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House Prices and Regressions

Introduction:

The real estate industry is one of the most significant sectors of our economy. The buying and selling of homes form an integral part of this industry, and the value of a home can be determined by several factors. A thorough understanding of these factors can enable real estate agents and investors to make informed decisions regarding the pricing of homes. In this study, we investigated the relationship between the sales price of homes in Ames, Iowa, and the square footage of the living area. Additionally, we explored whether the location of the house in different neighborhoods affected its sales price. Finally, we aimed to develop the most predictive model for sales prices of homes in Ames, Iowa, utilizing forward selection, backward elimination, stepwise selection, and a custom model.

Data Exploration:

To investigate the relationship between the sales price of homes, their living area and location, we first created a dataset by merging the test and train dataset into one. This was done simply to allow for more efficient data wrangling. We also kept in mind the 1459 NAs in the SalePrice column were from the test dataset. Additionally, we added a column to indicate whether the record was from the train or test dataset and verified the successful merge and addition of columns (Diagram 1). All the data marked with test in the Train column were omitted upon cleaning the data. Upon finalizing this dataset, we explored the data for insights into the Ames housing market as well as identified the variables we needed to change, clean and create.

Prior to conducting the study, we visualized which categories had the highest number of NA values and identified whether it would affect the two parameters we were concerned with: SalePrice and GrLivArea. From Diagram 2, we can see that there weren't too many NA values in the dataset, and those that were present were mostly associated with a lack of a certain feature within that respective house. For example, if a house didn't have a pool, then the PoolQC column would have NA for that record.

Analysis 1:

Next, to investigate the relationship between the SalePrice, the GrLivArea and Neighborhood, we plotted a scatterplot of SalePrice vs. GrLivArea and color-coded each point with the respective color associated with the Neighborhood (Diagram 3). Also, note that any records where SalePrice was NA was omitted from the visual plot. From the scatterplot, we can see that there is a clear relationship between SalePrice and GrLivArea. We can also see that the

Neighborhood category appears to have a similar relationship as the relationship between SalePrice and GrLivArea.

Despite the apparent relationship, we decided to perform a log transformation on the categories to see if we could identify a more linear relationship. In Diagram 4, we can see the scatterplot of the log transformed data. Here we can see that the relationship appears to be more linear than when the data wasn't transformed. This allowed us to determine that the log transformed data for SalePrice and GrLivArea would be used moving forward in our analysis.

Now that the data visually represented linearity more clearly, we, at this point, decided to narrow in and analyze the three neighborhoods that Century 21 operates in: NAmes, Edwards and BrkSide. When plotting this scatterplot, we took the relationship between the log of SalePrice and the log of GrLivArea and color-coded the points in respect to the three Neighborhoods. Also, note that the NA rows for SalePrice were omitted. Upon plotting the data, we can see in Diagram 5 that the relationship appears to be linear. With this result, we decided to fit a linear model using this dataset and assess whether it described the SalePrice accurately or not.

Diagram 5:

When conducting this portion of the analysis, we fit the models with and without interaction terms (Diagram 6 & 7). The interaction terms, logGrLivArea:NeighborhoodEdwards and logGrLivArea:NeighborhoodNAmes, were statistically significant with p-values of 0.0011 and 5.35e-05 respectively. Also, note that the model that included the interaction terms had a lower Press score of 14.609 versus a Press score of 15.001 for the model without interaction variables. These Press scores indicate that the relationship between the log SalePrice and log GrLivArea is different for each of the three neighborhoods. From this result, we decided to test whether the Edwards and NAmes neighborhoods were statistically different from each other.

Assumption Check:

In addition, we also plotted the studentized residuals to check for any violations of assumptions (Diagram 8, 9, 10 & 11). From these residual plots, we can clearly see there is insufficient evidence to indicate that there has been a violation of linearity, homoscedasticity, or normality. We also created residual plots, QQ plots, and fitted plots to identify if there were any influential points that needed to be investigated further (Diagram 12, 13, 14 & 15). The results of these plots were consistent with the assumptions of the linear model and we concluded that there were no influential points that needed to be investigated.

Comparing Competing Models:

The model that included the flexible slopes per neighborhood (interaction terms) performed better. More importantly, The interaction terms, logGrLivArea:NeighborhoodEdwards and logGrLivArea:NeighborhoodNAmes, were strongly significant with p-values of 0.0011 and 5.35e-05 respectively, suggesting that there were real differences in the characteristics for the neighborhood.

Parameters:

The confidence intervals for the model including the interaction terms were conducted with a significance level of 0.05. From the results in Diagram 16, we can say with 95% confidence that when all the independent variables are at zero, the estimated median SalePrice would be between ~$137 and ~$992.2. For the GrLivArea, we can say with 95% confidence that for every one unit increase in logGrLivArea, we can expect the median SalePrice to increase by ~$1,970 to ~$2,610. Next, we calculated for the difference in the intercept between the Edwards and NAmes neighborhoods compared to the BrkSide neighborhood. For each of these comparisons, we can say with 95% confidence the median SalePrice in the Edwards neighborhood is expected to be 2.28 to 28.83 times higher than BrkSide and the median SalePrice in the NAmes neighborhood is expected to be 4.06 and 42.98 times higher than BrkSide sales prices. The interaction terms represented the estimated change in the median SalePrice associated with a one unit increase in logGrLivArea for each neighborhood holding the BrkSide neighborhood as a reference point. We can say with 95% confidence that the effect of logGrLivArea on median SalePrice is between 0.62 and 0.89 times smaller in the Edwards neighborhood than BrkSide. To a similar effect, we can say with 95% confidence that the effect of logGrLivArea on median SalePrice is between 0.6 and 0.83 times smaller in the NAmes neighborhood compared to BrkSide.

Analysis 1 Conclusion:

Through the analysis performed on the relationship between SalePrice and GrLivArea, we discovered that there was a significant positive correlation between the sales price of homes and the square footage of the living area. Additionally, we identified that the location of the house in different neighborhoods does have a significant effect on its sales price.

Analysis 2:

In this section, we built four different models using forward selection, backward elimination, stepwise selection, and a custom model. We generated the R^2, RMSE, the AIC and Kaggle score for each model and determined which model was the best in terms of predicting future sales prices. We also examined residual plots to check whether the assumptions of the linear regression model had been met and addressed any outliers or influential observations through influential point analysis. Finally, we compared competing models based on the R^2, RMSE, the AIC and Kaggle score and drew conclusions based on our findings.

Data Cleaning:

In order to use a linear regression model, we converted all of the categorical variables into dummy variables. We also removed or imputed the NA values within the dataset by attempting to interpret what the NA value meant for each respective category (Diagram 17, 18 & 19). In most cases, this process created a new category of "none" for the variable. Any remaining values that were NA were imputed to the mean, and the data was split into training and testing sets.

Model Selection:

Once the data was cleaned accordingly, four different predictive models were utilized to determine which of these models would best predict future sale prices. The predictive models used during our analysis were the forward selection, backward elimination, stepwise selection, and a custom model utilizing the top ten parameters from the stepwise results. The question we hoped to answer was whether the increase in performance is worth the cost of performing a forward, backwards or stepwise model. We also wanted to identify if having only ten parameters would be too few to capture the complexity of the data.

Model Evaluation:

First, the forward selection was used, resulting in a R^2 score of 0.942, a RMSE of 0.096, an AIC score of -2504 and a Kaggle score of 0.1398. Next, we used the backward elimination model, and the resulting scores were a R^2 score of 0.944, a RMSE of 0.094, an AIC score of -2493 and a Kaggle score of 0.1458. Next, the stepwise predictive model was used to produce a R^2 score of 0.944, a RMSE of 0.094, an AIC score of -2494 and a Kaggle score of 0.1456. Lastly, a custom predictive model utilizing the top ten parameters ranked by importance from the stepwise model was performed. The expectation was that this custom model wouldn't perform as well as the others, but each parameter would be more explainable and the fitting would require much less computation. The custom model produced a R^2 score of 0.84, a RMSE of 0.16, an AIC score of -1190 and a Kaggle score of 0.1777 (Diagram 20).

Diagram 20:

Predictive Models	R^2	RMSE	AIC	Kaggle Score
Forward	0.942	0.096	-2504	0.1398
Backward	0.944	0.094	-2493	0.1458
Stepwise	0.944	0.094	-2494	0.1456
Custom	0.84	0.16	-1190	0.1777

We also identified the most important predictor variables for each of the predictive models used during the analysis. When looking at the forward selection model, we can see that the most important predictor variable was roof_matl_cly_tile with an overall importance score of 16.67, followed by overall_cond and ms_zoning_c_all with scores of 12.32 and 12.10 respectively (Diagram 21). When looking at the most important predictor variables for the backward elimination model, we can see that the most important predictor variable was log_gr_liv_area with an overall importance score of 16.98, followed by roof_matl_cly_tile and overall_cond with scores of 11.54 and 11.5 respectively (Diagram 22). The stepwise selection model showed that log_gr_liv_area was the most important predictor variable with a score of 17.00. The second and third were overall_cond and roof_matl_cly_tile with scores of 11.54 and 11.46 respectively (Diagram 23). The custom model's most important predictor variable was overall_qual with a score of 34.06, followed by log_gr_liv_area with a score of 26.71 and bsmt_fin_sf1 with a score of 19.63 (Diagram 24). For all of these predictive models, there were many predictor variables that were considered strong predictors and they can be observed in the associated diagrams in the appendix section.

Assumption Check:

Similar to Analysis 1, we also plotted the studentized residuals to check for any violations of assumptions (Diagram 25, 26 & 27). From these residual plots, we can clearly see there is insufficient evidence to indicate that there has been a violation of linearity, homoscedasticity, or normality. We also created residual plots, QQ plots, and fitted plots to identify if there were any influential points that needed to be investigated further (Diagram 28, 29, 30 & 31). The results of these plots contained several points with a Cook's d of approximately 1, but overall, the results were consistent with the assumptions of the linear model.

Conclusion:

Our findings provided valuable insights into the factors that influenced the sales price of homes in Ames, Iowa. Please keep in mind that our findings were centralized for the Ames housing market and isn't indicative of all housing markets in the United States. We discovered that the size, location and overall condition of the house were the most significant factors that affected its sales price. An interesting observation was made that sales prices were also heavily influenced by the presence of a clay tile roof. Additionally, we provided several predictive models that could be used to estimate future sales price of homes in Ames, Iowa. We concluded from our analysis that the forward selection model should be used when predicting future sales prices of homes in the Ames housing market.

