HOUSING PRICE AND PREDICTION ANALYSIS

Group 10

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INTRODUCTION

- We have used the famous Ames housing dataset and used Multiple Linear Regression and other machine learning models to predict the sale price of houses based on various features.
- The dataset is available on Kaggle which includes 81 features describing a wide range of characteristics of 1460 homes in Ames, Iowa that are sold between 2006 and 2010.
- The dataset consists of information about 1460 houses

Data Description

- ***Predictor Variables***
  - Quantitative variables

Variable	Description
LotFrontage	Linear feet of street connected to property
LotArea	Lot size in square feet
YearBuilt	Original construction date
YearRemodAdd	Remodel date (same as construction date if no remodeling or additions)
MasVnrArea	Masonry veneer area in square feet
BsmtFinSF1	Type 1 finished square feet
BsmtUnfSF	Unfinished square feet of basement area
TotalBsmtSF	Total square feet of basement area
1stFlrSF	First Floor square feet
2ndFlrSF	Second floor square feet
LowQualFinSF	Low quality finished square feet (all floors)
GrLivArea	Above grade (ground) living area square feet
BsmtFullBath	Basement full bathrooms
BsmtHalfBath	Basement half bathrooms
FullBath	Full bathrooms above grade
HalfBath	Half baths above grade
Bedroom	Bedrooms above grade (does NOT include basement bedrooms)
Kitchen	Kitchens above grade
TotRmsAbvGrd	Total rooms above grade (does not include bathrooms)
Fireplaces	Number of fireplaces
GarageYrBlt	Year garage was built
GarageCars	Size of garage in car capacity
GarageArea	Size of garage in square feet
WoodDeckSF	Wood deck area in square feet
OpenPorchSF	Open porch area in square feet
EnclosedPorch	Enclosed porch area in square feet
3SsnPorch	Three season porch area in square feet
ScreenPorch	Screen porch area in square feet
PoolArea	Pool area in square feet
MiscVal	$Value of miscellaneous feature
MoSold	Month Sold (MM)
YrSold	Year Sold (YYYY)

Table 1: Quantitative Variables

- Qualitative variables

Variable	Description
MSSubClass	Identifies the type of dwelling involved in the sale.
MSZoning	Identifies the general zoning classification of the sale.
Street	Type of road access to property
Alley	Type of alley access to property
LotShape	General shape of property
LandContour	Flatness of the property
Utilities	Type of utilities available
LotConfig	Lot configuration
LandSlope	Slope of property
Neighborhood	Physical locations within Ames city limits
Condition1	Proximity to various conditions
Condition2	Proximity to various conditions (if more than one is present)
BldgType	Type of dwelling
HouseStyle	Style of dwelling
OverallQual	Rates the overall material and finish of the house
OverallCond	Rates the overall condition of the house
RoofStyle	Type of roof
RoofMatl	Roof material
Exterior1st	Exterior covering on house
Exterior2nd	Exterior covering on house (if more than one material)
MasVnrType	Masonry veneer type
ExterQual	Evaluates the quality of the material on the exterior
ExterCond	Evaluates the present condition of the material on the exterior
Foundation	Type of foundation
BsmtQual	Evaluates the height of the basement
BsmtCond	Evaluates the general condition of the basement
BsmtExposure	Refers to walkout or garden level walls
BsmtFinType1	Rating of basement finished area
BsmtFinType2	Rating of basement finished area (if multiple types)
BsmtFinSF2	Type 2 finished square feet
Heating	Type of heating
HeatingQC	Heating quality and condition
CentralAir	Central air conditioning
Electrical	Electrical system
KitchenQual	Kitchen quality
Functional	Home functionality (Assume typical unless deductions are warranted)
FireplaceQu	Fireplace quality
GarageType	Garage location
GarageFinish	Interior finish of the garage
GarageQual	Garage quality
GarageCond	Garage condition
PavedDrive	Paved driveway
PoolQC	Pool quality
Fence	Fence quality
MiscFeature	Miscellaneous feature not covered in other categories
SaleType	Type of sale
SaleCondition	Condition of sale

Table 2: Qualitative Variables

- Cardinality of the data
    - Train data: 1460 rows x 79 features
    - Test data: 1459 rows x 79 features
- Response Variable
    - $ Sale Price

- ***Objective:***
  - Perform exploratory data analysis to understand the intricacies of dataset.
  - Perform feature selection to understand the variables affecting the housing prices.
  - Understanding categorical variables as sparse matrix can reduce the adjusted R^2 in a misleading way.
  - Check for all regression assumptions.
  - Hypothesis Testing to corroborate all the results.
  - Compare results with other advanced Machine Learning models.

EXPLORATORY DATA ANALYSIS AND DATA TRANSFORMATION

- *'SalePrice'* is the response variable that we need to predict.
- It is observed that the response variable is right skewed. Since (linear) models are likes normal distribution, we need to transform the variable to approximate it to normal distribution.
- With the log(1+x) transformation, the skew disappears from the distribution thereby making the response variable distribution to be normal distribution.

