0.267
## EnclosedPorch        -0.111 -0.483         0.248 -0.146  0.112 -0.191
## X3SsnPorch                   0.143  0.351  0.460 -0.128 -0.739 -0.145
## ScreenPorch           0.114        -0.761                -0.247
## PoolArea                    -0.500                       0.149 -0.541
## MiscVal                     -0.125         0.260  0.883         0.236
##               Comp.9
## LotArea       -0.291
## MasVnrArea    -0.109

## BsmtFinSF1    -0.133
## BsmtFinSF2
## BsmtUnfSF
## TotalBsmtSF   -0.199
## LowQualFinSF   0.276
## GrLivArea
## GarageArea
## WoodDeckSF     0.312

## OpenPorchSF    0.315
## EnclosedPorch -0.608
## X3SsnPorch     0.174
## ScreenPorch
```

```
## PoolArea       0.402
## MiscVal
```

```
# Two dimensional view of the Data using first two principal components
library(lattice)
screeplot(ames.pc, npcs = 10, type = "lines", main = "Scree Plot of Principal
Components" )

biplot (ames.pc , scale =1, col = c(1,3))
```

Fig D : Biplot of First and Second principal components



Combining Saleprice and Perform Linear regression modelling

```
PCA_SalePrice_dat = cbind(amesTranformed.dat,  SalePrice= contVar.dat[, 21])
dim(PCA_SalePrice_dat)

## [1] 2925   10
```

Handling Categorical Variables

```
categorical_dat = workingSet2[ , sapply(workingSet2, is.factor)]
names(categorical_dat)

##  [1] "MSZoning"      "Street"        "LotShape"      "LandContour"
##  [5] "Utilities"     "LotConfig"     "LandSlope"     "Neighborhood"
##  [9] "Condition1"    "Condition2"    "BldgType"      "HouseStyle"
```

```
## [13] "RoofStyle"     "RoofMatl"      "Exterior1st"   "Exterior2nd"
## [17] "MasVnrType"    "ExterQual"     "ExterCond"     "Foundation"
## [21] "Heating"       "HeatingQC"     "CentralAir"    "Electrical"
## [25] "KitchenQual"   "Functional"    "PavedDrive"    "SaleType"
## [29] "SaleCondition"
```

```
for (i in c(1:29)) {
     categorical_dat[,i] <- as.factor(categorical_dat[,i])
}
```

Combine Continous and categorical variables

```
finalWorkingSet = cbind(PCA_SalePrice_dat, categorical_dat)
dim(finalWorkingSet)
```

```
## [1] 2925   39
```

Appendix E:

3.4 Variable Selection

```
 [1] "Comp.1"         "Comp.2"         "Comp.3"         "Comp.4"         "Comp.5"
"Comp.6"         "Comp.7"
 [8] "Comp.8"         "Comp.9"         "SalePrice"      "MSZoning"       "Street"
"LotShape"       "LandContour"
[15] "Utilities"      "LotConfig"      "LandSlope"      "Neighborhood"
"Condition1"     "Condition2"     "BldgType"
[22] "HouseStyle"     "RoofStyle"      "RoofMatl"       "Exterior1st"
"Exterior2nd"    "MasVnrType"     "ExterQual"
[29] "ExterCond"      "Foundation"     "Heating"        "HeatingQC"
"CentralAir"     "Electrical"     "KitchenQual"
[36] "Functional"     "PavedDrive"     "SaleType"       "SaleCondition"
```

```
Full model : lmFinal.full = lm(SalePrice ~ ., data = finalWorkingSet)
Null Model : lmFinal.null = lm(SalePrice ~ 1, data = finalWorkingSet)
```

Stepwise Forward Selection

```
step(lmFinal.null, scope = list(lower = lmFinal.null, upper = lmFinal.full ), direction = "forward")
```

Best subset Model :

```
forward =  lm(formula = SalePrice ~ Comp.1 + Neighborhood + KitchenQual +
    ExterQual + HouseStyle + BldgType + MasVnrType + SaleCondition +
    Exterior1st + Functional + Foundation + Comp.8 + Comp.2 +
    Condition1 + HeatingQC + LandSlope + RoofMatl + LandContour +
    Street + Comp.5 + Comp.3 + LotConfig + ExterCond + Condition2 +
    RoofStyle + Comp.7 + Utilities + Comp.4 + SaleType, data =
finalWorkingSet)
```