RShiny App:

https://christianorji.shinyapps.io/house-prices-advanced-regression-techniques/

Personal Github Websites:

https://nicksager.github.io/

https://jgchung.github.io/

https://christianorji.github.io/

Appendix

Diagram 1:

```
##   Id MSSubClass MSZoning LotFrontage LotArea Street Alley LotShape LandContour
## 1  1         60       RL          65    8450   Pave  <NA>      Reg         Lvl
## 2  2         20       RL          80    9600   Pave  <NA>      Reg         Lvl
## 3  3         60       RL          68   11250   Pave  <NA>      IR1         Lvl
## 4  4         70       RL          60    9550   Pave  <NA>      IR1         Lvl
## 5  5         60       RL          84   14260   Pave  <NA>      IR1         Lvl
## 6  6         50       RL          85   14115   Pave  <NA>      IR1         Lvl
##   Utilities LotConfig LandSlope Neighborhood Condition1 Condition2 BldgType
## 1    AllPub    Inside       Gtl      CollgCr       Norm       Norm     1Fam
## 2    AllPub       FR2       Gtl      Veenker      Feedr       Norm     1Fam
## 3    AllPub    Inside       Gtl      CollgCr       Norm       Norm     1Fam
## 4    AllPub    Corner       Gtl      Crawfor       Norm       Norm     1Fam
## 5    AllPub       FR2       Gtl      NoRidge       Norm       Norm     1Fam
## 6    AllPub    Inside       Gtl      Mitchel       Norm       Norm     1Fam
##   HouseStyle OverallQual OverallCond YearBuilt YearRemodAdd RoofStyle RoofMatl
## 1     2Story           7           5      2003         2003     Gable  CompShg
## 2     1Story           6           8      1976         1976     Gable  CompShg
## 3     2Story           7           5      2001         2002     Gable  CompShg
## 4     2Story           7           5      1915         1970     Gable  CompShg
## 5     2Story           8           5      2000         2000     Gable  CompShg
## 6     1.5Fin           5           5      1993         1995     Gable  CompShg
##   Exterior1st Exterior2nd MasVnrType MasVnrArea ExterQual ExterCond Foundation
## 1     VinylSd     VinylSd    BrkFace        196        Gd        TA      PConc
## 2     MetalSd     MetalSd       None          0        TA        TA     CBlock
## 3     VinylSd     VinylSd    BrkFace        162        Gd        TA      PConc
## 4     Wd Sdng     Wd Shng       None          0        TA        TA     BrkTil
## 5     VinylSd     VinylSd    BrkFace        350        Gd        TA      PConc
## 6     VinylSd     VinylSd       None          0        TA        TA       Wood
##   BsmtQual BsmtCond BsmtExposure BsmtFinType1 BsmtFinSF1 BsmtFinType2
## 1       Gd       TA           No          GLQ        706          Unf
## 2       Gd       TA           Gd          ALQ        978          Unf
## 3       Gd       TA           Mn          GLQ        486          Unf
## 4       TA       Gd           No          ALQ        216          Unf
## 5       Gd       TA           Av          GLQ        655          Unf
## 6       Gd       TA           No          GLQ        732          Unf
##   BsmtFinSF2 BsmtUnfSF TotalBsmtSF Heating HeatingQC CentralAir Electrical
## 1          0       150         856    GasA        Ex          Y      SBrkr
## 2          0       284        1262    GasA        Ex          Y      SBrkr
## 3          0       434         920    GasA        Ex          Y      SBrkr
## 4          0       540         756    GasA        Gd          Y      SBrkr
## 5          0       490        1145    GasA        Ex          Y      SBrkr
## 6          0        64         796    GasA        Ex          Y      SBrkr
##   X1stFlrSF X2ndFlrSF LowQualFinSF GrLivArea BsmtFullBath BsmtHalfBath FullBath
## 1       856       854            0      1710            1            0        2
## 2      1262         0            0      1262            0            1        2
## 3       920       866            0      1786            1            0        2
## 4       961       756            0      1717            1            0        1
## 5      1145      1053            0      2198            1            0        2
## 6       796       566            0      1362            1            0        1
##   HalfBath BedroomAbvGr KitchenAbvGr KitchenQual TotRmsAbvGrd Functional
## 1        1            3            1          Gd            8        Typ
## 2        0            3            1          TA            6        Typ
## 3        1            3            1          Gd            6        Typ
## 4        0            3            1          Gd            7        Typ
## 5        1            4            1          Gd            9        Typ
## 6        1            1            1          TA            5        Typ
##   Fireplaces FireplaceQu GarageType GarageYrBlt GarageFinish GarageCars
## 1          0        <NA>     Attchd        2003          RFn          2
## 2          1          TA     Attchd        1976          RFn          2
## 3          1          TA     Attchd        2001          RFn          2
## 4          1          Gd     Detchd        1998          Unf          3
## 5          1          TA     Attchd        2000          RFn          3
## 6          0        <NA>     Attchd        1993          Unf          2
##   GarageArea GarageQual GarageCond PavedDrive WoodDeckSF OpenPorchSF
## 1        548         TA         TA          Y          0          61
## 2        460         TA         TA          Y        298           0
## 3        608         TA         TA          Y          0          42
## 4        642         TA         TA          Y          0          35
## 5        836         TA         TA          Y        192          84
## 6        480         TA         TA          Y         40          30
##   EnclosedPorch X3SsnPorch ScreenPorch PoolArea PoolQC Fence MiscFeature
## 1             0          0           0        0   <NA>  <NA>        <NA>
## 2             0          0           0        0   <NA>  <NA>        <NA>
## 3             0          0           0        0   <NA>  <NA>        <NA>
## 4           272          0           0        0   <NA>  <NA>        <NA>
## 5             0          0           0        0   <NA>  <NA>        <NA>
## 6             0        320           0        0   <NA> MnPrv        Shed
##   MiscVal MoSold YrSold SaleType SaleCondition SalePrice train
## 1       0      2   2008       WD        Normal    208500     1
## 2       0      5   2007       WD        Normal    181500     1
## 3       0      9   2008       WD        Normal    223500     1
## 4       0      2   2006       WD       Abnorml    140000     1
## 5       0     12   2008       WD        Normal    250000     1
## 6     700     10   2009       WD        Normal    143000     1
```

Diagram 2:

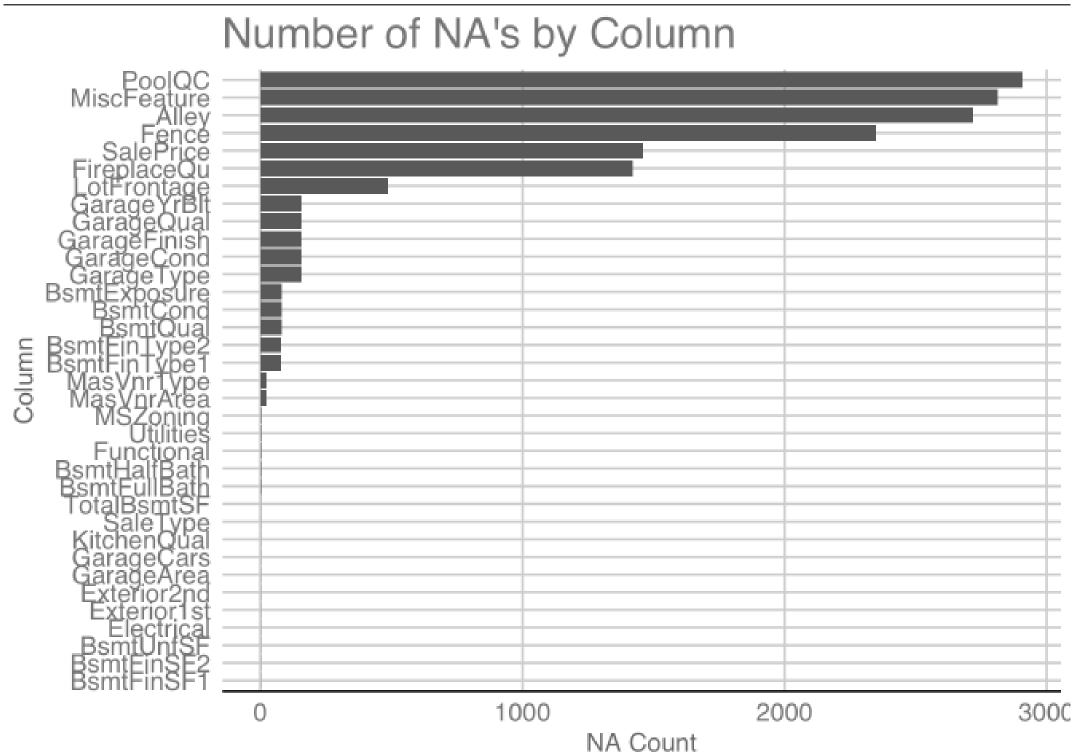


Diagram 3:

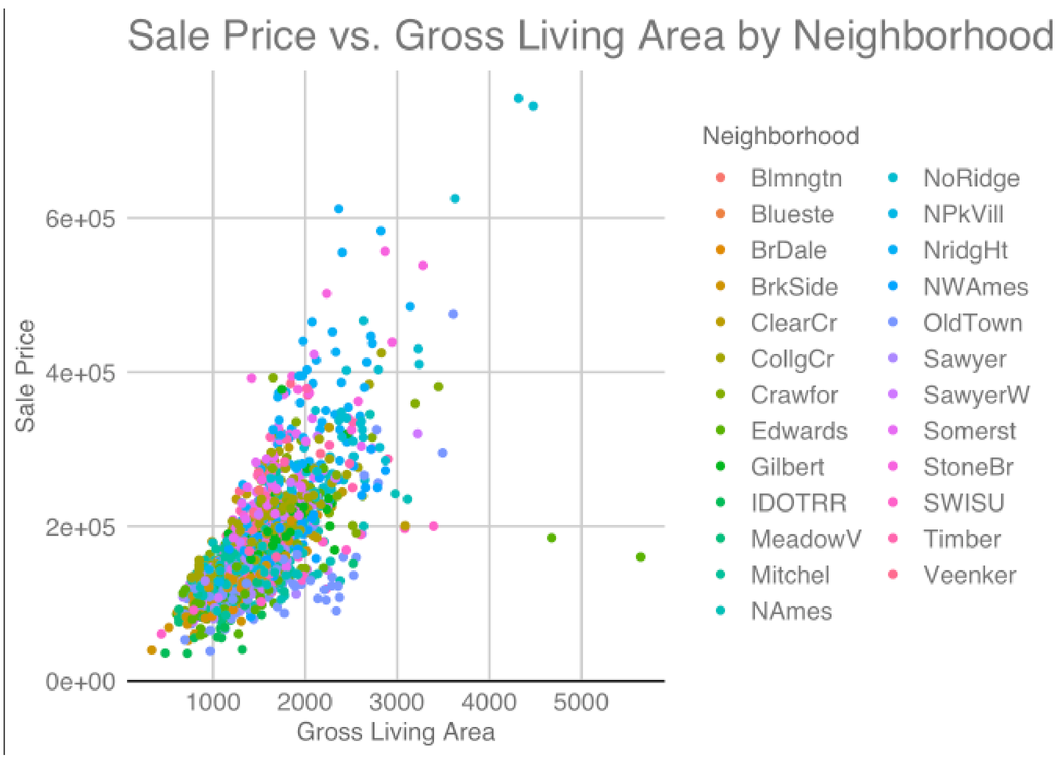


Diagram 4:

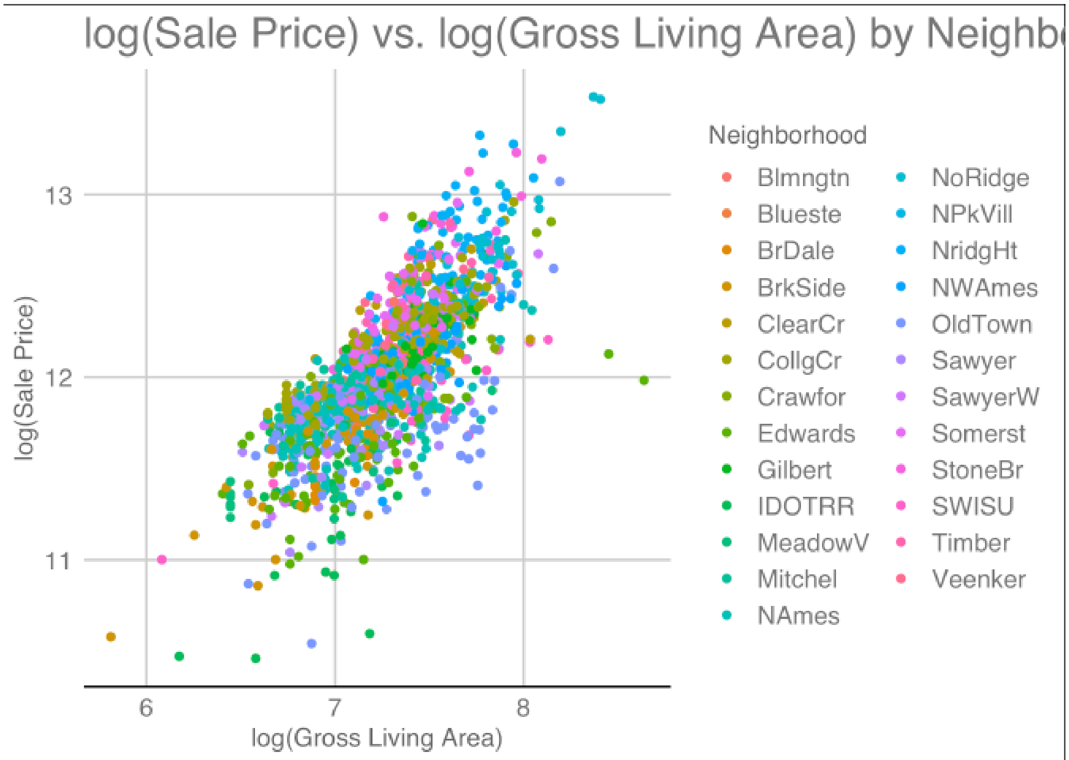


Diagram 5:

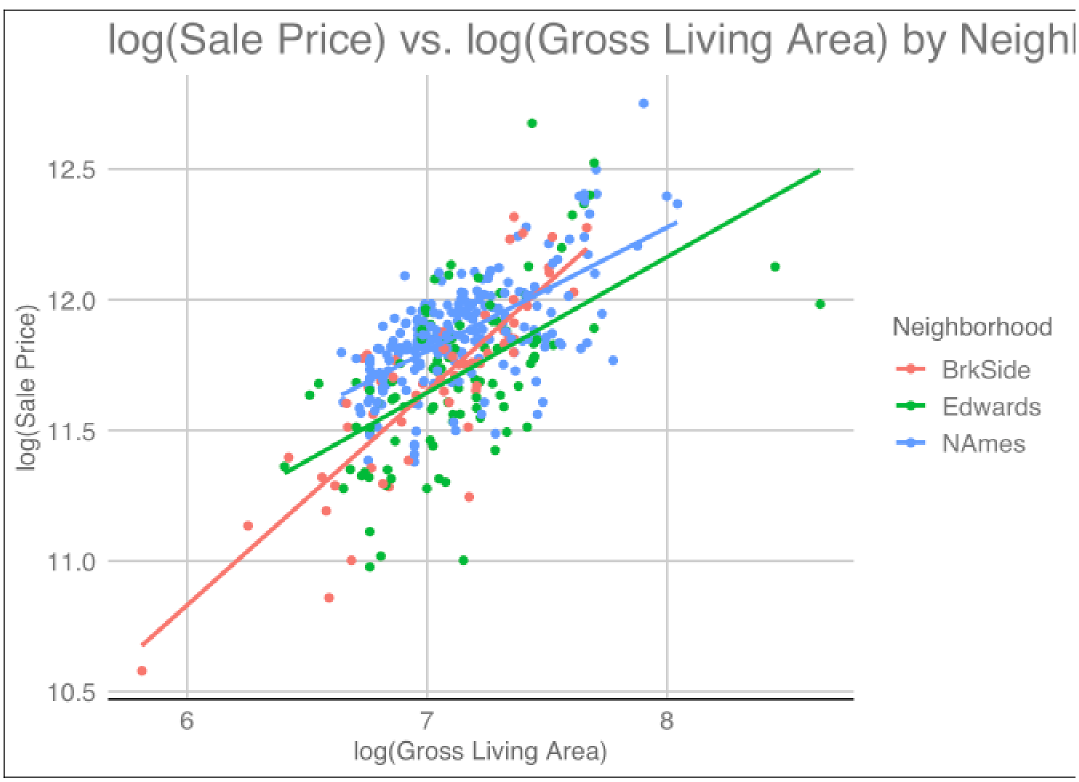


Diagram 6:

```
##
## Call:
## lm(formula = logSalePrice ~ logGrLivArea + Neighborhood, data = century21)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.72154 -0.10592  0.02469  0.11565  0.79364
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)          7.76936    0.22919  33.900  < 2e-16 ***
## logGrLivArea         0.55579    0.03237  17.171  < 2e-16 ***
## NeighborhoodEdwards -0.02044    0.03252  -0.629     0.53
## NeighborhoodNAmes    0.13279    0.02906   4.569 6.63e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1961 on 379 degrees of freedom
## Multiple R-squared:  0.4897, Adjusted R-squared:  0.4857
## F-statistic: 121.2 on 3 and 379 DF,  p-value: < 2.2e-16
```

Diagram 7:

```
##
## Call:
## lm(formula = logSalePrice ~ logGrLivArea * Neighborhood, data = century21)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.72080 -0.10353  0.02184  0.10586  0.80470
##
## Coefficients:
##                                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)                       5.91292    0.50459  11.718  < 2e-16 ***
## logGrLivArea                      0.81965    0.07163  11.443  < 2e-16 ***
## NeighborhoodEdwards               2.09359    0.64589   3.241   0.0013 **
## NeighborhoodNAmes                 2.57981    0.59988   4.301 2.17e-05 ***
## logGrLivArea:NeighborhoodEdwards -0.29998    0.09122  -3.289   0.0011 **
## logGrLivArea:NeighborhoodNAmes   -0.34662    0.08482  -4.087 5.35e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1923 on 377 degrees of freedom
## Multiple R-squared:  0.5121, Adjusted R-squared:  0.5056
## F-statistic: 79.14 on 5 and 377 DF,  p-value: < 2.2e-16
```

Diagram 8:

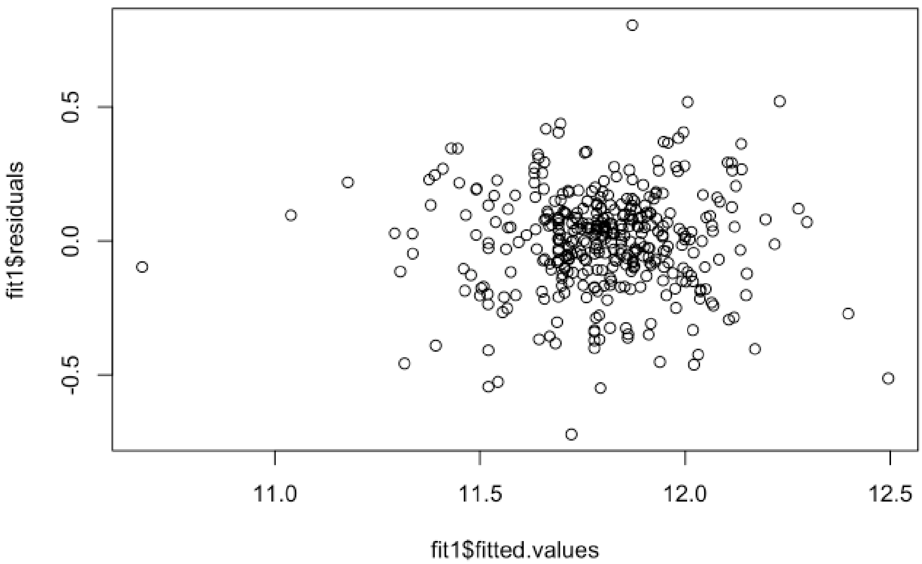


Diagram 9:

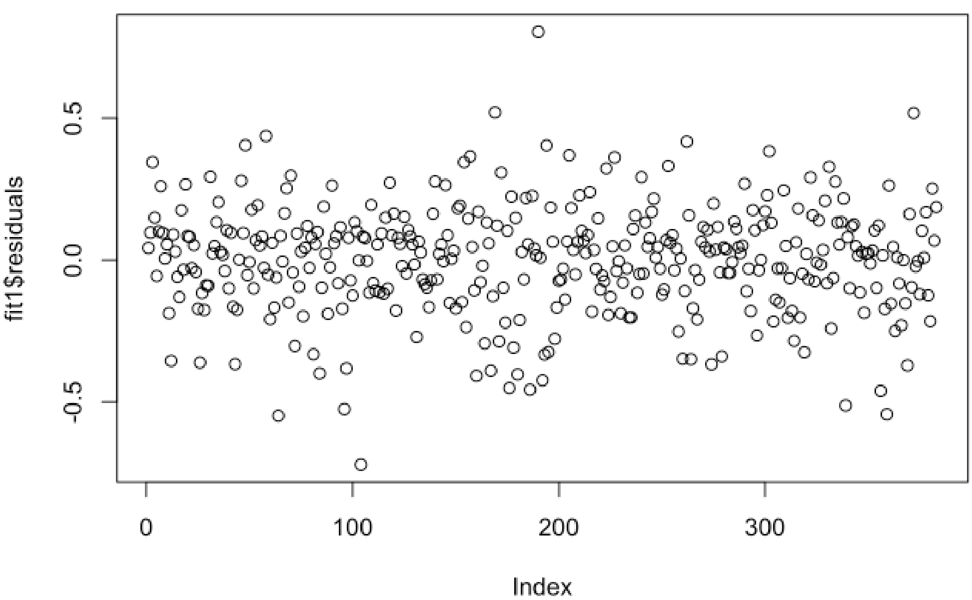


Diagram 10:

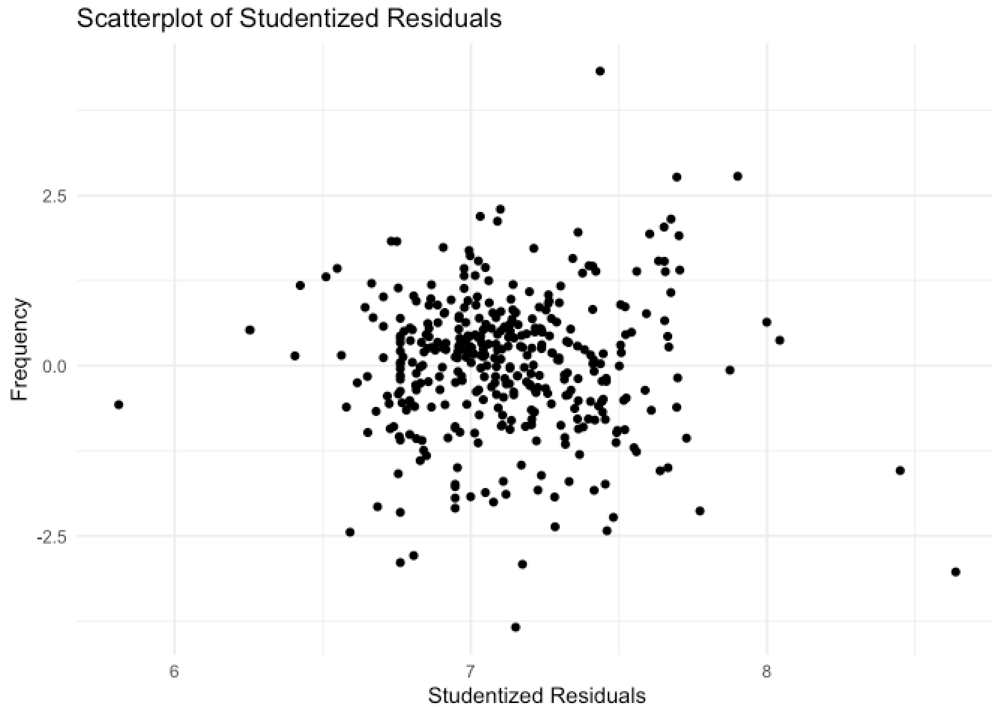


Diagram 11:

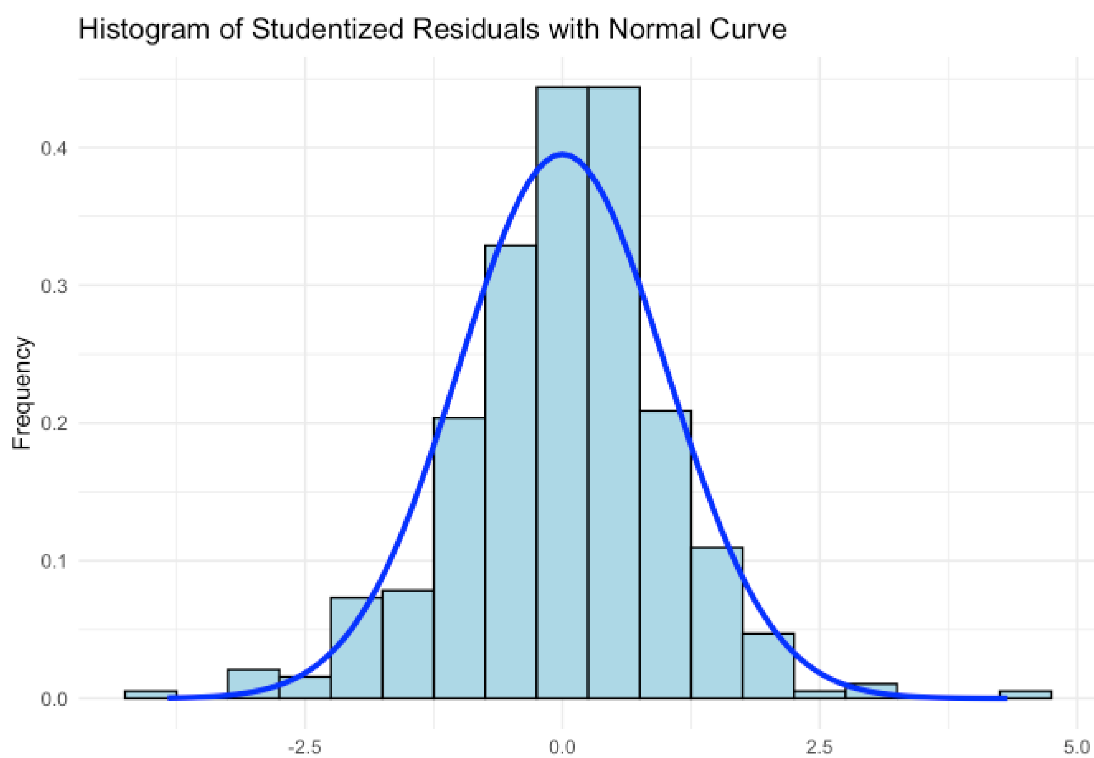


Diagram 12:

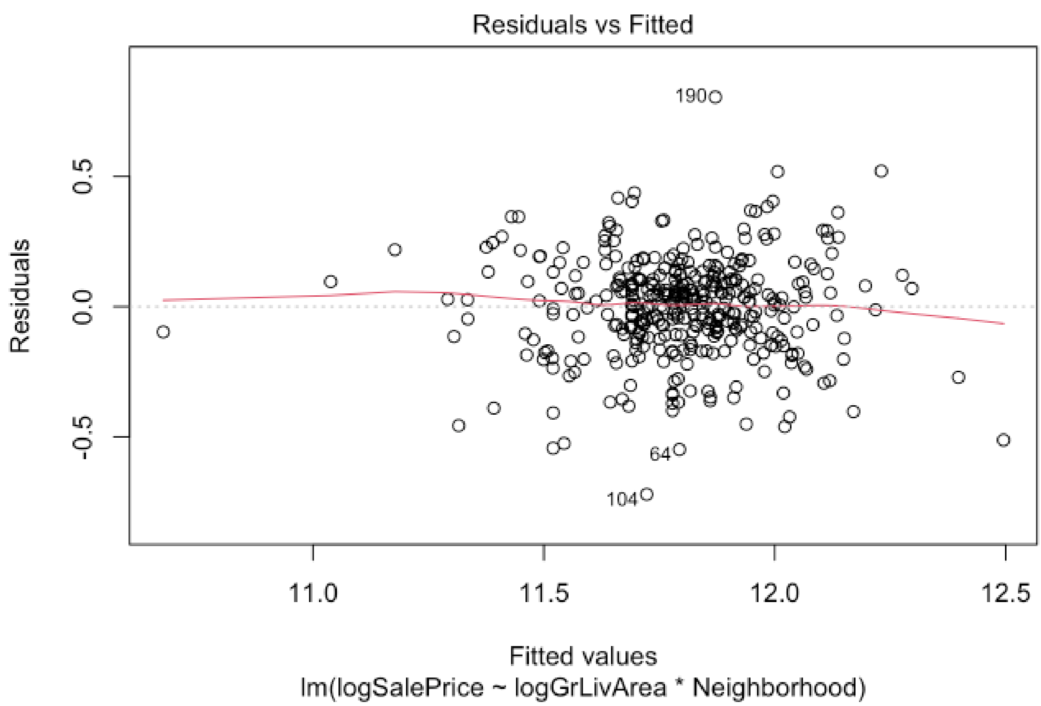


Diagram 13:

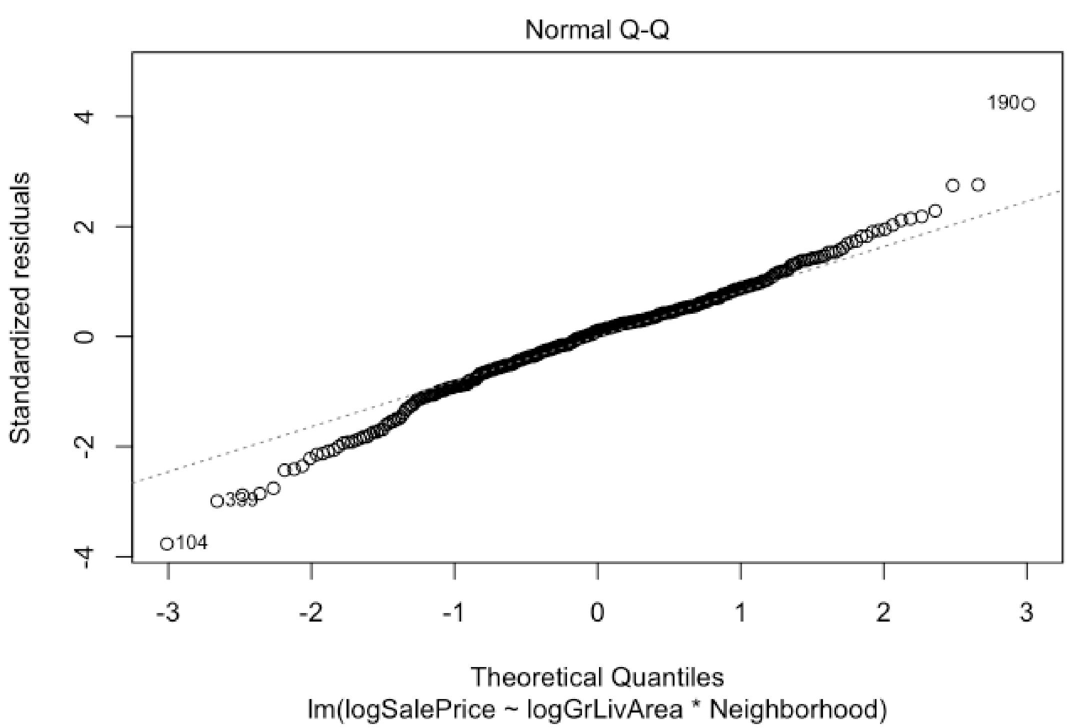


Diagram 14:

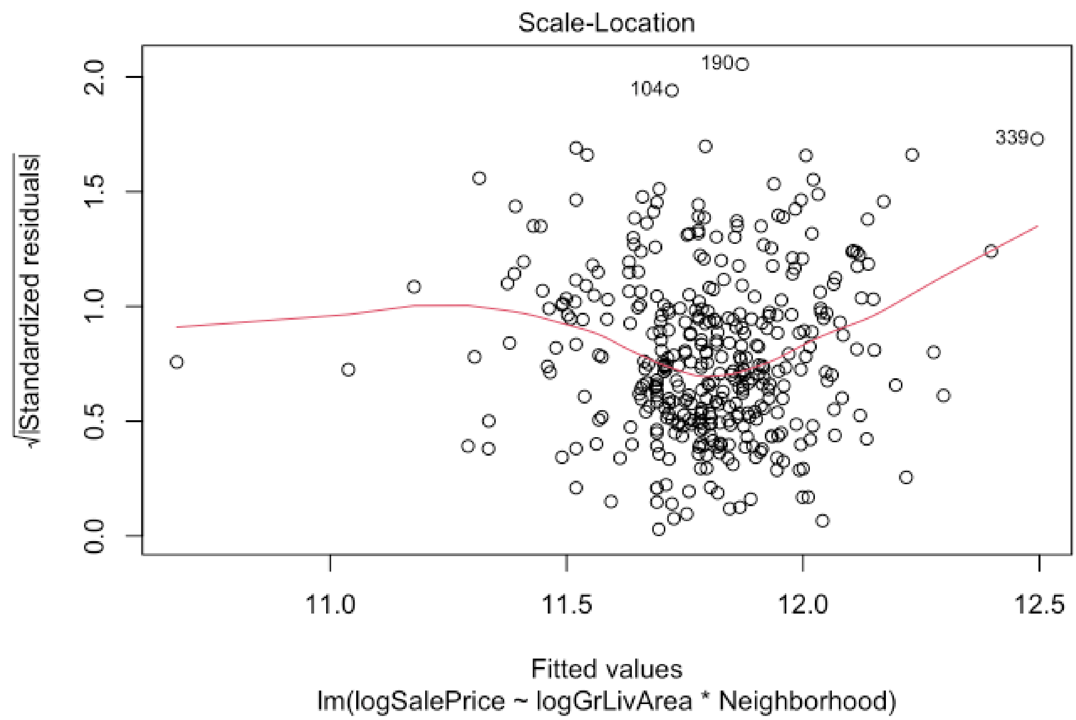


Diagram 15:

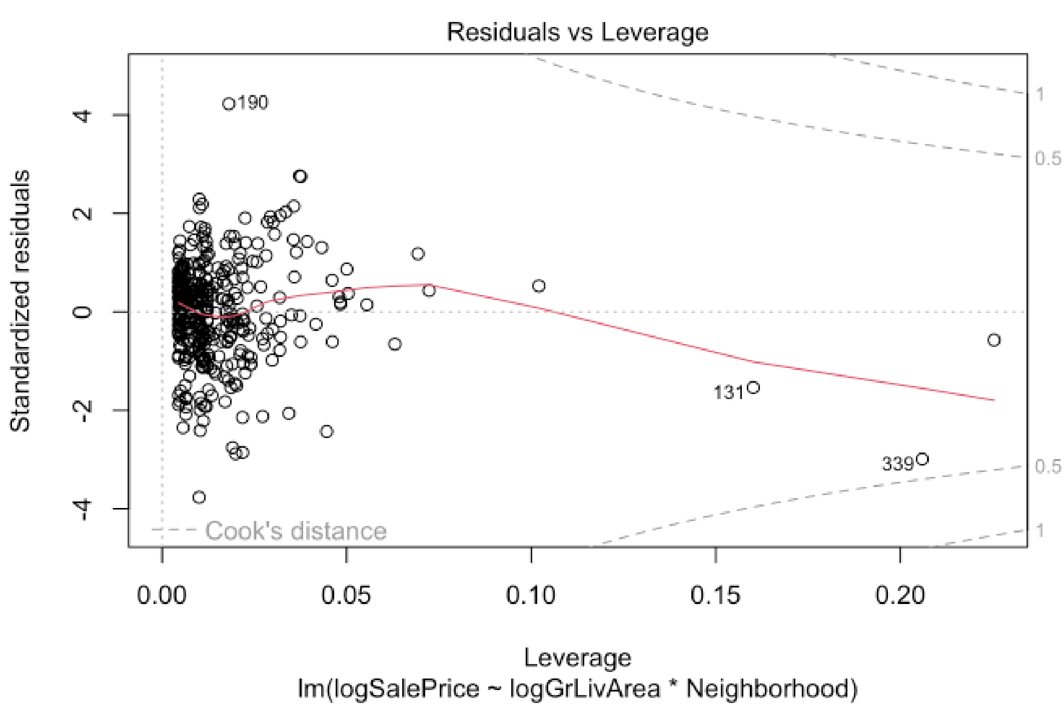


Diagram 16:

```
r$> confint(fit1)
                                      2.5 %     97.5 %
(Intercept)                       4.9207572  6.9050843
logGrLivArea                      0.6788064  0.9604897
NeighborhoodEdwards               0.8235795  3.3635933
NeighborhoodNAmes                 1.4002744  3.7593394
logGrLivArea:NeighborhoodEdwards -0.4793353 -0.1206263
logGrLivArea:NeighborhoodNAmes   -0.5134042 -0.1798447
```

Diagram 17:

```
# Data Cleaning

# If pool-related variables are NA, assume there is no pool and assign to 0
ames <- ames %>%
  mutate(
    PoolQC = ifelse(is.na(PoolQC), "None", PoolQC),
    PoolArea = ifelse(is.na(PoolArea), 0, PoolArea),
  )
# If garage-related variables are NA, assume there is no garage and assign to 0
ames <- ames %>%
  mutate(
    GarageType = ifelse(is.na(GarageType), "None", GarageType),
    #GarageYrBlt = ifelse(is.na(GarageYrBlt), 0, GarageYrBlt), #These will be changed to the mean because of large year valu
es
    GarageFinish = ifelse(is.na(GarageFinish), "None", GarageFinish),
    GarageCars = ifelse(is.na(GarageCars), 0, GarageCars),
    GarageArea = ifelse(is.na(GarageArea), 0, GarageArea),
    GarageQual = ifelse(is.na(GarageQual), "None", GarageQual),
    GarageCond = ifelse(is.na(GarageCond), "None", GarageCond)
  )
# If Bsmt-related variables are NA, assume there is no Bsmt and assign to 0
ames <- ames %>%
  mutate(
    BsmtQual = ifelse(is.na(BsmtQual), "None", BsmtQual),
    BsmtCond = ifelse(is.na(BsmtCond), "None", BsmtCond),
    BsmtExposure = ifelse(is.na(BsmtExposure), "None", BsmtExposure),
    BsmtFinType1 = ifelse(is.na(BsmtFinType1), "None", BsmtFinType1),
    BsmtFinSF1 = ifelse(is.na(BsmtFinSF1), 0, BsmtFinSF1),
    BsmtFinType2 = ifelse(is.na(BsmtFinType2), "None", BsmtFinType2),
    BsmtFinSF2 = ifelse(is.na(BsmtFinSF2), 0, BsmtFinSF2),
    BsmtUnfSF = ifelse(is.na(BsmtUnfSF), 0, BsmtUnfSF),
    TotalBsmtSF = ifelse(is.na(TotalBsmtSF), 0, TotalBsmtSF)
  )
# If Fence-related variables are NA, assume there is no Fence and assign to 0
ames <- ames %>%
  mutate(
    Fence = ifelse(is.na(Fence), "None", Fence),
  )
# If Misc-related variables are NA, assume there is no Misc features and assign to 0
ames <- ames %>%
  mutate(
    MiscFeature = ifelse(is.na(MiscFeature), "None", MiscFeature),
  )
# If Fireplace-related variables are NA, assume there is no Fireplace and assign to 0
ames <- ames %>%
  mutate(
    FireplaceQu = ifelse(is.na(FireplaceQu), "None", FireplaceQu),
  )
# If Alley-related variables are NA, assume there is no Alley and assign to 0
ames <- ames %>%
  mutate(
    Alley = ifelse(is.na(Alley), "None", Alley),
  )

# Summarize the amount of remaining NA's by column to check what's left
colSums(is.na(ames))
```

Diagram 18:

```
# Use the dummyVars() function to convert categorical variables into dummy variables
# Then use janitor::clean_names() to clean up the column names
dummy_model <- dummyVars(~ ., data = ames)
ames_dummy <- as.data.frame(predict(dummy_model, newdata = ames))
ames_dummy <- clean_names(ames_dummy)

# Fill in all remaining na values with the mean of the column
ames_dummy <- ames_dummy %>%
  mutate(across(
    c(-sale_price, -log_sale_price),
    ~ ifelse(is.na(.), mean(., na.rm = TRUE), .)
  ))
# Summarize the amount of remaining NA's by column
colSums(is.na(ames_dummy))
```

Diagram 19:

```
# Split the data into training and testing sets
train <- ames_dummy[ames_dummy$train == 1, ]
test <- ames_dummy[ames_dummy$train == 0, ]
```

Diagram 20:

Predictive Models	R^2	RMSE	AIC	Kaggle Score
Forward	0.942	0.096	-2504	0.1398
Backward	0.944	0.094	-2493	0.1458
Stepwise	0.944	0.094	-2494	0.1456
Custom	0.84	0.16	-1190	0.1777

Diagram 21:

```
r$> varImp(fit2$finalModel)%>%
      filter(Overall > 4) %>%
      arrange(desc(Overall))
                          Overall
roof_matl_cly_tile      16.670625
overall_cond            12.316543
ms_zoning_c_all         12.095573
total_bsmt_sf           11.388951
condition2pos_n          9.922932
year_built               9.699077
overall_qual             9.667944
log_gr_liv_area          9.091300
neighborhood_crawfor     7.850502
lot_area                 7.018695
ms_zoning_rm             6.353041
neighborhood_stone_br    5.836962
kitchen_qual_ex          5.560925
functional_maj2          5.489575
land_slope_sev           5.452246
neighborhood_nridg_ht    4.886112
bsmt_unf_sf              4.847542
neighborhood_edwards     4.778576
```

Diagram 22:

```
r$> varImp(fit3$finalModel)%>%
      filter(Overall > 4) %>%
      arrange(desc(Overall))
                          Overall
log_gr_liv_area         16.984408
roof_matl_cly_tile      11.542834
overall_cond            11.497800
condition2pos_n         10.287568
ms_zoning_c_all          9.065580
overall_qual             9.047682
bsmt_fin_sf1             8.842386
lot_area                 7.027994
sale_type_new            6.900116
neighborhood_edwards     6.697630
year_built               6.663097
functional_maj2          6.076291
kitchen_qual_ex          5.929819
neighborhood_crawfor     5.731806
bsmt_unf_sf              5.688449
condition1artery         5.647557
bsmt_fin_sf2             5.574467
land_slope_mod           5.512792
sale_condition_normal    5.292479
neighborhood_stone_br    5.180033
neighborhood_meadow_v    5.040680
```

Diagram 23:

```
r$> varImp(fit4$finalModel) %>%
      filter(Overall > 4) %>%
      arrange(desc(Overall))
                        Overall
log_gr_liv_area       16.998839
overall_cond          11.540682
roof_matl_cly_tile    11.463697
condition2pos_n       10.233332
ms_zoning_c_all        9.061792
overall_qual           8.923294
bsmt_fin_sf1           8.736801
sale_type_new          6.862606
lot_area               6.806617
neighborhood_edwards   6.739504
year_built             6.698790
functional_maj2        6.103470
kitchen_qual_ex        5.958244
neighborhood_crawfor   5.710567
condition1artery       5.645616
bsmt_unf_sf            5.556263
bsmt_fin_sf2           5.514768
land_slope_mod         5.312905
sale_condition_normal  5.303034
neighborhood_stone_br  5.254721
neighborhood_meadow_v  5.077700
functional_mod         4.956417
```

Diagram 24:

```
r$> varImp(fit5) %>%
      filter(Overall > 4) %>%
      arrange(desc(Overall))
                     Overall
overall_qual       34.059059
log_gr_liv_area    26.711591
bsmt_fin_sf1       19.634865
roof_matl_cly_tile 14.793029
sale_type_new      10.923877
lot_area            8.249606
condition2pos_n     7.929971
ms_zoning_c_all     7.765308
overall_cond        6.073940
```

Diagram 25:

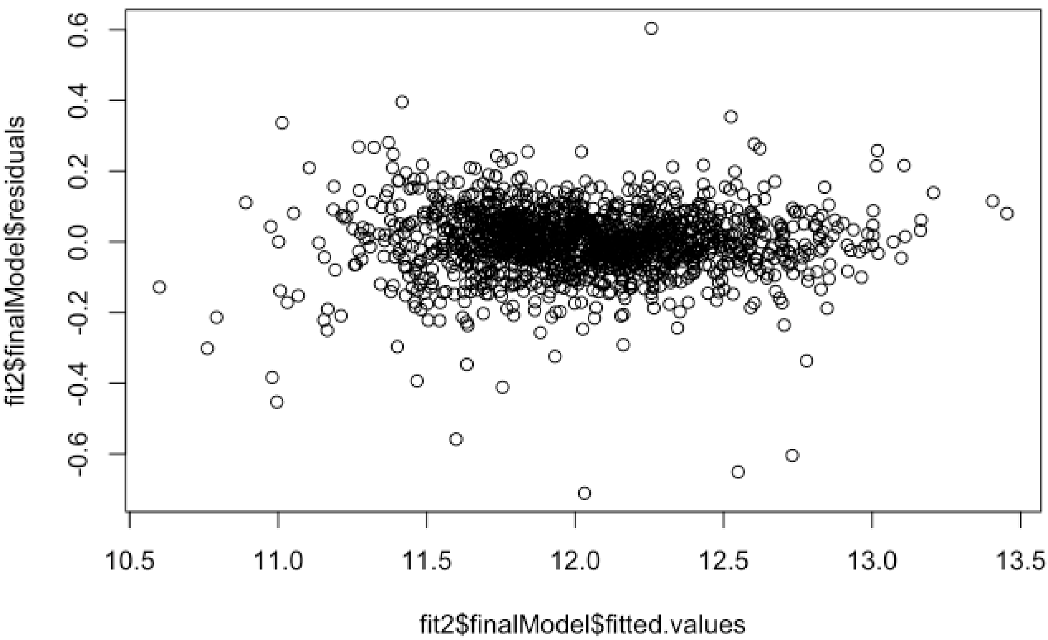


Diagram 26:

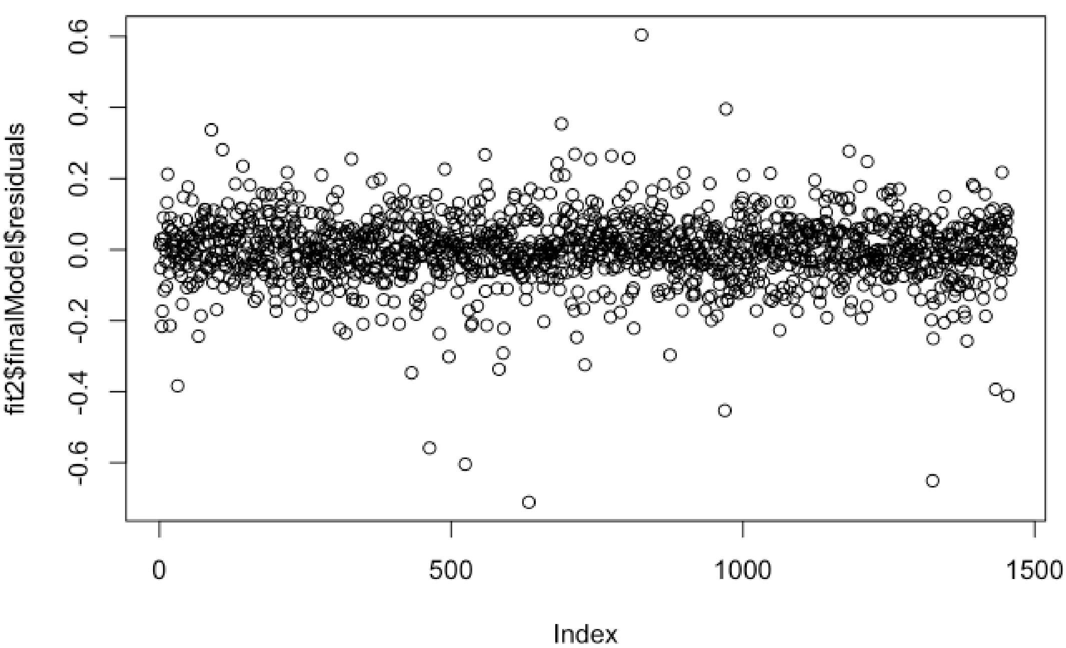


Diagram 27:

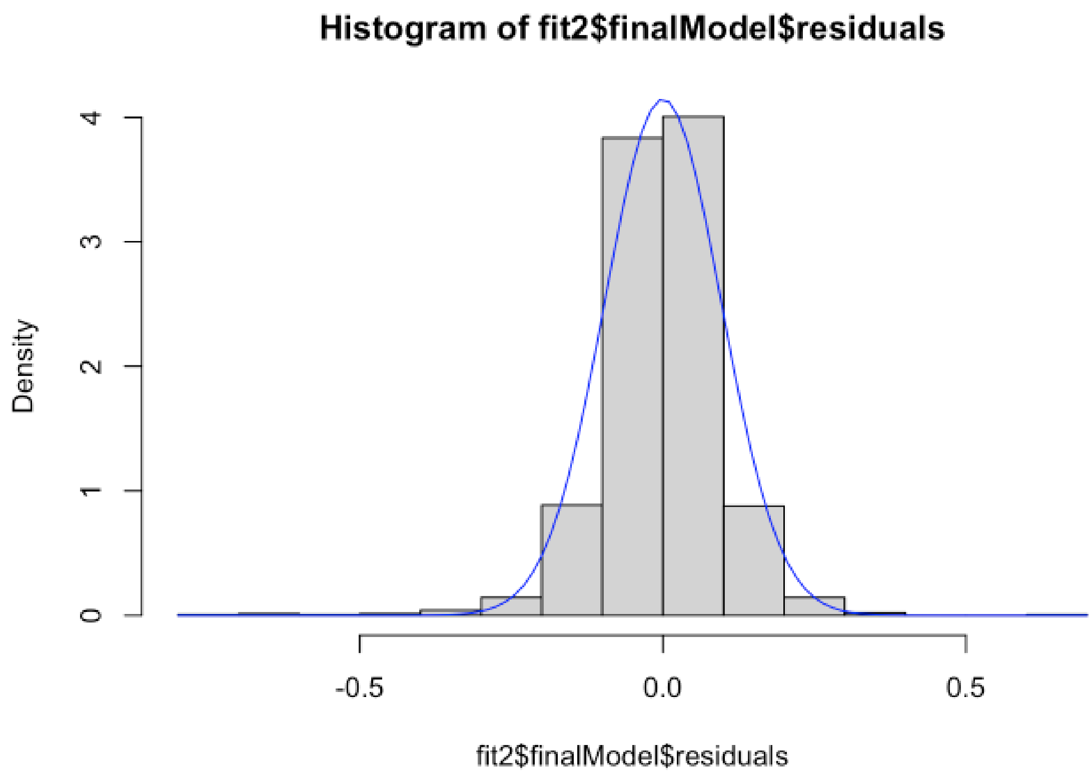


Diagram 28:

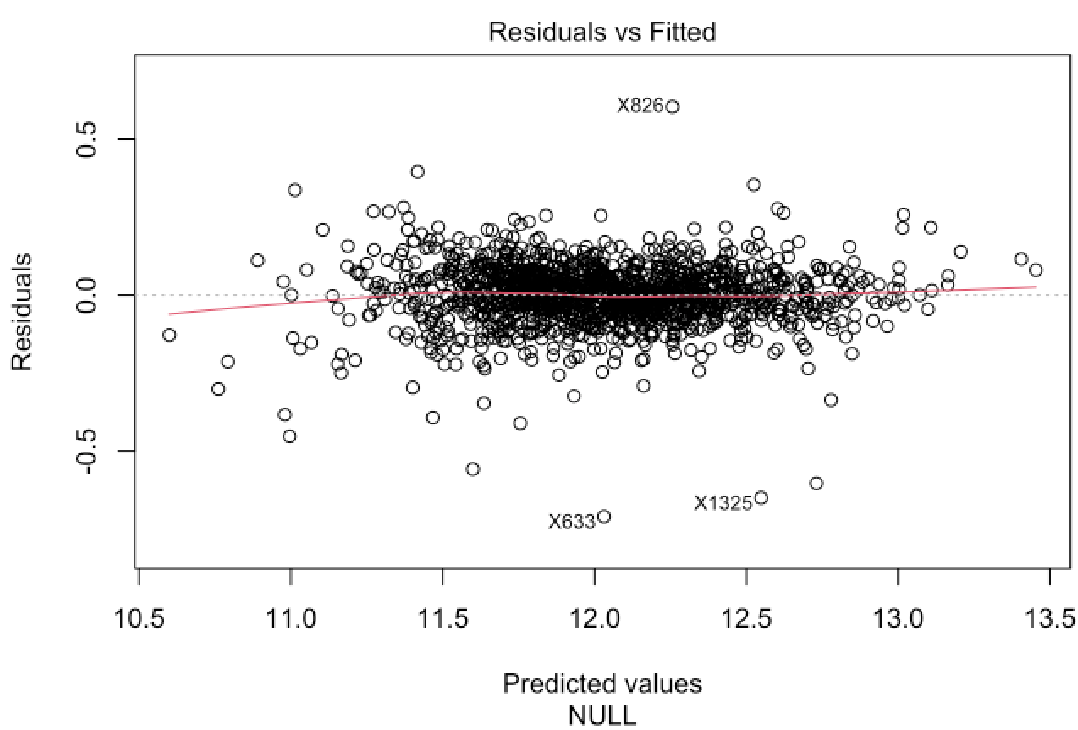


Diagram 29:

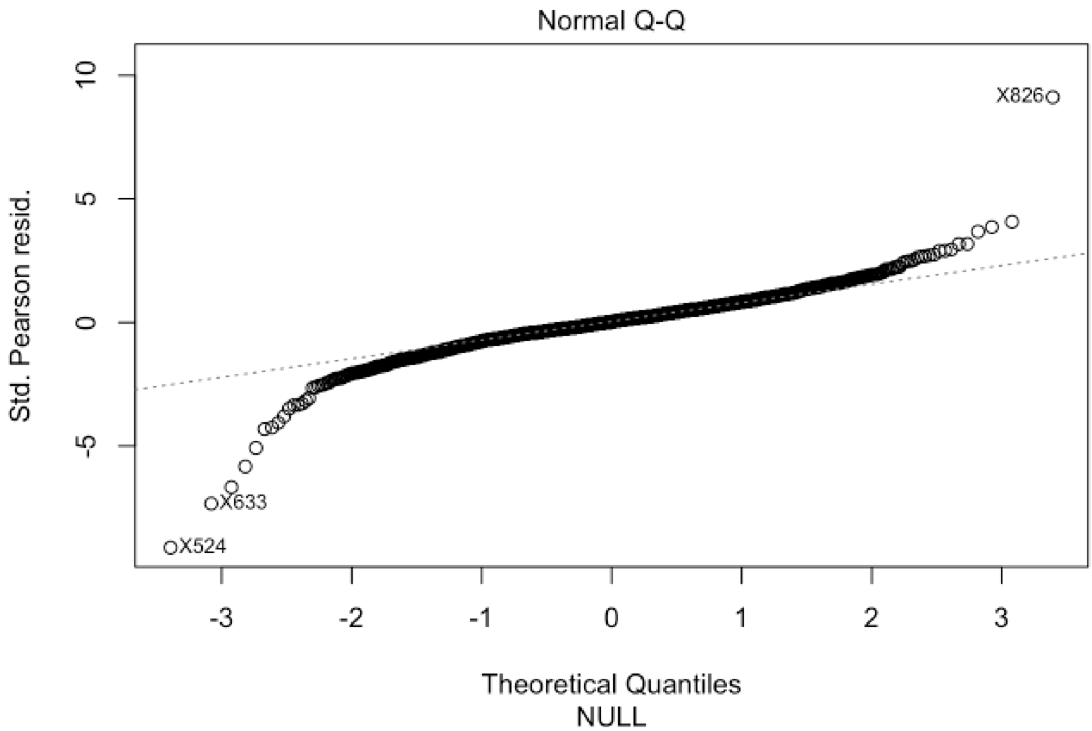


Diagram 30:

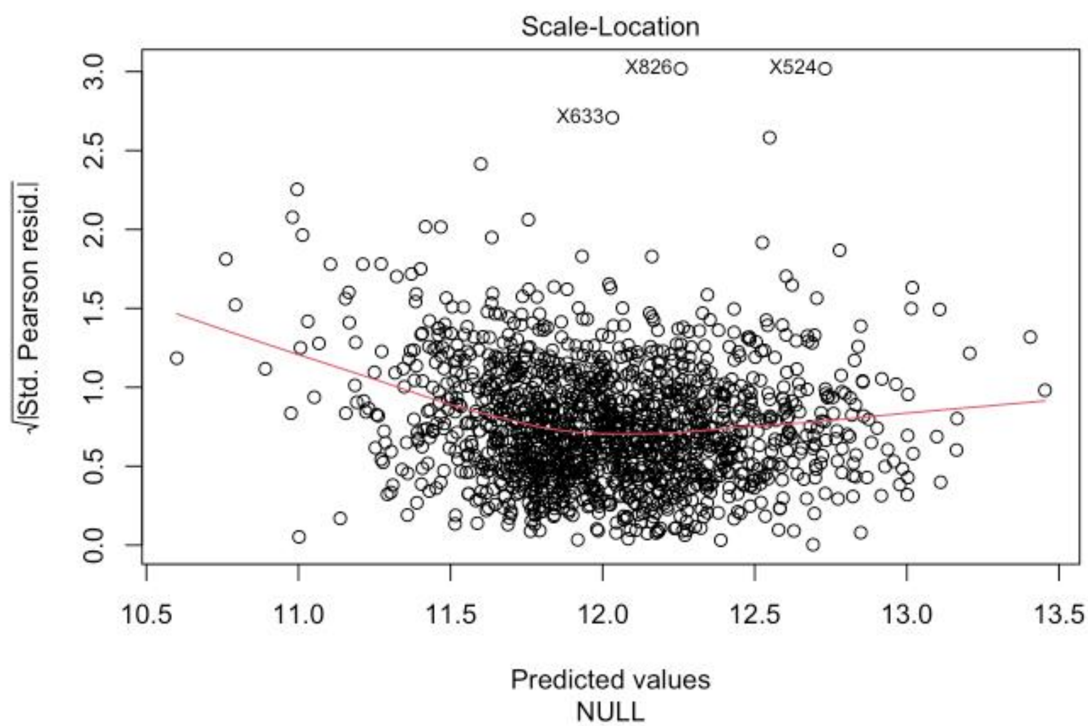
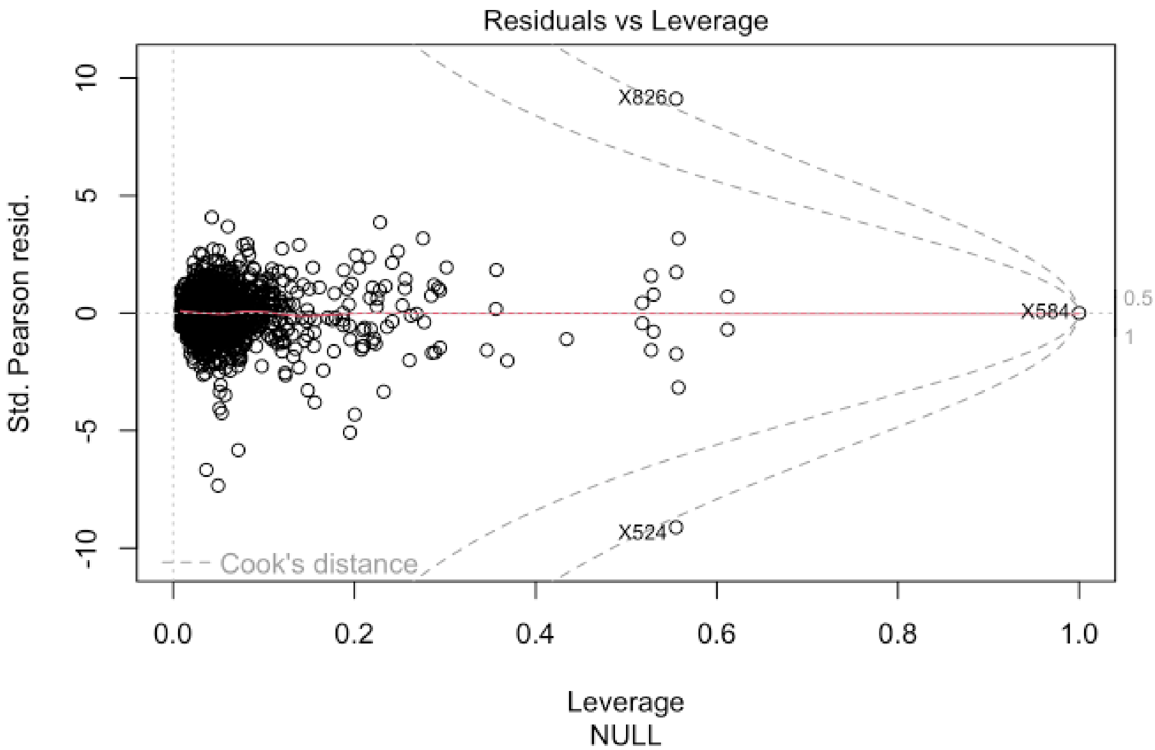


Diagram 31:


Residuals vs Leverage
Std. Pearson resid.
10
5
0
-5
-10
X826
X584
X524
Cook's distance
0.5
1
0.0
0.2
0.4
0.6
0.8
1.0
Leverage
NULL