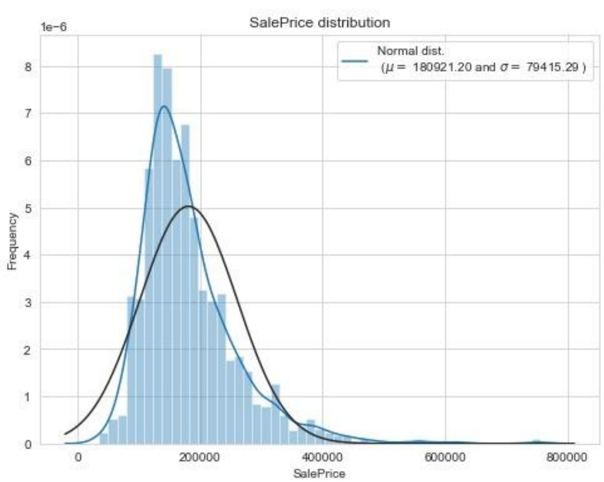

Figure 1: Frequency plot before log Transformation

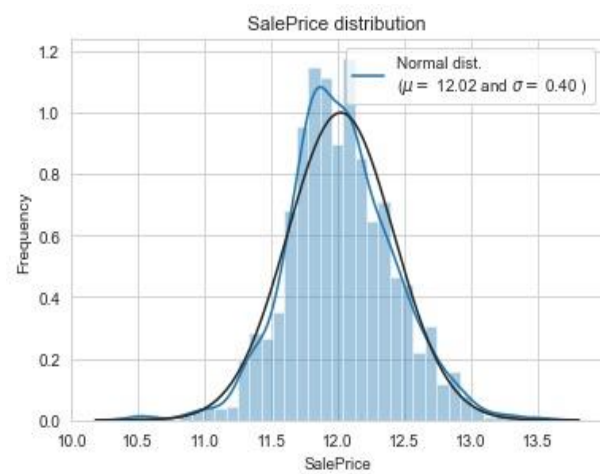

Figure 2: Frequency plot after log Transformation

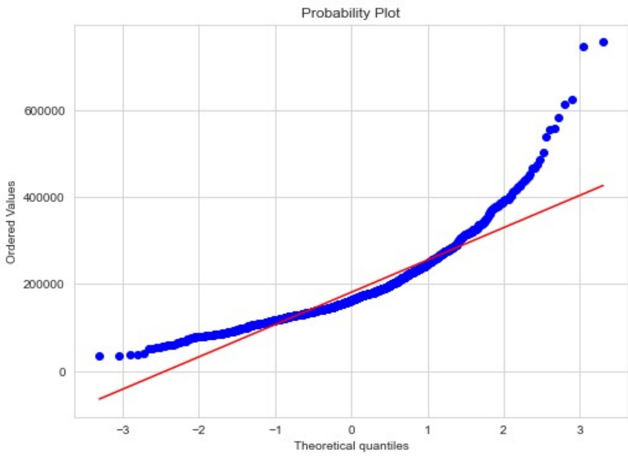

Figure 3: QQ plot before Transformation

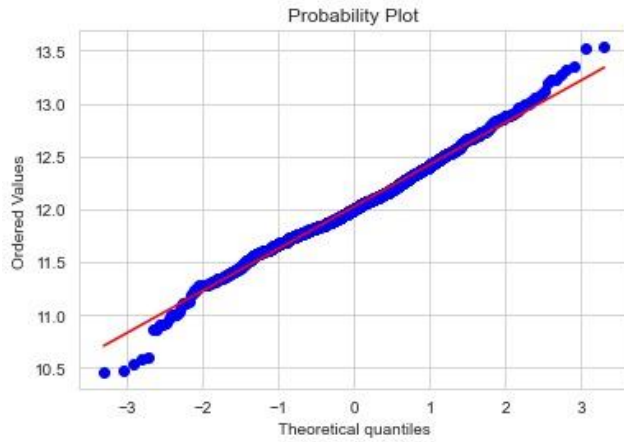

Figure 4: QQ plot after log transformation

- From the above figure, it is evident that after box cox transformation, the distribution of the response variable is close to normal.
- The correlation of response vs quantitative variables showcases the following (*non-Exhaustive list*)
    - High Correlation factors
        - Overall Quality
        - Garage Capacity (Cars)
        - Garage Area
        - Living Area
        - Total basement square ft
        - Year Built, Year Remodeled
        - Area of the first, second floor (Sq.ft)
    - Weak Correlation
        - Enclosed Porch area
        - Pool Area (Sq.ft)
        - Year, Month Sold

- From the above analysis, we observe that the price of the house is dependent on fairly intuitive factors.
- ***Missing Data:***
    - The data was checked for missing variables as multiple linear regression cannot handle missing data
    - A column with more than 80 per cent of missing values were removed
    - Looking at figure 5, we have removed the top 4 columns with highest missing values.

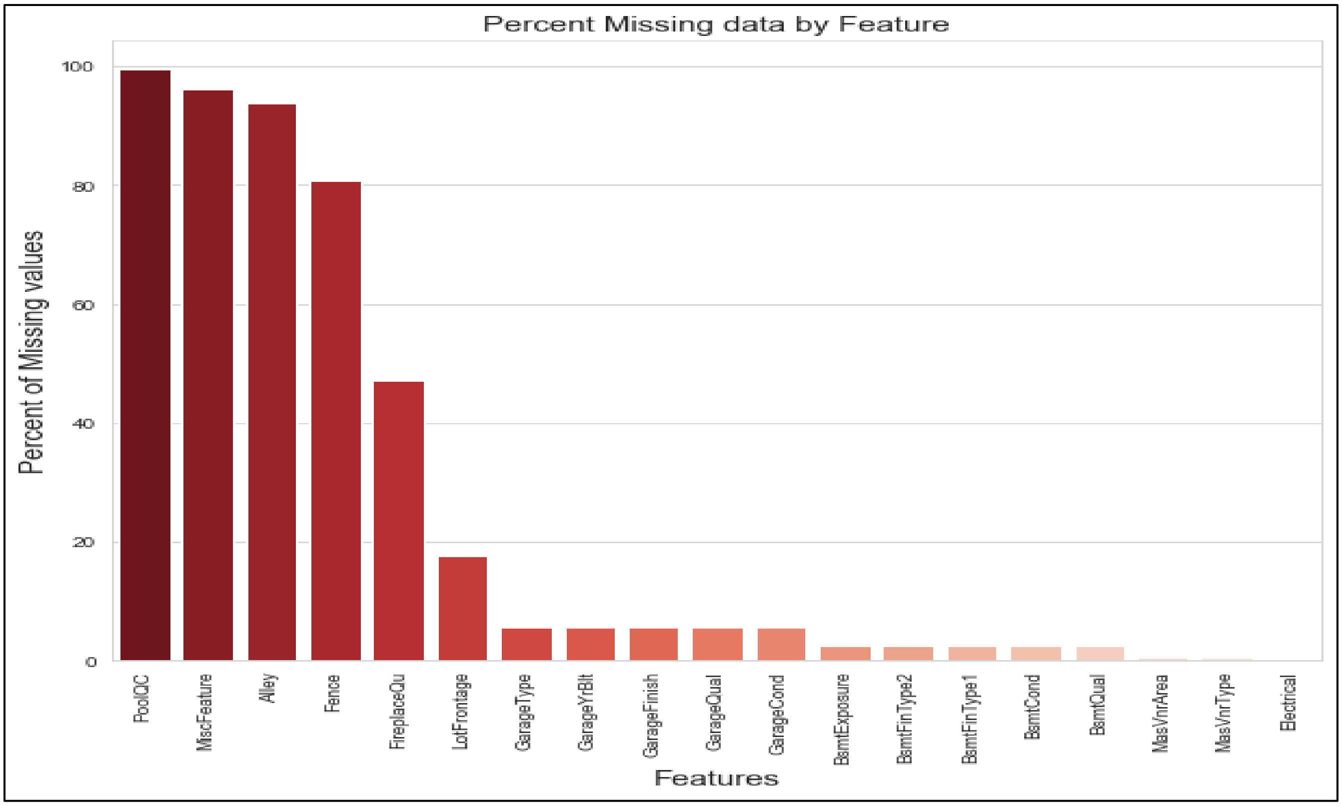

Figure 5: Percentage of Missing Data

- Missing data handling
  - Few of the columns of the dataset had several NaN values which needs to be addressed either through removing them or imputing them with some specific values.
  - As the data size wasn't big enough, so it was logical to efficiently impute the gaps in the data. To achieve this target, we used Simple Imputer and Iterative Imputer for filling the values with the following rules (using Sklearn's Column Transformer):
    - List of 'NaN' including columns where NaN's mean's none
    - List of 'NaN' including columns where NaN's mean's 0
    - List of 'NaN' including columns where NaN's actually missing gonna replaced with mode
    - List of 'NaN' including columns where NaN's actually missing gonna replaced most common type of the related
    - Transforming rare values (less than 10) into one group
  - Based on the above Imputation target, columns of the complete data was split into different sub-sections and missing values were handled as discussed.
    - Cols_none
      - This subsection contained qualitative variables such as Garage type, Garage quality, Basement finish type etc

        - A missing value in such a column indicates that the feature is not present in a particular house.
        - A '*None*' value was imputed (*using simple imputer*) here in case of a missing value indicating that the feature wasn't present in the house
    - Cols_zero
        - This subsection contained quantitative variables such as finished area in basement (Sq.ft), Total Area of Basement, Number of cars handled by garage etc.
        - A missing value in such a column indicates that the feature has zero value for the particular variable.
        - Hence, a *zero* was imputed (*using simple imputer*) here in case of a missing value indicating the feature value is zero.
    - Cols_mode
        - This subsection contained qualitative variables such as Electrical system, Kitchen quality, type of utilities etc
        - A missing value in such a column indicates that the feature data might have been unreported. It doesn't make sense that the home has no utilities.
        - *Mode* value of the column was imputed (*using simple imputer*) here in case of a missing value indicating that the most common features were available in the particular house
- Categorical Data handling
    - 47 features in our data are qualitative, as depicted in Table 2.
    - To model the behavior of qualitative variables, a boxplot of qualitative data vs the response variables was created.
    - For some categorical variables, it is observed that the mean of the category constituents is close.
        - In case of roof style, Hip, Flat and barn roof has quite similar means and hence it might be difficult or the model to differentiate between categories
        - So, we have removed such categorical variables like Roof style, land slope, utilities, Basement Exposure etc.
    - Now the rest of the variables are transformed into dummy variables and added to the data frame.