```
summary(forward)
```

```
##
## Call:
## lm(formula = SalePrice ~ Comp.1 + Neighborhood + KitchenQual +
##     ExterQual + HouseStyle + BldgType + MasVnrType + SaleCondition +
##     Exterior1st + Functional + Foundation + Comp.8 + Comp.2 +
##     Condition1 + HeatingQC + LandSlope + RoofMatl + LandContour +
##     Street + Comp.5 + Comp.3 + LotConfig + ExterCond + Condition2 +
##     RoofStyle + Comp.7 + Utilities + Comp.4 + SaleType, data =
finalWorkingSet)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -157897  -13437    -364   12565  165097
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)           202783.9    23454.1   8.646  < 2e-16 ***
## Comp.1                -25578.5      494.1 -51.763  < 2e-16 ***
## NeighborhoodBlueste   -11107.4     9885.3  -1.124 0.261268
## NeighborhoodBrDale    -30134.5     7690.3  -3.919 9.12e-05 ***
## NeighborhoodBrkSide   -34626.7     6344.9  -5.457 5.26e-08 ***
## NeighborhoodClearCr   -28772.3     7083.6  -4.062 5.00e-05 ***
## NeighborhoodCollgCr   -31927.7     5472.1  -5.835 6.02e-09 ***
## NeighborhoodCrawfor   -13165.4     6182.4  -2.129 0.033301 *
## NeighborhoodEdwards   -41721.1     5856.7  -7.124 1.33e-12 ***
## NeighborhoodGilbert   -26441.6     5778.5  -4.576 4.95e-06 ***
## NeighborhoodGreens     11443.4    10743.7   1.065 0.286912
## NeighborhoodGrnHill   107632.2    18634.8   5.776 8.50e-09 ***
## NeighborhoodIDOTRR    -45964.9     6388.8  -7.195 8.02e-13 ***
## NeighborhoodLandmrk   -21763.6    26022.3  -0.836 0.403033
## NeighborhoodMeadowV   -39899.5     7689.1  -5.189 2.27e-07 ***
## NeighborhoodMitchel   -38986.6     6018.2  -6.478 1.09e-10 ***
## NeighborhoodNAmes     -41174.3     5745.1  -7.167 9.79e-13 ***
## NeighborhoodNoRidge     7603.4     6267.1   1.213 0.225151
## NeighborhoodNPkVill    -2955.1     8004.1  -0.369 0.712008
```

```
## NeighborhoodNridgHt     1198.8     5640.5   0.213 0.831708
## NeighborhoodNWAmes    -35357.6     6038.9  -5.855 5.33e-09 ***
## NeighborhoodOldTown   -48870.5     5968.0  -8.189 3.97e-16 ***
## NeighborhoodSawyer    -36297.9     6025.0  -6.025 1.92e-09 ***
## NeighborhoodSawyerW   -32221.6     5811.2  -5.545 3.22e-08 ***
## NeighborhoodSomerst   -16883.3     5495.1  -3.072 0.002144 **
## NeighborhoodStoneBr    28762.7     6371.8   4.514 6.63e-06 ***
## NeighborhoodSWISU     -42938.5     6889.7  -6.232 5.29e-10 ***
## NeighborhoodTimber    -22292.7     6156.0  -3.621 0.000298 ***
## NeighborhoodVeenker   -22581.3     7680.9  -2.940 0.003310 **
## KitchenQualFa         -40466.6     4351.9  -9.299  < 2e-16 ***
## KitchenQualGd         -32202.4     2564.8 -12.556  < 2e-16 ***
## KitchenQualPo         -21010.1    26555.6  -0.791 0.428909
## KitchenQualTA         -40336.8     2834.4 -14.231  < 2e-16 ***
## ExterQualFa           -37108.4     6589.0  -5.632 1.96e-08 ***
## ExterQualGd           -33058.3     3507.5  -9.425  < 2e-16 ***
## ExterQualTA           -42929.6     3902.9 -10.999  < 2e-16 ***
## HouseStyle1.5Unf       -2218.7     6193.1  -0.358 0.720183
## HouseStyle1Story       -9155.7     1923.8  -4.759 2.04e-06 ***
## HouseStyle2.5Fin        4566.6    10168.8   0.449 0.653409
## HouseStyle2.5Unf       12665.6     5605.4   2.260 0.023926 *
## HouseStyle2Story        7073.8     2026.6   3.490 0.000490 ***
## HouseStyleSFoyer         639.9     3543.0   0.181 0.856685
## HouseStyleSLvl          3064.0     2999.7   1.021 0.307140
## BldgType2fmCon        -12037.5     3531.1  -3.409 0.000661 ***
## BldgTypeDuplex        -10678.3     2920.1  -3.657 0.000260 ***
## BldgTypeTwnhs         -28838.3     3771.6  -7.646 2.83e-14 ***
## BldgTypeTwnhsE        -24371.2     2363.5 -10.312  < 2e-16 ***
## MasVnrTypeBrkCmn      -11089.9     7543.8  -1.470 0.141655
## MasVnrTypeBrkFace      -6486.6     5516.7  -1.176 0.239772
## MasVnrTypeCBlock     -152145.8    30971.7  -4.912 9.52e-07 ***
## MasVnrTypeNone          -417.4     5466.1  -0.076 0.939137
## MasVnrTypeStone         3036.5     5628.8   0.539 0.589616
## SaleConditionAdjLand   21882.7     8110.3   2.698 0.007015 **
## SaleConditionAlloca    16113.3     6068.8   2.655 0.007973 **
## SaleConditionFamily     3596.3     4283.6   0.840 0.401241
## SaleConditionNormal    10998.9     2137.8   5.145 2.86e-07 ***
## SaleConditionPartial   19036.4    10991.5   1.732 0.083400 .
## Exterior1stAsphShn     22772.6    18664.4   1.220 0.222527
## Exterior1stBrkComm     17048.1    11492.8   1.483 0.138088
## Exterior1stBrkFace     30427.6     5079.2   5.991 2.36e-09 ***
## Exterior1stCBlock      14107.6    18894.4   0.747 0.455335
## Exterior1stCemntBd     15582.9     5199.7   2.997 0.002751 **
## Exterior1stHdBoard      4979.4     4439.5   1.122 0.262125
## Exterior1stImStucc     -2906.7    25880.7  -0.112 0.910583
## Exterior1stMetalSd      9857.4     4297.0   2.294 0.021864 *
## Exterior1stPlywood      7493.3     4709.9   1.591 0.111730
## Exterior1stPreCast    102340.3    26790.4   3.820 0.000136 ***
## Exterior1stStone       44205.8    19267.9   2.294 0.021849 *
## Exterior1stStucco      14638.7     5683.1   2.576 0.010051 *
```