RMD:

```
knitr::opts_chunk$set(echo = TRUE, warning=FALSE, message=FALSE)

# Required Libraries
library(tidyverse)
library(knitr)
library(kableExtra)
library(ggthemes)
library(caret)
library(janitor)
library(doParallel)

#library(e1071)
#library(class)
train <- read.csv("Data/train.csv")
test <- read.csv("Data/test.csv")

# Merge the data frames and add a column indicating whether they come from the train or test set
train$train <- 1
test$SalePrice <- NA
test$train <- 0
ames <- rbind(train, test)

# Verify data frame
head(ames)
str(ames)
summary(ames)
# Summarize NA's by  column
ames %>%
  summarise_all(funs(sum(is.na(.)))) %>%
  gather(key = "Column", value = "NA_Count", -1) %>%
  filter(NA_Count > 0) %>%
  ggplot(aes(x = reorder(Column, NA_Count), y = NA_Count)) +
```

```r
  geom_col() +
  coord_flip() +
  theme_gdocs() +
  labs(title = "Number of NA's by Column", x = "Column", y = "NA Count")

# Create a table of the missing NAs by column
ames %>%
  summarise_all(funs(sum(is.na(.)))) %>%
  gather(key = "Column", value = "NA_Count", -1) %>%
  filter(NA_Count > 0) %>%
  arrange(desc(NA_Count)) %>%
  kable()
# Plot Sale Price vs. Gross Living Area colored by neighborhood, omitting rows where SalePrice is NA
ames %>%
  filter(!is.na(SalePrice)) %>%
  ggplot(aes(x = GrLivArea, y = SalePrice, color = Neighborhood)) +
  geom_point() +
  theme_gdocs() +
  labs(title = "Sale Price vs. Gross Living Area by Neighborhood", x = "Gross Living Area", y = "Sale Price")
# Plot log(Sale Price) vs. log(Gross Living Area) colored by neighborhood, omitting rows where SalePrice is NA
ames %>%
  filter(!is.na(SalePrice)) %>%
  ggplot(aes(x = log(GrLivArea), y = log(SalePrice), color = Neighborhood)) +
  geom_point() +
  theme_gdocs() +
  labs(
    title = "log(Sale Price) vs. log(Gross Living Area) by Neighborhood",
    x = "log(Gross Living Area)",
    y = "log(Sale Price)"
  )
# Create columns for log(SalePrice) and log(GrLivArea)
ames$logSalePrice <- log(ames$SalePrice)
ames$logGrLivArea <- log(ames$GrLivArea)
```

```r
PRESS <- function(linear.model) {
  #' calculate the predictive residuals
  pr <- residuals(linear.model) / (1 - lm.influence(linear.model)$hat)
  #' calculate the PRESS
  PRESS <- sum(pr^2)

  return(PRESS)
}
# Function for calculating PRESS
# Tom Hopper
# https://gist.github.com/tomhopper/8c204d978c4a0cbcb8c0
# Plot log(Sale Price) vs. log(Gross Living Area) colored by neighborhood,
omitting rows where SalePrice is NA for only the neighborhoods of interest
century21 <-
  ames %>%
  filter(!is.na(SalePrice)) %>%
  filter(Neighborhood %in% c("NAmes", "Edwards", "BrkSide"))
century21 %>%
  ggplot(aes(x = logGrLivArea, y = logSalePrice, color = Neighborhood)) +
  geom_point() +
  theme_gdocs() +
  labs(
    title = "log(Sale Price) vs. log(Gross Living Area) by Neighborhood",
    x = "log(Gross Living Area)",
    y = "log(Sale Price)"
  )
# Fit a linear model to the data
fit1x <- lm(logSalePrice ~ logGrLivArea + Neighborhood, data = century21)
summary(fit1x)
PRESS(fit1x)

# Fit a linear model to the data with interaction variables
fit1 <- lm(logSalePrice ~ logGrLivArea * Neighborhood, data = century21)
summary(fit1)
```

```r
PRESS(fit1)
confint(fit1) %>% kable()

# Plot the data with the linear model superposed
century21 %>%
  ggplot(aes(x = logGrLivArea, y = logSalePrice, color = Neighborhood)) +
  geom_point() +
  theme_gdocs() +
  labs(
    title = "log(Sale Price) vs. log(Gross Living Area) by Neighborhood",
    x = "log(Gross Living Area)",
    y = "log(Sale Price)"
  ) +
  geom_smooth(
    method = "lm", formula = y ~ x, se = FALSE, linewidth = 1,
    data = data.frame(
      logGrLivArea = century21$logGrLivArea,
      Neighborhood = century21$Neighborhood,
      logSalePrice = predict(fit1)
    )
  )

# # Print parameter estimate table nicely. Not working, needs debugging
# fit1 %>%
#   summary() %>%
#   {cbind(as.data.frame(coef(.)), .[["coefficients"]][, 2:4])} %>%
#   setNames(c("Estimate", "Std. Error", "t-value", "Pr(>|t|)")) %>%
#   rownames_to_column(var = "Term") %>%
#   mutate(Term = ifelse(Term == "(Intercept)", "Intercept", Term)) %>%
#   add_row(Term = "Adjusted R-squared", Estimate = round(.$adj.r.squared,
3), Std..Error = NA, `t-value` = NA, `Pr(>|t|)` = NA) %>%
#   kable(digits = 3, align = "c") %>%
#   kable_styling(full_width = FALSE)
# Plot the studentized residuals using base R
plot(fit1$fitted.values, fit1$residuals, type = "p")
```

```
plot(fit1$residuals)

# Decide which of these we like better ggplot or R

# Calculate studentized residuals
stud_res <- rstudent(fit1)
# Create a data frame with the studentized residuals
df <- data.frame(stud_res, logGrLivArea = model.frame(fit1)$logGrLivArea)

# Create a scatterplot of the studentized residuals
ggplot(df, aes(x = logGrLivArea, y = stud_res)) +
  geom_point() +
  labs(title = "Scatterplot of Studentized Residuals",
  x = "Studentized Residuals",
  y = "Frequency") +
  theme_minimal()

# Create histogram with normal curve
ggplot(df, aes(x = stud_res)) +
  geom_histogram(aes(y = ..density..), binwidth = 0.5, fill = "lightblue",
color = "black") +
  stat_function(fun = dnorm, args = list(mean = mean(df$stud_res), sd =
sd(df$stud_res)), color = "blue", size = 1.2) +
  labs(title = "Histogram of Studentized Residuals with Normal Curve",
  x = "Studentized Residuals",
  y = "Frequency") +
  theme_minimal()
# Plot the residuals vs. the fitted values
fit1 %>%
  plot()
# Data Cleaning

# If pool-related variables are NA, assume there is no pool and assign to 0
ames <- ames %>%
  mutate(
```

```
    PoolQC = ifelse(is.na(PoolQC), "None", PoolQC),
    PoolArea = ifelse(is.na(PoolArea), 0, PoolArea),
  )
# If garage-related variables are NA, assume there is no garage and assign to
0
ames <- ames %>%
  mutate(
    GarageType = ifelse(is.na(GarageType), "None", GarageType),
    #GarageYrBlt = ifelse(is.na(GarageYrBlt), 0, GarageYrBlt), #These will be
changed to the mean because of large year values
    GarageFinish = ifelse(is.na(GarageFinish), "None", GarageFinish),
    GarageCars = ifelse(is.na(GarageCars), 0, GarageCars),
    GarageArea = ifelse(is.na(GarageArea), 0, GarageArea),
    GarageQual = ifelse(is.na(GarageQual), "None", GarageQual),
    GarageCond = ifelse(is.na(GarageCond), "None", GarageCond)
  )
# If Bsmt-related variables are NA, assume there is no Bsmt and assign to 0
ames <- ames %>%
  mutate(
    BsmtQual = ifelse(is.na(BsmtQual), "None", BsmtQual),
    BsmtCond = ifelse(is.na(BsmtCond), "None", BsmtCond),
    BsmtExposure = ifelse(is.na(BsmtExposure), "None", BsmtExposure),
    BsmtFinType1 = ifelse(is.na(BsmtFinType1), "None", BsmtFinType1),
    BsmtFinSF1 = ifelse(is.na(BsmtFinSF1), 0, BsmtFinSF1),
    BsmtFinType2 = ifelse(is.na(BsmtFinType2), "None", BsmtFinType2),
    BsmtFinSF2 = ifelse(is.na(BsmtFinSF2), 0, BsmtFinSF2),
    BsmtUnfSF = ifelse(is.na(BsmtUnfSF), 0, BsmtUnfSF),
    TotalBsmtSF = ifelse(is.na(TotalBsmtSF), 0, TotalBsmtSF)
  )
# If Fence-related variables are NA, assume there is no Fence and assign to 0
ames <- ames %>%
  mutate(
    Fence = ifelse(is.na(Fence), "None", Fence),
  )
# If Misc-related variables are NA, assume there is no Misc features and
assign to 0
```

```
ames <- ames %>%
  mutate(
    MiscFeature = ifelse(is.na(MiscFeature), "None", MiscFeature),
  )
# If Fireplace-related variables are NA, assume there is no Fireplace and
assign to 0
ames <- ames %>%
  mutate(
    FireplaceQu = ifelse(is.na(FireplaceQu), "None", FireplaceQu),
  )
# If Alley-related variables are NA, assume there is no Alley and assign to 0
ames <- ames %>%
  mutate(
    Alley = ifelse(is.na(Alley), "None", Alley),
  )

# Summarize the amount of remaining NA's by column to check what's left
colSums(is.na(ames))

# Use the dummyVars() function to convert categorical variables into dummy
variables
# Then use janitor::clean_names() to clean up the column names
dummy_model <- dummyVars(~ ., data = ames)
ames_dummy <- as.data.frame(predict(dummy_model, newdata = ames))
ames_dummy <- clean_names(ames_dummy)

# Fill in all remaining na values with the mean of the column
ames_dummy <- ames_dummy %>%
  mutate(across(
    c(-sale_price, -log_sale_price),
    ~ ifelse(is.na(.), mean(., na.rm = TRUE), .)
  ))
# Summarize the amount of remaining NA's by column
colSums(is.na(ames_dummy))
```

```r
# Split the data into training and testing sets
train <- ames_dummy[ames_dummy$train == 1, ]
test <- ames_dummy[ames_dummy$train == 0, ]
# Forward Selection

# # Testing olsrr method.
# library(olsrr)
# fit2x <- lm(log_sale_price ~ . - sale_price, data = train)
# fit2y <- ols_step_forward_p(fit2x, penter = 0.15)$model
# summary(fit2y)
# defaultSummary(data.frame(pred = predict(fit2y), obs =
train$log_sale_price))
# PRESS(fit2y)

# Check if the model object exists, train if it doesn't
if (file.exists("Models/lm_forwards.rds")) {
  # Load the model object from disk
  fit2 <- readRDS("Models/lm_forwards.rds")
} else {
  # Perform stepwise selection

  # Set up a parallel backend with the number of cores you want to use
  cores <- 8 # Change this to the number of cores you want to use
  cl <- makePSOCKcluster(cores)
  registerDoParallel(cl)

  set.seed(137)
  ctrl <- trainControl(
    method = "boot",
    number = 5,
    allowParallel = TRUE
  )
  fit2 <- train(log_sale_price ~ . - sale_price,
    data = train,
    method = "glmStepAIC",
```

```r
    trControl = ctrl,
    direction = "forward",
    penter = 0.05 # Not Working.
  )

  # Stop the parallel backend
  stopCluster(cl)

  # Save the model object to disk
  saveRDS(fit2, "Models/lm_forwards.rds")
}

summary(fit2$finalModel)
defaultSummary(data.frame(pred = predict(fit2), obs = train$log_sale_price))
PRESS(fit2$finalModel) #Press not working with caret models
varImp(fit2$finalModel)%>%
  filter(Overall > 4) %>%
  arrange(desc(Overall))

# Output the predictions for the test set to a csv file
# fit2x <- glm(formula = formula(fit2), data = train)
forward_pred <- predict(fit2$finalModel, test)

forward_pred %>%
  data.frame() %>%
  rownames_to_column(var = "id") %>%
  mutate(SalePrice = exp(forward_pred)) %>%
  dplyr::select(id, SalePrice) %>%
  write_csv("Predictions/forward_predictions.csv")
# Backwards Selection

# Check if the model object exists, train if it doesn't
if (file.exists("Models/lm_backwards.rds")) {
  # Load the model object from disk
```

```r
  fit3 <- readRDS("Models/lm_backwards.rds")
} else {
  # Perform stepwise selection

  # Set up a parallel backend with the number of cores you want to use
  cores <- 8 # Change this to the number of cores you want to use
  cl <- makePSOCKcluster(cores)
  registerDoParallel(cl)

  set.seed(137)
  fit3 <- train(log_sale_price ~ . - sale_price,
    data = train,
    method = "glmStepAIC",
    trControl = trainControl(method = "cv", number = 5, allowParallel =
TRUE),
    direction = "backward",
    penter = 0.05 # Not Working.
  )

  # Stop the parallel backend
  stopCluster(cl)

  # Save the model object to disk
  saveRDS(fit3, "Models/lm_backwards.rds")
}

summary(fit3$finalModel)
defaultSummary(data.frame(pred = predict(fit3), obs = train$log_sale_price))
PRESS(fit3$finalModel) # Press not working with caret models
varImp(fit3$finalModel)%>%
  filter(Overall > 4) %>%
  arrange(desc(Overall))



# Output the predictions for the test set to a csv file
```

```
# fit3x <- glm(formula = formula(fit3), data = train)
backward_pred <- predict(fit3$finalModel, newdata = test)

backward_pred %>%
  data.frame() %>%
  rownames_to_column(var = "id") %>%
  mutate(SalePrice = exp(backward_pred)) %>%
  dplyr::select(id, SalePrice) %>%
  write_csv("Predictions/backward_predictions.csv")
# Stepwise Selection

# Check if the model object exists, train if it doesn't
if (file.exists("Models/lm_stepwise.rds")) {
  # Load the model object from disk
  fit4 <- readRDS("Models/lm_stepwise.rds")
} else {
  # Perform stepwise selection

  # Set up a parallel backend with the number of cores you want to use
  cores <- 8 # Change this to the number of cores you want to use
  cl <- makePSOCKcluster(cores)
  registerDoParallel(cl)

  set.seed(137)
  fit4 <- train(log_sale_price ~ . - sale_price,
    data = train,
    method = "glmStepAIC",
    trControl = trainControl(method = "cv", number = 5, allowParallel =
TRUE),
    direction = "both",
    penter = 0.05 # Not Working.
  )

  # Stop the parallel backend
  stopCluster(cl)
```

```r
  # Save the model object to disk
  saveRDS(fit4, "Models/lm_stepwise.rds")
}

summary(fit4$finalModel)
defaultSummary(data.frame(pred = predict(fit4), obs = train$log_sale_price))
PRESS(fit4$finalModel) # Press not working with caret models
varImp(fit4$finalModel) %>%
  filter(Overall > 4) %>%
  arrange(desc(Overall))

# Output the predictions for the test set to a csv file
# fit4x <- glm(formula = formula(fit4), data = train)
stepwise_pred <- predict(fit4$finalModel, newdata = test)

stepwise_pred %>%
  data.frame() %>%
  rownames_to_column(var = "id") %>%
  mutate(SalePrice = exp(stepwise_pred)) %>%
  dplyr::select(id, SalePrice) %>%
  write_csv("Predictions/stepwise_predictions.csv")
# Custom Feature Selection
top10 <- varImp(fit4$finalModel) %>%
  filter(Overall > 4) %>%
  arrange(desc(Overall)) %>%
  head(10) %>%
  rownames()

form <- as.formula(paste("log_sale_price ~", paste(top10, collapse = "+")))
fit5 <- lm(form, data = train)



summary(fit5)
```

```r
defaultSummary(data.frame(pred = predict(fit5), obs = train$log_sale_price))
PRESS(fit5) # Press not working with caret models
# varImp(fit5$finalModel) %>%
  # filter(Overall > 4) %>%
  # arrange(desc(Overall))

# Output the predictions for the test set to a csv file
# fit4x <- glm(formula = formula(fit4), data = train)
custom_pred <- predict(fit5, newdata = test)

custom_pred %>%
  data.frame() %>%
  rownames_to_column(var = "id") %>%
  mutate(SalePrice = exp(custom_pred)) %>%
  dplyr::select(id, SalePrice) %>%
  write_csv("Predictions/custom_predictions.csv")
```