FITTING THE BASELINE (Linear Regression) MODEL

- After cleaning the data and converting the categorical variables to dummy variables, all the generated features were regressed on Sale Price of house.
- A baseline model was obtained.
- The number of predictor variables in the model were 211(*higher because of the dummy variables*)
- Some coefficients for the model and Interpretation
    - GarageArea
        - An increase of 1 unit in the scaled Garage area would result in increase in log(1+saleprice) by 0.014 holding all other variables constant
        - An increase of 1 unit in the scaled Garage area would result in increase in sale price by 0.014 holding all other variables constant
    - GarageCars
        - An increase of 1 unit in the scaled Garage cars would result in increase in log(1+saleprice) by 0.014 holding all other variables constant
        - An increase of 1 unit in the scaled Garage cars would result in increase in sale price by 0.014 holding all other variables constant
    - Total basement square ft
        - An increase of 1 unit in the scaled Total basement area would result in increase in log(1+saleprice) by 0.014 holding all other variables constant
        - An increase of 1 unit in the scaled Total basement area would result in increase in sale price by 0.014 holding all other variables constant
    - Intercept
        - Holding all other variables zero, the average sale price of a house is $169,719
    - Overall Quality
        - This feature was converted into a categorical variable
        - This indicates that the sale price of a bad quality house will be 0.0325 less than the sale price of a good quality house-keeping everything else constant.
- Summary Statistic of the model are as follows:

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              SalePrice   R-squared:                       0.911
Model:                            OLS   Adj. R-squared:                  0.898
Method:                 Least Squares   F-statistic:                     72.23
Date:                Wed, 20 Apr 2022   Prob (F-statistic):               0.00
Time:                        03:46:02   Log-Likelihood:                 1034.2
No. Observations:                1460   AIC:                            -1704.
Df Residuals:                    1278   BIC:                            -742.3
Df Model:                         181
Covariance Type:            nonrobust
```

Figure 6: Model Summary Baseline

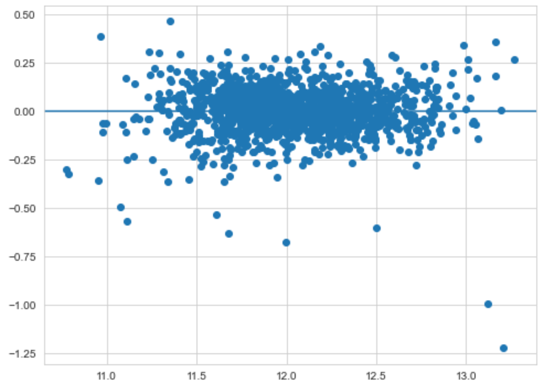

Figure 7: Residual vs Fitted For Baseline

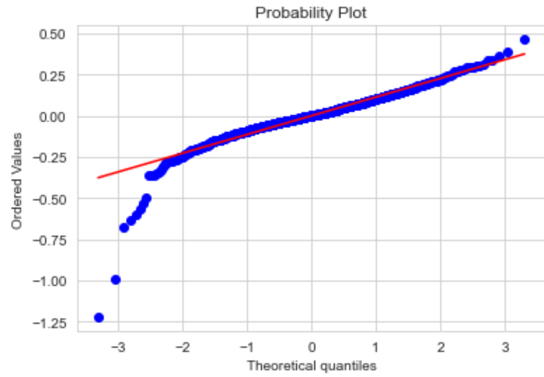

Figure 8: QQ plot residual

- Even though it can be observed that the baseline model follows regression assumptions, there are still a few outliers as observed in Figure 7.

OUTLIER REMOVAL AND MULTICOLLINEARITY

- ***Outlier Detection and Removal***
    - As we observed a few outliers, its pertinent we remove the outliers in the data.
    - We use cook's distance in our analysis for outlier removal.
    - Cook's Distance is calculated by removing the ith data point from the model and recalculating the regression. It summarizes how much all the values in the regression model change when the ith observation is removed.
    - Initially, all data points with cooks' distance greater than 4/n_obs were investigated
        - This yielded 115 points
        - However, so many points couldn't be removed from the data as removing these data points would lead to a loss of 10% of data which would have adverse results on our analysis.
    - Hence, the criterion that cook's distance greater than 1 was checked and all such data points were removed.
- ***Multicollinearity***
    - In regression, "multicollinearity" refers to predictors that are correlated with other predictors.
    - Multicollinearity occurs when your model includes multiple factors that are correlated not just to your response variable, but also to each other. In other words, it results when you have factors that are a bit redundant.
    - VIF was used to tackle the problem of multicollinearity.
    - VIF score of an independent variable represents how well the variable is explained by other independent variables.
    - VIF was calculated for all the columns in our dataset and if VIF of column was greater than maximum of 10 and $1/(1+R^2)$, then the column was removed as it indicated high multicollinearity
    - A total of 107 variables were left after removing multicollinearity from the model.

- Updated Model Summary Statistics:

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              SalePrice   R-squared:                       0.883
Model:                            OLS   Adj. R-squared:                  0.874
Method:                 Least Squares   F-statistic:                     93.38
Date:                Wed, 20 Apr 2022   Prob (F-statistic):               0.00
Time:                        03:46:09   Log-Likelihood:                 833.49
No. Observations:                1457   AIC:                            -1447.
Df Residuals:                    1347   BIC:                            -865.7
Df Model:                         109
Covariance Type:            nonrobust
==============================================================================
```

Figure 9: Model Summary Stats after VIF and Outlier removal

- It can be observed that even though R^2 and Adjusted R^2 have decreased, the BIC has also decreased which explains a greater goodness of fit as compared to the previous model (*Figure 6*)

FEATURE SELECTION AND ENGINEERING

- Feature engineering is an important part of model building activity. It involves creation, deletion and modification of features using the domain knowledge persistent to the dataset.
- Before performing any featuring engineering operations, we tried to understand the relationship between/amongst response and/or explanatory variables.
- From the above correlation matrix, it is evident that the response variable ('SalePrice') is strongly correlated with variables likes Overall Quality, Garage Cars, Garage Area, etc.
- In addition, we can also eyeball through few highly correlated pair of explanatory variables such (Garage Cars, Garage Area), (1st floor Surface Area, Total basement area), etc.
- ***Data Wrangling:***
    - Converting several quantitative variables to string types as it would better align with robust model implementation.
    - Dropping few irrelevant columns ('PoolQC', 'MiscFeature', 'Fence', 'Alley', 'FireplaceQu').
    - Creating new quantitative variable ('TotalSF' – computed as sum of areas, in sq. ft., of Basement, 1st floor and 2nd floor.
    - Transforming the Overall condition and Overall quality variables to binary ouput based on the logical below:
        - If Overall condition >= 8, then OC_Good; Else OC_Bad
        - If Overall quality >= 8, then OQ_Good; Else OQ_Bad
- ***Variable Transformation:***
    - Several variables such as 'YearBuilt', 'YearRemodAdd', GarageYrBlt', 'MoSold', 'YrSold' were transformed based on the min-max values as described below:

$$\boldsymbol{New(Target\,Variable)} = \frac{\boldsymbol{OldValue(Target\,Variable) - MIN\big(OldValue(Target\,Variable)\big)}}{\boldsymbol{\big(Max\big(OldValue(Target\,Variable)\big) - MIN\big(OldValue(Target\,Variable)\big)\big)}}$$

- As the data consisted of a lot of features, more effort was dedicated towards feature selection rather than new feature creation.
- However, few unique new features were created like Total Area that would take total area of basement, first and second floor into account.