```
## Exterior1stVinylSd     10782.3     4367.1   2.469 0.013610 *
## Exterior1stWd Sdng      7690.9     4287.7   1.794 0.072968 .
## Exterior1stWdShing     12314.5     5363.1   2.296 0.021741 *
## FunctionalMaj2          -359.5    10635.4  -0.034 0.973038
## FunctionalMin1         10457.9     6917.7   1.512 0.130712
## FunctionalMin2          5632.4     6891.9   0.817 0.413855
## FunctionalMod          -3251.3     7605.8  -0.427 0.669064
## FunctionalSal         -30633.2    22354.8  -1.370 0.170697
## FunctionalSev         -36597.9    19624.6  -1.865 0.062301 .
## FunctionalTyp          18152.7     6148.4   2.952 0.003179 **
## FoundationCBlock         672.1     2097.9   0.320 0.748716
## FoundationPConc         6589.4     2291.7   2.875 0.004068 **
## FoundationSlab         21847.6     4471.0   4.887 1.08e-06 ***
## FoundationStone         9671.0     8003.1   1.208 0.226991
## FoundationWood           685.9    11711.4   0.059 0.953304
## Comp.8                   859.4      534.2   1.609 0.107748
## Comp.2                  2666.8      433.3   6.155 8.58e-10 ***
## Condition1Feedr         1501.4     3581.7   0.419 0.675120
## Condition1Norm         10683.6     2946.4   3.626 0.000293 ***
## Condition1PosA         22664.4     6870.4   3.299 0.000983 ***
## Condition1PosN         13933.0     5303.8   2.627 0.008662 **
## Condition1RRAe         -3634.1     5945.0  -0.611 0.541062
## Condition1RRAn          5967.8     4932.7   1.210 0.226437
## Condition1RRNe          7164.9    11083.0   0.646 0.518028
## Condition1RRNn           451.4     9192.0   0.049 0.960833
## HeatingQCFa           -13365.6     3023.5  -4.421 1.02e-05 ***
## HeatingQCGd            -2912.0     1522.4  -1.913 0.055878 .
## HeatingQCPo            -9633.0    17046.2  -0.565 0.572045
## HeatingQCTA            -7149.3     1460.4  -4.896 1.04e-06 ***
## LandSlopeMod            8365.3     2897.5   2.887 0.003919 **
## LandSlopeSev          -35064.7     8015.9  -4.374 1.26e-05 ***
## RoofMatlMembran       121691.1    28993.1   4.197 2.79e-05 ***
## RoofMatlMetal          36206.1    28869.6   1.254 0.209901
## RoofMatlRoll          -18330.0    25967.0  -0.706 0.480313
## RoofMatlTar&Grv         9021.0     9876.4   0.913 0.361118
## RoofMatlWdShake         1300.4     9619.8   0.135 0.892476
## RoofMatlWdShngl        48186.5    11095.7   4.343 1.46e-05 ***
## LandContourHLS          8931.5     3663.7   2.438 0.014837 *
## LandContourLow        -14095.1     4701.3  -2.998 0.002741 **
## LandContourLvl           -780.4     2714.3  -0.288 0.773737
## StreetPave             31309.7     8247.2   3.796 0.000150 ***
## Comp.5                  2090.0      492.0   4.248 2.23e-05 ***
## Comp.3                 -2330.1      487.3  -4.782 1.83e-06 ***
## LotConfigCulDSac       10358.3     2357.8   4.393 1.16e-05 ***
## LotConfigFR2           -1656.5     3119.3  -0.531 0.595420
## LotConfigFR3            5998.8     6982.5   0.859 0.390354
## LotConfigInside         1663.3     1303.2   1.276 0.201960
## ExterCondFa           -14205.4     8432.6  -1.685 0.092182 .
## ExterCondGd              727.4     7711.9   0.094 0.924866
## ExterCondPo           -18783.3    18381.0  -1.022 0.306923
```

```
## ExterCondTA            -2274.3     7620.2  -0.298 0.765375
## Condition2Feedr       -10204.1    13758.2  -0.742 0.458347
## Condition2Norm           131.2    11868.2   0.011 0.991182
## Condition2PosA         55691.1    18368.1   3.032 0.002452 **
## Condition2PosN         -8982.6    19491.3  -0.461 0.644943
## Condition2RRAe        -75093.9    33017.1  -2.274 0.023018 *
## Condition2RRAn          2973.3    28379.4   0.105 0.916567
## Condition2RRNn           164.2    21726.8   0.008 0.993970
## RoofStyleGable          4335.1    11331.7   0.383 0.702073
## RoofStyleGambrel         324.4    12632.1   0.026 0.979513
## RoofStyleHip            7980.3    11416.8   0.699 0.484611
## RoofStyleMansard         269.7    14038.5   0.019 0.984672
## RoofStyleShed          61562.4    19603.5   3.140 0.001705 **
## Comp.7                   300.2      507.7   0.591 0.554333
## UtilitiesNoSeWa       -69687.6    25974.3  -2.683 0.007341 **
## UtilitiesNoSewr       -20237.8    18872.6  -1.072 0.283663
## Comp.4                 -1331.0      470.3  -2.830 0.004685 **
## SaleTypeCon            41413.6    12018.9   3.446 0.000578 ***
## SaleTypeConLD           4790.3     6021.1   0.796 0.426345
## SaleTypeConLI          -7332.5     9058.4  -0.809 0.418312
## SaleTypeConLw           2787.5     9627.0   0.290 0.772184
## SaleTypeCWD            21138.3     7964.1   2.654 0.007995 **
## SaleTypeNew             8211.0    11379.5   0.722 0.470622
## SaleTypeOth            12202.0    10055.9   1.213 0.225074
## SaleTypeVWD            13968.1    25768.2   0.542 0.587817
## SaleTypeWD              3454.1     3069.7   1.125 0.260584
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 25230 on 2780 degrees of freedom
## Multiple R-squared:  0.902,  Adjusted R-squared:  0.8969
## F-statistic: 177.6 on 144 and 2780 DF,  p-value: < 2.2e-16
```

Appendix F

3.6 Stepwise Backward Selection

```
step(lmFinal.full, data = finalWorkingSet, direction = "backward")

backward = lm(formula = SalePrice ~ Comp.1 + Comp.2 + Comp.3 + Comp.4 +
    Comp.5 + Comp.7 + Comp.8 + Street + LandContour + Utilities +
    LotConfig + LandSlope + Neighborhood + Condition1 + Condition2 +
    BldgType + HouseStyle + RoofStyle + RoofMatl + Exterior1st +
    MasVnrType + ExterQual + ExterCond + Foundation + HeatingQC +
    KitchenQual + Functional + SaleType + SaleCondition, data =
finalWorkingSet)
summary(backward)
```

```
##
## Call:
## lm(formula = SalePrice ~ Comp.1 + Comp.2 + Comp.3 + Comp.4 +
##     Comp.5 + Comp.7 + Comp.8 + Street + LandContour + Utilities +
##     LotConfig + LandSlope + Neighborhood + Condition1 + Condition2 +
##     BldgType + HouseStyle + RoofStyle + RoofMatl + Exterior1st +
##     MasVnrType + ExterQual + ExterCond + Foundation + HeatingQC +
##     KitchenQual + Functional + SaleType + SaleCondition, data =
finalWorkingSet)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -157897  -13437    -364   12565  165097
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)           202783.9    23454.1   8.646  < 2e-16 ***
## Comp.1                -25578.5      494.1 -51.763  < 2e-16 ***
## Comp.2                  2666.8      433.3   6.155 8.58e-10 ***
## Comp.3                 -2330.1      487.3  -4.782 1.83e-06 ***
## Comp.4                 -1331.0      470.3  -2.830 0.004685 **
## Comp.5                  2090.0      492.0   4.248 2.23e-05 ***
## Comp.7                   300.2      507.7   0.591 0.554333
## Comp.8                   859.4      534.2   1.609 0.107748
## StreetPave             31309.7     8247.2   3.796 0.000150 ***
## LandContourHLS          8931.5     3663.7   2.438 0.014837 *
## LandContourLow        -14095.1     4701.3  -2.998 0.002741 **
## LandContourLvl          -780.4     2714.3  -0.288 0.773737
## UtilitiesNoSeWa       -69687.6    25974.3  -2.683 0.007341 **
## UtilitiesNoSewr       -20237.8    18872.6  -1.072 0.283663
## LotConfigCulDSac       10358.3     2357.8   4.393 1.16e-05 ***
## LotConfigFR2           -1656.5     3119.3  -0.531 0.595420
## LotConfigFR3            5998.8     6982.5   0.859 0.390354
## LotConfigInside         1663.3     1303.2   1.276 0.201960
## LandSlopeMod            8365.3     2897.5   2.887 0.003919 **
## LandSlopeSev          -35064.7     8015.9  -4.374 1.26e-05 ***
## NeighborhoodBlueste   -11107.4     9885.3  -1.124 0.261268
## NeighborhoodBrDale    -30134.5     7690.3  -3.919 9.12e-05 ***
## NeighborhoodBrkSide   -34626.7     6344.9  -5.457 5.26e-08 ***
## NeighborhoodClearCr   -28772.3     7083.6  -4.062 5.00e-05 ***
## NeighborhoodCollgCr   -31927.7     5472.1  -5.835 6.02e-09 ***
## NeighborhoodCrawfor   -13165.4     6182.4  -2.129 0.033301 *
## NeighborhoodEdwards   -41721.1     5856.7  -7.124 1.33e-12 ***
## NeighborhoodGilbert   -26441.6     5778.5  -4.576 4.95e-06 ***
## NeighborhoodGreens     11443.4    10743.7   1.065 0.286912
## NeighborhoodGrnHill   107632.2    18634.8   5.776 8.50e-09 ***
## NeighborhoodIDOTRR    -45964.9     6388.8  -7.195 8.02e-13 ***
## NeighborhoodLandmrk   -21763.6    26022.3  -0.836 0.403033
## NeighborhoodMeadowV   -39899.5     7689.1  -5.189 2.27e-07 ***
## NeighborhoodMitchel   -38986.6     6018.2  -6.478 1.09e-10 ***
```