Lasso CV

- Least absolute shrinkage and selection operator is a regression analysis method that performs both variable selection and regularization to enhance the prediction accuracy and interpretability of the resulting model.
- Trying to minimize the cost function, Lasso regression will automatically select those features that are useful, discarding the useless or redundant features.
- In Lasso regression, discarding a feature will make its coefficient equal to 0.
- Lasso was used on the complete model after outlier removal, and it shrunk a few coefficients to zero.
- The number of non-zero coefficients left after Lasso CV are 67.
- Summary of the model

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              SalePrice   R-squared:                       0.867
Model:                            OLS   Adj. R-squared:                  0.861
Method:                 Least Squares   F-statistic:                     137.6
Date:                Wed, 20 Apr 2022   Prob (F-statistic):               0.00
Time:                        03:46:12   Log-Likelihood:                 741.62
No. Observations:                1460   AIC:                            -1349.
Df Residuals:                    1393   BIC:                            -995.1
Df Model:                          66
Covariance Type:            nonrobust
```

Figure 10: Summary Stats for Lasso

- Some coefficients for the model and Interpretation
  - GarageArea
    - An increase of 1 unit in the scaled Garage area would result in increase in log(1+saleprice) by 0.014 holding all other variables constant
    - An increase of 1 unit in the scaled Garage area would result in increase in sale price by 0.014 holding all other variables constant
  - GarageCars
    - An increase of 1 unit in the scaled Garage cars would result in increase in log(1+saleprice) by 0.014 holding all other variables constant
    - An increase of 1 unit in the scaled Garage cars would result in increase in sale price by 0.014 holding all other variables constant
  - Total basement square ft
    - An increase of 1 unit in the scaled Total basement area would result in increase in log(1+saleprice) by 0.014 holding all other variables constant

- An increase of 1 unit in the scaled Total basement area would result in increase in sale price by 0.014 holding all other variables constant
- Intercept
  - Holding all other variables zero, the average sale price of a house is $169,719
- Overall Quality
  - This feature was converted into a categorical variable
  - This indicates that the sale price of a bad quality house will be 0.0325 less than the sale price of a good quality house keeping everything else constant.

- The model assumptions also hold true.

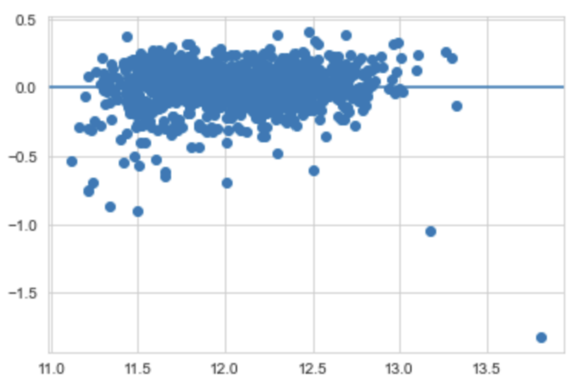

Figure 11: Residuals vs Fitted for Lasso

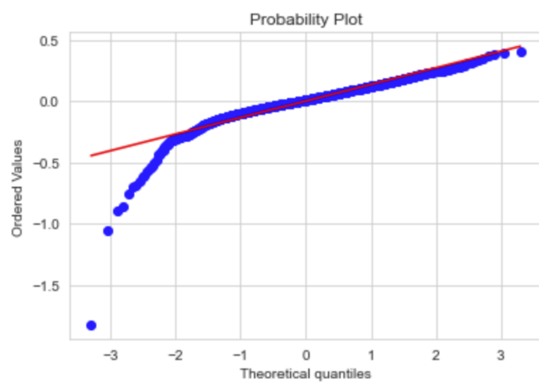

Figure 12: QQ plot for Lasso

Backward Selection

- Backward stepwise selection is a variable selection method which begins with a model that contains all variables under consideration
- Then it starts removing the least significant variables one after the other until a pre-specified stopping rule is reached or until no variable is left in the model.
- Backward selection was used in the analysis to select the appropriate number of variables in this scenario.
- It gave back the selected number of features to be to be used in the model to be 78.
- Summary Stats for the model:

OLS Regression Results

Dep. Variable:	SalePrice	R-squared:	0.899
Model:	OLS	Adj. R-squared:	0.893
Method:	Least Squares	F-statistic:	157.4
Date:	Wed, 20 Apr 2022	Prob (F-statistic):	0.00
Time:	04:21:11	Log-Likelihood:	941.33
No. Observations:	1460	AIC:	-1725.
Df Residuals:	1381	BIC:	-1307.
Df Model:	78		
Covariance Type:	nonrobust		

- The model coefficients and hypothesis testing intervals are added in the appendix

- The model assumptions also hold true.

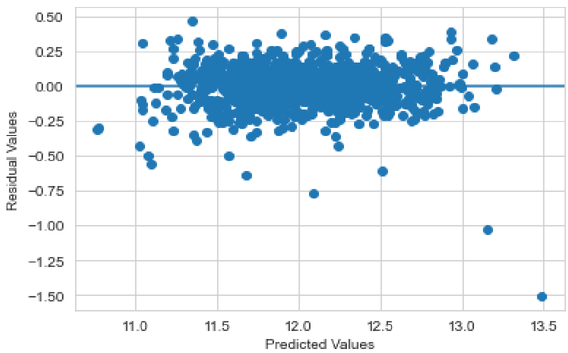

Figure 13: Residuals vs Fitted Backward Selection

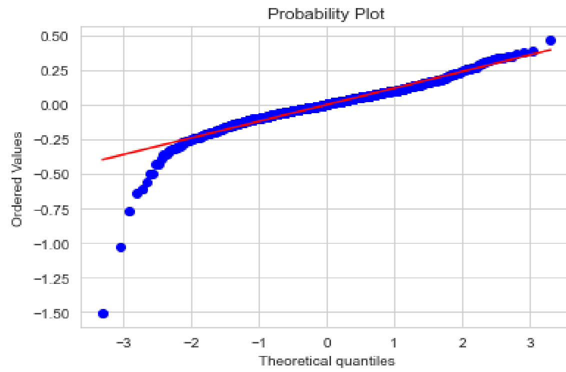

Figure 14: QQ plot for Backwards

RFEC (Recursive Feature Elimination with CV)

- RFE is popular because it is easy to configure and use and because it is effective at selecting those features (columns) in a training dataset that are more or most relevant in predicting the target variable.
- The recursive feature elimination with cross validation approach selected a total of 31 features from the whole 211 features
- The model statistics are as follows:

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              SalePrice   R-squared:                       0.862
Model:                            OLS   Adj. R-squared:                  0.859
Method:                 Least Squares   F-statistic:                     228.3
Date:                Wed, 20 Apr 2022   Prob (F-statistic):               0.00
Time:                        03:49:32   Log-Likelihood:                 716.79
No. Observations:                1460   AIC:                            -1354.
Df Residuals:                    1420   BIC:                            -1142.
Df Model:                          39
Covariance Type:            nonrobust
```

Figure 15: Model Metrics

- The model selection process yielded Mean squared error vs the features as follows:

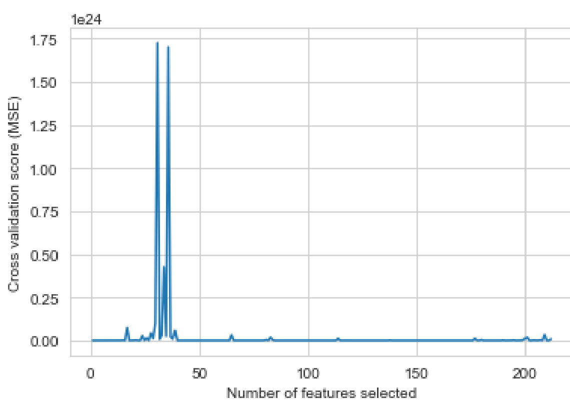

Figure 16: Cross validation score vs features for RFEC

- The hypothesis testing and the appropriate coefficient factors can be found in the appendix.

MODEL EVALUATION

Model	R-squared	BIC	Mean Squared Error	Mean Absolute Error	Mean Absolute Percentage Error
Baseline	0.911	-742	0.0142	0.0832	0.00696
Baseline (Outlier Removed)	0.925	-994	0.0120	0.0769	0.00644
Baseline (VIF)	0.886	-877	0.0181	0.0996	0.00833
Lasso	0.872	-1009	0.0204	0.0959	0.00803
Backward Selection	0.890	-1336	0.0176	0.0925	0.00774
RFEC	0.911	-756	0.0142	0.0832	0.00696
Random Forest	0.684	-	0.0504	0.1676	0.01399

Table 3: Model Metrics

- After training the above-mentioned models, some interesting results were observed. A prior regarding the model performance for Lasso was assumed. But since Lasso gave a low R-squared, this means there were many multi-collinear variables in the original design matrix.
- After observing the all the metrics for the models from Table 3, it is clear there is no point in fixating over R-squared alone but looking at model performance by combining it with BIC. As MSE, MAE and MAPE are very close, and we can disregard them for plain model comparison. BIC values bias more and R-squared values variability. Observing these two the right bias-variance tradeoff.

- Baseline with VIF:
  - Baseline with VIF here mean the baseline model with all the features was trained first and then another version by removing outliers and another after handling multicollinearity.
  - The R-squared score for this final model is 0.886 which reduced from the very first baseline model and the BIC is -877. This value improves from the very first baseline model suggesting that the original model had many non-contributing features.

- Lasso
  - Since the prior about the model does not give good results, further investigation suggests that there many variables which calculate similar features about the those, for example, garage area and garage capacity. Higher garage area will have higher car capacity. This argument is further corroborated by the fact that backward selection omits garage area and keeps garage car, but Lasso does the opposite. Furthermore, from the correlation matrix the correlation between these two features is the same indicating similarity between features. This information is sufficient to reject the prior about which model would perform the best.
  - The BIC value, which penalizes model complexity, has a value of -1009. This shows many features have been reduced to zero. The feature selected by the model are 63.

- RFEC Model
  - Another feature selection method used to then train an OLS model was RFEC which takes an object of the OLS, calculates the feature importance, and drops the variable with the lowest importance. The features thus obtained from this method are intuitive, but the constant variance graph shows some clustering and further investigation might be required. The R-squared for this model is 0.911 but a BIC score of -756 which is slightly better than the baseline suggests that there is overfitting.

- Backward Selection
  - The OLS model trained after selecting features with backward selection gives a R-squared of 0.89 with a BIC of -1336. This suggests a little underfitting compared to RFEC model.
  - Considering the number of features are double than RFEC and still there is some underfitting this model will perform better on incoming test set better.

- Random Forrest
  - The scope of this report does not delve into the technicalities of the report. But just presents the scores obtained after running a very basic version of the model without much hyper-parameter tuning. This model has a significantly low R-squared score. Because random forest is hard to interpret and is often termed as a black-box model. Hence, we reject this model for the time being. Further hyper-parameter tuning and feature selection with decision tree-based methods may give better results but again at a loss of interpretability.

- As a concluding statement, the backward selection model hits the right balance of goodness of fit and bias-variance tradeoff and as a result is the best model out of all.

Appendix:

```
                            OLS Regression Results
==============================================================================
=====
Dep. Variable:              SalePrice   R-squared:
0.911
Model:                            OLS   Adj. R-squared:
0.898
Method:                 Least Squares   F-statistic:
72.23
Date:                Wed, 20 Apr 2022   Prob (F-statistic):
0.00
Time:                        23:35:08   Log-Likelihood:
1034.2
No. Observations:                1460   AIC:                              -
1704.
Df Residuals:                    1278   BIC:                              -
742.3
Df Model:                         181
Covariance Type:            nonrobust
==============================================================================
=====
                 coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
-----
Intercept     12.0241      0.003   3607.304      0.000      12.018
12.031
a0            -0.0076      0.005     -1.501      0.134      -0.018
0.002
a1             0.0021      0.007      0.311      0.756      -0.011
0.015
a2            -0.0056      0.005     -1.185      0.236      -0.015
0.004
a3            -0.0128      0.007     -1.880      0.060      -0.026
0.001
a4             0.0214      0.006      3.819      0.000       0.010
0.032
a5             0.0055      0.004      1.397      0.163      -0.002
0.013
a6            -0.1098      0.145     -0.757      0.449      -0.394
0.175
a7             0.0058      0.009      0.632      0.527      -0.012
0.024
a8             0.0407      0.009      4.475      0.000       0.023
0.058
a9            -0.0011      0.006     -0.194      0.847      -0.012
0.010
a10           -0.0082      0.005     -1.636      0.102      -0.018
0.002
a11           -0.0222      0.019     -1.174      0.241      -0.059
0.015
```

a12	0.0238	0.006	4.262	0.000	0.013	0.035
a13	0.0243	0.012	2.008	0.045	0.001	0.048
a14	0.0266	0.006	4.429	0.000	0.015	0.038
a15	0.0436	0.009	4.889	0.000	0.026	0.061
a16	0.0339	0.008	4.071	0.000	0.018	0.050
a17	0.0106	0.005	2.291	0.022	0.002	0.020
a18	0.0613	0.006	10.141	0.000	0.049	0.073
a19	0.0199	0.007	3.009	0.003	0.007	0.033
a20	0.0141	0.006	2.466	0.014	0.003	0.025
a21	0.0046	0.006	0.755	0.450	-0.007	0.016
a22	-0.0156	0.007	-2.355	0.019	-0.029	-0.003
a23	0.0147	0.008	1.775	0.076	-0.002	0.031
a24	0.0208	0.005	4.449	0.000	0.012	0.030
a25	0.0137	0.004	3.419	0.001	0.006	0.022
a26	0.0037	0.004	0.890	0.374	-0.004	0.012
a27	0.0105	0.004	2.569	0.010	0.002	0.018
a28	0.0077	0.004	2.129	0.033	0.001	0.015
a29	0.0193	0.004	5.203	0.000	0.012	0.027
a30	-0.0082	0.004	-2.091	0.037	-0.016	-0.001
a31	-0.0020	0.004	-0.530	0.596	-0.009	0.005
a32	-0.0028	0.004	-0.769	0.442	-0.010	0.004
a33	-0.0014	0.004	-0.377	0.706	-0.009	0.006
a34	0.0317	0.003	9.790	0.000	0.025	0.038
a35	-0.0370	0.004	-8.786	0.000	-0.045	-0.029
a36	0.0090	0.008	1.074	0.283	-0.007	0.025
a37	0.0044	0.004	1.027	0.305	-0.004	0.013
a38	0.0075	0.008	0.920	0.358	-0.009	0.024