```
## NeighborhoodNAmes     -41174.3     5745.1  -7.167 9.79e-13 ***
## NeighborhoodNoRidge     7603.4     6267.1   1.213 0.225151
## NeighborhoodNPkVill    -2955.1     8004.1  -0.369 0.712008
## NeighborhoodNridgHt     1198.8     5640.5   0.213 0.831708
## NeighborhoodNWAmes    -35357.6     6038.9  -5.855 5.33e-09 ***
## NeighborhoodOldTown   -48870.5     5968.0  -8.189 3.97e-16 ***
## NeighborhoodSawyer    -36297.9     6025.0  -6.025 1.92e-09 ***
## NeighborhoodSawyerW   -32221.6     5811.2  -5.545 3.22e-08 ***
## NeighborhoodSomerst   -16883.3     5495.1  -3.072 0.002144 **
## NeighborhoodStoneBr    28762.7     6371.8   4.514 6.63e-06 ***
## NeighborhoodSWISU     -42938.5     6889.7  -6.232 5.29e-10 ***
## NeighborhoodTimber    -22292.7     6156.0  -3.621 0.000298 ***
## NeighborhoodVeenker   -22581.3     7680.9  -2.940 0.003310 **
## Condition1Feedr         1501.4     3581.7   0.419 0.675120
## Condition1Norm         10683.6     2946.4   3.626 0.000293 ***
## Condition1PosA         22664.4     6870.4   3.299 0.000983 ***
## Condition1PosN         13933.0     5303.8   2.627 0.008662 **
## Condition1RRAe         -3634.1     5945.0  -0.611 0.541062
## Condition1RRAn          5967.8     4932.7   1.210 0.226437
## Condition1RRNe          7164.9    11083.0   0.646 0.518028
## Condition1RRNn           451.4     9192.0   0.049 0.960833
## Condition2Feedr       -10204.1    13758.2  -0.742 0.458347
## Condition2Norm           131.2    11868.2   0.011 0.991182
## Condition2PosA         55691.1    18368.1   3.032 0.002452 **
## Condition2PosN         -8982.6    19491.3  -0.461 0.644943
## Condition2RRAe        -75093.9    33017.1  -2.274 0.023018 *
## Condition2RRAn          2973.3    28379.4   0.105 0.916567
## Condition2RRNn           164.2    21726.8   0.008 0.993970
## BldgType2fmCon        -12037.5     3531.1  -3.409 0.000661 ***
## BldgTypeDuplex        -10678.3     2920.1  -3.657 0.000260 ***
## BldgTypeTwnhs         -28838.3     3771.6  -7.646 2.83e-14 ***
## BldgTypeTwnhsE        -24371.2     2363.5 -10.312  < 2e-16 ***
## HouseStyle1.5Unf       -2218.7     6193.1  -0.358 0.720183
## HouseStyle1Story       -9155.7     1923.8  -4.759 2.04e-06 ***
## HouseStyle2.5Fin        4566.6    10168.8   0.449 0.653409
## HouseStyle2.5Unf       12665.6     5605.4   2.260 0.023926 *
## HouseStyle2Story        7073.8     2026.6   3.490 0.000490 ***
## HouseStyleSFoyer         639.9     3543.0   0.181 0.856685
## HouseStyleSLvl          3064.0     2999.7   1.021 0.307140
## RoofStyleGable          4335.1    11331.7   0.383 0.702073
## RoofStyleGambrel         324.4    12632.1   0.026 0.979513
## RoofStyleHip            7980.3    11416.8   0.699 0.484611
## RoofStyleMansard         269.7    14038.5   0.019 0.984672
## RoofStyleShed          61562.4    19603.5   3.140 0.001705 **
## RoofMatlMembran       121691.1    28993.1   4.197 2.79e-05 ***
## RoofMatlMetal          36206.1    28869.6   1.254 0.209901
## RoofMatlRoll          -18330.0    25967.0  -0.706 0.480313
## RoofMatlTar&Grv         9021.0     9876.4   0.913 0.361118
## RoofMatlWdShake         1300.4     9619.8   0.135 0.892476
## RoofMatlWdShngl        48186.5    11095.7   4.343 1.46e-05 ***
```