a39	-0.0038	0.004	-0.947	0.344	-0.012	0.004
a40	-0.0013	0.004	-0.318	0.750	-0.009	0.007
a41	0.0038	0.004	0.962	0.336	-0.004	0.011
a42	-0.0103	0.004	-2.611	0.009	-0.018	-0.003
a43	-0.0109	0.004	-2.697	0.007	-0.019	-0.003
a44	0.0047	0.004	1.161	0.246	-0.003	0.013
a45	-0.0009	0.005	-0.181	0.856	-0.010	0.008
a46	0.0079	0.004	2.056	0.040	0.000	0.015
a47	0.0059	0.004	1.583	0.114	-0.001	0.013
a48	0.0120	0.004	2.976	0.003	0.004	0.020
a49	-0.0063	0.004	-1.702	0.089	-0.013	0.001
a50	-0.0027	0.004	-0.774	0.439	-0.010	0.004
a51	0.0314	0.012	2.565	0.010	0.007	0.055
a183[0]	0.0312	0.011	2.795	0.005	0.009	0.053
a183[1]	-0.0132	0.004	-3.501	0.000	-0.021	-0.006
a53	-0.0087	0.006	-1.409	0.159	-0.021	0.003
a54	-0.0065	0.004	-1.665	0.096	-0.014	0.001
a55	-0.0139	0.007	-2.085	0.037	-0.027	-0.001
a56	-0.0189	0.010	-1.898	0.058	-0.038	0.001
a57	-0.0084	0.007	-1.171	0.242	-0.023	0.006
a58	-0.0291	0.014	-2.150	0.032	-0.056	-0.003
a59	0.0042	0.009	0.477	0.633	-0.013	0.022
a60	-0.0527	0.012	-4.502	0.000	-0.076	-0.030
a61	-0.0266	0.011	-2.520	0.012	-0.047	-0.006
a62	-0.0247	0.009	-2.754	0.006	-0.042	-0.007
a63	-0.0341	0.007	-4.980	0.000	-0.048	-0.021
a64	-0.0251	0.008	-2.955	0.003	-0.042	-0.008

a65	-0.0443	0.016	-2.760	0.006	-0.076	-0.013
a66	-0.0052	0.005	-0.956	0.339	-0.016	0.005
a67	-0.0252	0.010	-2.526	0.012	-0.045	-0.006
a68	-0.0046	0.008	-0.570	0.569	-0.020	0.011
a69	0.0146	0.011	1.387	0.166	-0.006	0.035
a70	-0.0463	0.014	-3.358	0.001	-0.073	-0.019
a71	-0.0144	0.007	-2.010	0.045	-0.029	-0.000
a72	-0.0293	0.010	-2.894	0.004	-0.049	-0.009
a73	-0.0210	0.009	-2.316	0.021	-0.039	-0.003
a74	-0.0096	0.013	-0.767	0.443	-0.034	0.015
a75	0.0094	0.007	1.417	0.157	-0.004	0.023
a76	-0.0130	0.008	-1.679	0.093	-0.028	0.002
a86[0]	-0.0071	0.003	-2.084	0.037	-0.014	-0.000
a86[1]	-2.143e-16	5.52e-16	-0.388	0.698	-1.3e-15	8.69e-16
a78	0.0039	0.004	1.080	0.280	-0.003	0.011
a88[0]	-0.0114	0.003	-3.723	0.000	-0.017	-0.005
a88[1]	1.403e-15	1.7e-15	0.825	0.410	-1.93e-15	4.74e-15
a89[0]	0.0109	0.002	5.250	0.000	0.007	0.015
a89[1]	0.0045	0.002	2.252	0.024	0.001	0.008
a90[0]	-1.89e-15	2.25e-15	-0.839	0.402	-6.31e-15	2.53e-15
a90[1]	3.529e-16	4.77e-16	0.739	0.460	-5.84e-16	1.29e-15
a82	-0.0028	0.004	-0.809	0.419	-0.010	0.004
a83	-0.0071	0.004	-1.993	0.046	-0.014	-0.000
a84	0.0052	0.004	1.456	0.146	-0.002	0.012
a85	-1.415e-15	1.69e-15	-0.837	0.403	-4.73e-15	1.9e-15
a87	-0.0045	0.002	-2.252	0.024	-0.008	-0.001
a91	0.0151	0.018	0.842	0.400	-0.020	0.050

a92	0.0150	0.006	2.566	0.010	0.004	0.027
a93	0.0124	0.009	1.446	0.149	-0.004	0.029
a94	-0.0052	0.005	-1.108	0.268	-0.014	0.004
a95	-0.0069	0.009	-0.751	0.453	-0.025	0.011
a96	0.0006	0.005	0.123	0.902	-0.008	0.009
a97	-0.0155	0.016	-0.949	0.343	-0.047	0.017
a98	-0.0079	0.005	-1.468	0.142	-0.019	0.003
a99	0.0084	0.004	1.872	0.061	-0.000	0.017
a100	-0.0228	0.013	-1.732	0.084	-0.049	0.003
a101	-0.0022	0.005	-0.456	0.649	-0.011	0.007
a102	-0.0331	0.005	-6.136	0.000	-0.044	-0.023
a103	-0.0131	0.004	-3.081	0.002	-0.021	-0.005
a104	-0.0011	0.012	-0.092	0.927	-0.024	0.022
a105	-0.0870	0.045	-1.948	0.052	-0.175	0.001
a106	-0.0167	0.010	-1.660	0.097	-0.036	0.003
a107	-0.0730	0.043	-1.696	0.090	-0.157	0.011
a108	-0.0125	0.008	-1.528	0.127	-0.028	0.004
a109	0.0048	0.003	1.557	0.120	-0.001	0.011
a110	0.0024	0.003	0.789	0.430	-0.004	0.008
a111	-0.0102	0.005	-1.864	0.063	-0.021	0.001
a112	-1.824e-15	2.01e-15	-0.907	0.365	-5.77e-15	2.12e-15
a126[0]	0.0013	0.008	0.155	0.877	-0.015	0.017
a126[1]	-0.0095	0.008	-1.223	0.222	-0.025	0.006
a127[0]	1.157e-15	1.24e-15	0.935	0.350	-1.27e-15	3.58e-15
a127[1]	1.1e-15	1.29e-15	0.851	0.395	-1.43e-15	3.63e-15
a115	-4.148e-16	4.75e-16	-0.874	0.382	-1.35e-15	5.17e-16
a142[0]	0.0152	0.008	1.955	0.051	-5.45e-05	0.030

a142[1]	-0.0052	0.006	-0.846	0.398	-0.017	0.007
a142[2]	0.0080	0.022	0.355	0.722	-0.036	0.052
a148[0]	-1.338e-15	1.43e-15	-0.935	0.350	-4.15e-15	1.47e-15
a148[1]	-8.781e-16	1.05e-15	-0.838	0.402	-2.93e-15	1.18e-15
a148[2]	0.0557	0.040	1.392	0.164	-0.023	0.134
a118	-0.0149	0.017	-0.861	0.389	-0.049	0.019
a119	-0.0052	0.005	-1.078	0.281	-0.015	0.004
a133[0]	0.0008	0.014	0.056	0.955	-0.027	0.029
a133[1]	-0.0027	0.013	-0.210	0.834	-0.028	0.023
a135[0]	0.0193	0.019	0.996	0.319	-0.019	0.057
a135[1]	-0.0075	0.018	-0.405	0.686	-0.044	0.029
a136[0]	0.0080	0.010	0.781	0.435	-0.012	0.028
a136[1]	-0.0031	0.010	-0.299	0.765	-0.023	0.017
a138[0]	0.0005	0.007	0.067	0.947	-0.013	0.014
a138[1]	-0.0058	0.007	-0.880	0.379	-0.019	0.007
a139[0]	-0.0075	0.022	-0.338	0.736	-0.051	0.036
a139[1]	0.0170	0.020	0.855	0.393	-0.022	0.056
a140[0]	-0.0159	0.013	-1.244	0.214	-0.041	0.009
a140[1]	0.0190	0.011	1.727	0.084	-0.003	0.041
a128	-7.315e-17	8.9e-17	-0.822	0.411	-2.48e-16	1.01e-16
a131	0.0244	0.017	1.456	0.146	-0.008	0.057
a132	-0.0032	0.006	-0.580	0.562	-0.014	0.008
a134	0.0064	0.004	1.470	0.142	-0.002	0.015
a151[0]	-1.149e-16	1.66e-16	-0.692	0.489	-4.41e-16	2.11e-16
a151[1]	0.0091	0.014	0.652	0.515	-0.018	0.036
a151[2]	0.0130	0.006	2.037	0.042	0.000	0.025
a141	-0.0030	0.006	-0.496	0.620	-0.015	0.009

a143	0.0051	0.023	0.216	0.829	-0.041	0.051
a145	0.0034	0.006	0.537	0.591	-0.009	0.016
a146	-0.0014	0.004	-0.353	0.724	-0.009	0.006
a147	0.0249	0.025	1.014	0.311	-0.023	0.073
a149	0.0616	0.040	1.545	0.122	-0.017	0.140
a150	0.0092	0.012	0.774	0.439	-0.014	0.033
a152	0.0113	0.007	1.647	0.100	-0.002	0.025
a153	0.0026	0.004	0.707	0.479	-0.005	0.010
a154	0.0112	0.005	2.382	0.017	0.002	0.020
a161[0]	0.0372	0.054	0.689	0.491	-0.069	0.143
a161[1]	0.0038	0.016	0.245	0.807	-0.027	0.035
a162[0]	0.0265	0.046	0.582	0.561	-0.063	0.116
a162[1]	-0.0058	0.020	-0.285	0.776	-0.046	0.034
a163[0]	0.0497	0.068	0.729	0.466	-0.084	0.183
a163[1]	0.0060	0.014	0.440	0.660	-0.021	0.033
a164[0]	0.0152	0.033	0.456	0.648	-0.050	0.081
a164[1]	0.0030	0.024	0.126	0.900	-0.044	0.050
a165[0]	0.0264	0.043	0.607	0.544	-0.059	0.112
a165[1]	0.0004	0.026	0.015	0.988	-0.050	0.051
a193[0]	0.0251	0.069	0.366	0.715	-0.110	0.160
a193[1]	0.0077	0.047	0.162	0.872	-0.085	0.101
a193[2]	0.1075	0.138	0.780	0.435	-0.163	0.378
a167	-0.0021	0.002	-0.967	0.334	-0.006	0.002
a168	0.0116	0.003	3.913	0.000	0.006	0.017
a169	-2.613e-18	2.41e-18	-1.086	0.278	-7.33e-18	2.11e-18
a170	-0.0100	0.003	-3.221	0.001	-0.016	-0.004
a171	0.0128	0.005	2.769	0.006	0.004	0.022

a196[0]	-0.0244	0.005	-4.877	0.000	-0.034	-0.015
a196[1]	-0.0064	0.004	-1.448	0.148	-0.015	0.002
a173	0.0030	0.004	0.734	0.463	-0.005	0.011
a174	0.0028	0.004	0.705	0.481	-0.005	0.010
a175	-0.0019	0.004	-0.466	0.641	-0.010	0.006
a176	9.373e-19	1.36e-18	0.688	0.492	-1.74e-18	3.61e-18
a177	0.0129	0.006	2.216	0.027	0.001	0.024
a178	-0.0256	0.004	-6.813	0.000	-0.033	-0.018
a179	-0.0113	0.004	-2.962	0.003	-0.019	-0.004
a180	-5.223e-31	2.97e-31	-1.756	0.079	-1.11e-30	6.11e-32
a181	-0.0103	0.004	-2.779	0.006	-0.018	-0.003
a182	-0.0122	0.004	-3.189	0.001	-0.020	-0.005
a184	-1.558e-32	8.87e-33	-1.756	0.079	-3.3e-32	1.83e-33
a185	0.0088	0.022	0.398	0.691	-0.034	0.052
a186	0.1443	0.168	0.858	0.391	-0.186	0.474
a187	0.0343	0.039	0.885	0.376	-0.042	0.110
a188	0.0611	0.082	0.746	0.456	-0.099	0.222
a189	0.0213	0.027	0.789	0.430	-0.032	0.074
a190	0.1252	0.151	0.827	0.408	-0.172	0.422
a191	0.1056	0.120	0.880	0.379	-0.130	0.341
a192	0.1073	0.127	0.846	0.398	-0.142	0.356
a194	0.0116	0.004	2.830	0.005	0.004	0.020
a195	-8.513e-05	0.004	-0.021	0.983	-0.008	0.008
a197	-0.0026	0.004	-0.703	0.482	-0.010	0.005
a198	6.667e-05	0.004	0.017	0.986	-0.008	0.008
a199	0	0	nan	nan	0	0
a200	0	0	nan	nan	0	0

```
a201                0          0        nan        nan           0
0
a202                0          0        nan        nan           0
0
a203                0          0        nan        nan           0
0
a204           0.0168      0.022      0.749      0.454      -0.027
0.061
a205                0          0        nan        nan           0
0
a206           0.0106      0.004      2.954      0.003       0.004
0.018
a207          -0.0088      0.021     -0.425      0.671      -0.049
0.032
a208           0.0027      0.006      0.472      0.637      -0.009
0.014
a209           0.0010      0.008      0.121      0.904      -0.015
0.017
a210          -0.0030      0.010     -0.300      0.764      -0.022
0.017
a211           0.0095      0.031      0.310      0.757      -0.051
0.070
==========================================================================
=====
Omnibus:                      626.890   Durbin-Watson:
1.922
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
10641.606
Skew:                          -1.553   Prob(JB):
0.00
Kurtosis:                      15.856   Cond. No.
6.22e+16
==========================================================================
=====

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The smallest eigenvalue is 5.46e-30. This might indicate that there
are
strong multicollinearity problems or that the design matrix is singular.

                            OLS Regression Results
==========================================================================
=====
Dep. Variable:              SalePrice   R-squared:
0.925
Model:                            OLS   Adj. R-squared:
0.914
Method:                 Least Squares   F-statistic:
87.04
Date:                Wed, 20 Apr 2022   Prob (F-statistic):
0.00
```

```
Time:                        23:35:19   Log-Likelihood:
1154.3
No. Observations:                1458   AIC:                            -
1947.
Df Residuals:                    1277   BIC:                            -
990.1
Df Model:                         180
Covariance Type:            nonrobust
=========================================================================
=====
                 coef    std err          t      P>|t|      [0.025
0.975]
-------------------------------------------------------------------------
-----
Intercept     12.0260      0.003   3917.614      0.000      12.020
12.032
a0             0.0199      0.005      3.986      0.000       0.010
0.030
a1             0.0035      0.006      0.564      0.573      -0.009
0.016
a2            -0.0050      0.004     -1.155      0.248      -0.014
0.004
a3             0.0169      0.007      2.587      0.010       0.004
0.030
a4             0.0120      0.005      2.320      0.020       0.002
0.022
a5             0.0024      0.004      0.657      0.511      -0.005
0.010
a6            -0.0317      0.134     -0.237      0.813      -0.294
0.230
a7             0.0205      0.009      2.402      0.016       0.004
0.037
a8             0.0180      0.008      2.126      0.034       0.001
0.035
a9            -0.0015      0.005     -0.295      0.768      -0.012
0.009
a10            0.0070      0.005      1.475      0.140      -0.002
0.016
a11           -0.0125      0.017     -0.719      0.472      -0.047
0.022
a12            0.0242      0.005      4.709      0.000       0.014
0.034
a13            0.0368      0.011      3.296      0.001       0.015
0.059
a14            0.0298      0.006      5.394      0.000       0.019
0.041
a15            0.0374      0.008      4.553      0.000       0.021
0.054
a16            0.0322      0.008      4.194      0.000       0.017
0.047
a17            0.0073      0.004      1.714      0.087      -0.001
0.016
a18            0.0549      0.006      9.855      0.000       0.044
0.066
```