```
## Exterior1stAsphShn     22772.6    18664.4   1.220 0.222527
## Exterior1stBrkComm     17048.1    11492.8   1.483 0.138088
## Exterior1stBrkFace     30427.6     5079.2   5.991 2.36e-09 ***
## Exterior1stCBlock      14107.6    18894.4   0.747 0.455335
## Exterior1stCemntBd     15582.9     5199.7   2.997 0.002751 **
## Exterior1stHdBoard      4979.4     4439.5   1.122 0.262125
## Exterior1stImStucc     -2906.7    25880.7  -0.112 0.910583
## Exterior1stMetalSd      9857.4     4297.0   2.294 0.021864 *
## Exterior1stPlywood      7493.3     4709.9   1.591 0.111730
## Exterior1stPreCast    102340.3    26790.4   3.820 0.000136 ***
## Exterior1stStone       44205.8    19267.9   2.294 0.021849 *
## Exterior1stStucco      14638.7     5683.1   2.576 0.010051 *
## Exterior1stVinylSd     10782.3     4367.1   2.469 0.013610 *
## Exterior1stWd Sdng      7690.9     4287.7   1.794 0.072968 .
## Exterior1stWdShing     12314.5     5363.1   2.296 0.021741 *
## MasVnrTypeBrkCmn      -11089.9     7543.8  -1.470 0.141655
## MasVnrTypeBrkFace      -6486.6     5516.7  -1.176 0.239772
## MasVnrTypeCBlock     -152145.8    30971.7  -4.912 9.52e-07 ***
## MasVnrTypeNone          -417.4     5466.1  -0.076 0.939137
## MasVnrTypeStone         3036.5     5628.8   0.539 0.589616
## ExterQualFa           -37108.4     6589.0  -5.632 1.96e-08 ***
## ExterQualGd           -33058.3     3507.5  -9.425  < 2e-16 ***
## ExterQualTA           -42929.6     3902.9 -10.999  < 2e-16 ***
## ExterCondFa           -14205.4     8432.6  -1.685 0.092182 .
## ExterCondGd             727.4     7711.9   0.094 0.924866
## ExterCondPo           -18783.3    18381.0  -1.022 0.306923
## ExterCondTA            -2274.3     7620.2  -0.298 0.765375
## FoundationCBlock         672.1     2097.9   0.320 0.748716
## FoundationPConc         6589.4     2291.7   2.875 0.004068 **
## FoundationSlab         21847.6     4471.0   4.887 1.08e-06 ***
## FoundationStone         9671.0     8003.1   1.208 0.226991
## FoundationWood           685.9    11711.4   0.059 0.953304
## HeatingQCFa           -13365.6     3023.5  -4.421 1.02e-05 ***
## HeatingQCGd            -2912.0     1522.4  -1.913 0.055878 .
## HeatingQCPo            -9633.0    17046.2  -0.565 0.572045
## HeatingQCTA            -7149.3     1460.4  -4.896 1.04e-06 ***
## KitchenQualFa         -40466.6     4351.9  -9.299  < 2e-16 ***
## KitchenQualGd         -32202.4     2564.8 -12.556  < 2e-16 ***
## KitchenQualPo         -21010.1    26555.6  -0.791 0.428909
## KitchenQualTA         -40336.8     2834.4 -14.231  < 2e-16 ***
## FunctionalMaj2          -359.5    10635.4  -0.034 0.973038
## FunctionalMin1         10457.9     6917.7   1.512 0.130712
## FunctionalMin2          5632.4     6891.9   0.817 0.413855
## FunctionalMod          -3251.3     7605.8  -0.427 0.669064
## FunctionalSal         -30633.2    22354.8  -1.370 0.170697
## FunctionalSev         -36597.9    19624.6  -1.865 0.062301 .
## FunctionalTyp          18152.7     6148.4   2.952 0.003179 **
## SaleTypeCon            41413.6    12018.9   3.446 0.000578 ***
## SaleTypeConLD           4790.3     6021.1   0.796 0.426345
## SaleTypeConLI          -7332.5     9058.4  -0.809 0.418312
```

```
## SaleTypeConLw           2787.5     9627.0   0.290 0.772184
## SaleTypeCWD            21138.3     7964.1   2.654 0.007995 **
## SaleTypeNew             8211.0    11379.5   0.722 0.470622
## SaleTypeOth            12202.0    10055.9   1.213 0.225074
## SaleTypeVWD            13968.1    25768.2   0.542 0.587817
## SaleTypeWD              3454.1     3069.7   1.125 0.260584
## SaleConditionAdjLand   21882.7     8110.3   2.698 0.007015 **
## SaleConditionAlloca    16113.3     6068.8   2.655 0.007973 **
## SaleConditionFamily     3596.3     4283.6   0.840 0.401241
## SaleConditionNormal    10998.9     2137.8   5.145 2.86e-07 ***
## SaleConditionPartial   19036.4    10991.5   1.732 0.083400 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 25230 on 2780 degrees of freedom
## Multiple R-squared:  0.902,  Adjusted R-squared:  0.8969
## F-statistic: 177.6 on 144 and 2780 DF,  p-value: < 2.2e-16
```

Appendix :G

3.7 Model Improvement By removing insignificant variables

```
forward1 = update(forward, ~.-LotConfig)
summary(forward1)
```

```
## Residual standard error: 25310 on 2784 degrees of freedom
## Multiple R-squared:  0.9012, Adjusted R-squared:  0.8962
## F-statistic: 181.3 on 140 and 2784 DF,  p-value: < 2.2e-16
```

```
forward2= update(forward1, ~. -RoofStyle)
summary(forward2)
```

```
##
## Residual standard error: 25370 on 2789 degrees of freedom
## Multiple R-squared:  0.9005, Adjusted R-squared:  0.8957
## F-statistic: 186.9 on 135 and 2789 DF,  p-value: < 2.2e-16
```

```
forward3= update(forward2, ~. -ExterCond)
summary(forward3)
```

```
##
## Residual standard error: 25430 on 2793 degrees of freedom
## Multiple R-squared:  0.8999, Adjusted R-squared:  0.8952
## F-statistic: 191.7 on 131 and 2793 DF,  p-value: < 2.2e-16
```

```
forward4= update(forward3, ~. -Condition2)
summary(forward4)
```

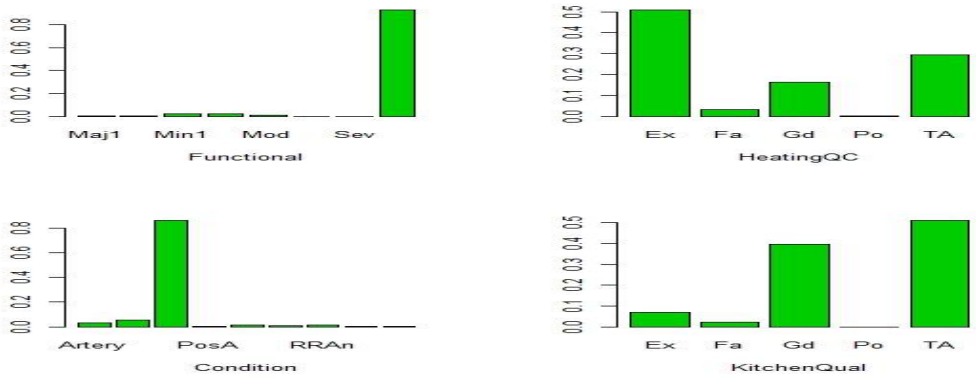
```
## Residual standard error: 25480 on 2800 degrees of freedom
## Multiple R-squared:  0.8992, Adjusted R-squared:  0.8948
## F-statistic: 201.5 on 124 and 2800 DF,  p-value: < 2.2e-16
```

```
forward5= update(forward4, ~. -Exterior1st)
summary(forward5)
```

```
## Residual standard error: 25830 on 2815 degrees of freedom
## Multiple R-squared:  0.8959, Adjusted R-squared:  0.8919
## F-statistic: 222.3 on 109 and 2815 DF,  p-value: < 2.2e-16
```

Appendix H:

Bar Plot of for selected set of categorical predictor variable as shown below:



Combining the Categorical Variable levels

```
#Comining variable levels
WS_combLevel = finalWorkingSet
levels(WS_combLevel$Functional)<-c("NonTyp", "NonTyp", "NonTyp", "NonTyp",
"NonTyp" , "NonTyp" , "NonTyp", "Typ")
levels(WS_combLevel$HeatingQC)<-c("Gd", "Po", "Gd", "Po", "Gd")
levels(WS_combLevel$Condition1)= c("AbNorm", "AbNorm"  , "Norm",    "AbNorm"
,  "AbNorm",   "AbNorm",   "AbNorm",   "AbNorm",   "AbNorm")
levels(WS_combLevel$KitchenQual) = c("Gd", "Po", "Gd", "Po", "Gd")
par(mfrow = c(1,1))
```

Appendix I:

```
Final Model :

finalmodel = lm(formula = SalePrice ~ Comp.1 + Neighborhood + KitchenQual +
    ExterQual + HouseStyle + BldgType + MasVnrType + SaleCondition +
    Functional + Foundation + Comp.8 + Comp.2 + Condition1 +
    HeatingQC + LandSlope + RoofMatl + LandContour + Street +
    Comp.5 + Comp.3 + Comp.7 + Utilities + Comp.4 ,
    data = WS_combLevel)
summary(finalmodel)
```

Appendix J:

```
#confint(finalmodel)
                             2.5 %      97.5 %
(Intercept)           182851.2857 225999.9542
Comp.1                -30346.6980 -28819.8951
NeighborhoodBlueste   -31560.5476   2286.7231
NeighborhoodBrDale    -41979.3515 -15928.9029
NeighborhoodBrkSide   -39887.8499 -18591.0149
NeighborhoodClearCr   -41168.4033 -17349.8359
NeighborhoodCollgCr   -38231.8795 -19437.8399
NeighborhoodCrawfor   -22020.0263  -1145.4013
NeighborhoodEdwards   -43763.9221 -23841.9010
NeighborhoodGilbert   -35023.6897 -15307.3974
NeighborhoodGreens    -18786.9995  17554.0386
NeighborhoodGrnHill    61880.5227 125943.4282
NeighborhoodIDOTRR    -50109.3737 -28481.3528
NeighborhoodLandmrk   -68386.5131  21559.2437
NeighborhoodMeadowV   -41779.4315 -17662.9635
NeighborhoodMitchel   -48269.2556 -27818.0230
NeighborhoodNAmes     -45361.8723 -25950.0874
NeighborhoodNoRidge   -17888.8870   3494.3978
NeighborhoodNPkVill   -27501.3974   -946.7607
NeighborhoodNridgHt   -13019.3598   6266.8555
```

```
NeighborhoodNWAmes    -44564.3181 -24250.9156
NeighborhoodOldTown   -50913.3408 -30762.5693
NeighborhoodSawyer    -43787.9970 -23415.9885
NeighborhoodSawyerW   -41403.4533 -21667.9486
NeighborhoodSomerst   -26941.0746  -8208.3137
NeighborhoodStoneBr     8425.5973  30129.0274
NeighborhoodSWISU     -47985.3177 -24553.1885
NeighborhoodTimber    -34497.9068 -13384.9365
NeighborhoodVeenker   -34565.0164  -8899.9223
KitchenQualPo          -5467.7554   5724.6881
ExterQualFa           -63223.2194 -42736.5945
ExterQualGd           -46245.0979 -35629.1277
ExterQualTA           -59412.7966 -47486.4567
HouseStyle1.5Unf      -10594.8021  10452.3233
HouseStyle1Story       -9014.7803  -2582.6517
HouseStyle2.5Fin       -8401.5527  27343.3718
HouseStyle2.5Unf       -2104.4749  16949.7559
HouseStyle2Story        4984.4220  11789.5080
HouseStyleSFoyer       -1692.2900  10337.7943
HouseStyleSLvl          1025.1453  11213.9796
BldgType2fmCon        -22446.9040 -10630.5535
BldgTypeDuplex        -20874.4069 -11187.3031
BldgTypeTwnhs         -24667.5634 -11914.1169
BldgTypeTwnhsE        -20016.0421 -12045.5596
MasVnrTypeBrkCmn      -27869.8668  -2045.7592
MasVnrTypeBrkFace     -19806.8468   -850.9340
MasVnrTypeCBlock     -139866.0363 -49881.2420
MasVnrTypeNone         -8571.4944  10245.0055
MasVnrTypeStone       -11026.7073   8363.3518
SaleConditionAdjLand    -421.8999  26427.7850
```

```
SaleConditionAlloca     1422.2729  21824.2167
SaleConditionFamily    -4526.0586   9963.6633
SaleConditionNormal     6705.5807  13479.2520
SaleConditionPartial   17472.3803  26995.6299
FunctionalTyp          10103.3198  16926.7972
FoundationCBlock       -3241.3625   3732.7590
FoundationPConc         3657.8328  11306.8546
FoundationSlab         20875.2857  35891.3065
FoundationStone        -9765.0183  17549.8388
FoundationWood        -21213.0575  19090.9813
Comp.8                  2759.3551   4583.6490
Comp.2                  1771.4262   3241.0990
Condition1Norm          2959.5543   7928.7409
HeatingQCPo           -12841.0368  -3273.8355
LandSlopeMod             -732.7108   9145.5899
LandSlopeSev          -45787.7638 -19328.3697
RoofMatlMembran        51549.3196 142929.8103
RoofMatlMetal          -9175.5236  82948.5255
RoofMatlRoll          -70781.2701  17442.5519
RoofMatlTar&Grv         -227.9124  19150.5599
RoofMatlWdShake        -8662.8693  21011.2780
RoofMatlWdShngl        24330.9820  61653.0452
LandContourHLS           802.8874  13301.2070
LandContourLow        -23207.5293  -7207.7699
LandContourLvl         -6590.5451   2634.8431
StreetPave             13045.1092  40918.9112
Comp.5                 -2756.6027  -1063.5845
Comp.3                 -2413.7479   -762.5051
Comp.7                   343.9032   2158.2173
UtilitiesNoSeWa       -94543.3783  -5706.0471
```

```
UtilitiesNoSewr       -44779.1323  19203.6890

Comp.4                   173.0461   1783.5262
```

Appendix K: Variation inflation factor

```
> vif(finalmodel)
                    GVIF Df GVIF^(1/(2*Df))
Comp.1          3.332651  1        1.825555
Neighborhood  140.980143 27        1.095971
KitchenQual     1.139315  1        1.067387
ExterQual       4.627359  3        1.290889
HouseStyle      3.908208  7        1.102260
BldgType        4.480834  4        1.206201
MasVnrType      2.307916  5        1.087231
SaleCondition   1.891901  5        1.065835
Functional      1.149456  1        1.072127
Foundation      5.460732  5        1.185018
Comp.8          1.199420  1        1.095180
Comp.2          1.360140  1        1.166251
Condition1      1.133461  1        1.064641
HeatingQC       1.104490  1        1.050947
LandSlope       2.158355  2        1.212078
RoofMatl        1.564670  6        1.038011
LandContour     2.642336  3        1.175794
Street          1.218978  1        1.104074
Comp.5          1.134756  1        1.065249
Comp.3          1.330244  1        1.153362
Comp.7          1.202917  1        1.096776
Utilities       1.112537  2        1.027019
Comp.4          1.066031  1        1.032488
```