a19	0.0120	0.006	1.970	0.049	5.16e-05	0.024
a20	0.0119	0.005	2.256	0.024	0.002	0.022
a21	0.0032	0.006	0.584	0.559	-0.008	0.014
a22	-0.0165	0.006	-2.708	0.007	-0.028	-0.005
a23	0.0116	0.008	1.522	0.128	-0.003	0.027
a24	0.0188	0.004	4.357	0.000	0.010	0.027
a25	0.0123	0.004	3.312	0.001	0.005	0.020
a26	0.0052	0.004	1.372	0.170	-0.002	0.013
a27	0.0077	0.004	2.046	0.041	0.000	0.015
a28	0.0072	0.003	2.170	0.030	0.001	0.014
a29	0.0167	0.003	4.899	0.000	0.010	0.023
a30	0.0030	0.004	0.802	0.423	-0.004	0.010
a31	-0.0014	0.003	-0.400	0.689	-0.008	0.005
a32	-0.0030	0.003	-0.907	0.365	-0.010	0.004
a33	0.0004	0.003	0.121	0.904	-0.006	0.007
a34	0.0437	0.003	14.186	0.000	0.038	0.050
a35	-0.0359	0.004	-9.256	0.000	-0.044	-0.028
a36	0.0102	0.008	1.324	0.186	-0.005	0.025
a37	0.0049	0.004	1.232	0.218	-0.003	0.013
a38	0.0098	0.008	1.305	0.192	-0.005	0.025
a39	-0.0045	0.004	-1.233	0.218	-0.012	0.003
a40	-0.0009	0.004	-0.228	0.820	-0.008	0.007
a41	0.0049	0.004	1.347	0.178	-0.002	0.012
a42	0.0007	0.004	0.200	0.841	-0.007	0.008
a43	-0.0050	0.004	-1.345	0.179	-0.012	0.002
a44	0.0047	0.004	1.254	0.210	-0.003	0.012
a45	-0.0054	0.004	-1.229	0.219	-0.014	0.003

a46	0.0055	0.004	1.568	0.117	-0.001	0.012
a47	0.0046	0.003	1.353	0.176	-0.002	0.011
a48	0.0117	0.004	3.161	0.002	0.004	0.019
a49	-0.0050	0.003	-1.474	0.141	-0.012	0.002
a50	-0.0017	0.003	-0.535	0.592	-0.008	0.005
a51	0.0317	0.011	2.814	0.005	0.010	0.054
a183[0]	0.0314	0.010	3.060	0.002	0.011	0.052
a183[1]	-0.0152	0.003	-4.400	0.000	-0.022	-0.008
a53	-0.0064	0.006	-1.126	0.260	-0.018	0.005
a54	-0.0052	0.004	-1.424	0.155	-0.012	0.002
a55	-0.0128	0.006	-2.094	0.036	-0.025	-0.001
a56	-0.0115	0.009	-1.260	0.208	-0.029	0.006
a57	-0.0070	0.007	-1.054	0.292	-0.020	0.006
a58	-0.0268	0.012	-2.147	0.032	-0.051	-0.002
a59	0.0081	0.008	0.995	0.320	-0.008	0.024
a60	-0.0441	0.011	-4.088	0.000	-0.065	-0.023
a61	-0.0230	0.010	-2.362	0.018	-0.042	-0.004
a62	-0.0187	0.008	-2.263	0.024	-0.035	-0.002
a63	-0.0301	0.006	-4.768	0.000	-0.042	-0.018
a64	-0.0225	0.008	-2.886	0.004	-0.038	-0.007
a65	-0.0383	0.015	-2.590	0.010	-0.067	-0.009
a66	-0.0027	0.005	-0.533	0.594	-0.012	0.007
a67	-0.0210	0.009	-2.290	0.022	-0.039	-0.003
a68	-0.0084	0.007	-1.134	0.257	-0.023	0.006
a69	0.0083	0.010	0.858	0.391	-0.011	0.027
a70	-0.0360	0.013	-2.833	0.005	-0.061	-0.011
a71	-0.0102	0.007	-1.548	0.122	-0.023	0.003

a72	-0.0243	0.009	-2.618	0.009	-0.043	-0.006
a73	-0.0189	0.008	-2.268	0.023	-0.035	-0.003
a74	-0.0099	0.012	-0.856	0.392	-0.033	0.013
a75	0.0090	0.006	1.474	0.141	-0.003	0.021
a76	-0.0131	0.007	-1.828	0.068	-0.027	0.001
a86[0]	-0.0075	0.003	-2.395	0.017	-0.014	-0.001
a86[1]	-9.88e-16	2.46e-15	-0.402	0.688	-5.81e-15	3.83e-15
a78	0.0021	0.003	0.638	0.524	-0.004	0.009
a88[0]	-0.0070	0.003	-2.479	0.013	-0.013	-0.001
a88[1]	5.498e-16	6.58e-16	0.836	0.403	-7.41e-16	1.84e-15
a89[0]	0.0111	0.002	5.824	0.000	0.007	0.015
a89[1]	0.0059	0.002	3.164	0.002	0.002	0.010
a90[0]	7.623e-17	1.15e-16	0.666	0.506	-1.48e-16	3.01e-16
a90[1]	4.428e-16	7.91e-16	0.560	0.576	-1.11e-15	1.99e-15
a82	-0.0072	0.003	-2.231	0.026	-0.014	-0.001
a83	-0.0077	0.003	-2.333	0.020	-0.014	-0.001
a84	0.0030	0.003	0.911	0.362	-0.003	0.009
a85	1.333e-16	3.55e-16	0.376	0.707	-5.63e-16	8.29e-16
a87	-0.0059	0.002	-3.164	0.002	-0.010	-0.002
a91	0.0105	0.017	0.634	0.526	-0.022	0.043
a92	0.0095	0.005	1.750	0.080	-0.001	0.020
a93	0.0067	0.008	0.842	0.400	-0.009	0.022
a94	-0.0050	0.004	-1.161	0.246	-0.013	0.003
a95	-0.0044	0.008	-0.520	0.603	-0.021	0.012
a96	0.0013	0.004	0.319	0.750	-0.007	0.009
a97	-0.0229	0.015	-1.523	0.128	-0.052	0.007
a98	-0.0066	0.005	-1.322	0.186	-0.016	0.003

a99	0.0103	0.004	2.483	0.013	0.002	0.018
a100	-0.0121	0.012	-0.999	0.318	-0.036	0.012
a101	-0.0027	0.004	-0.619	0.536	-0.011	0.006
a102	-0.0281	0.005	-5.652	0.000	-0.038	-0.018
a103	-0.0145	0.004	-3.690	0.000	-0.022	-0.007
a104	-0.0018	0.011	-0.162	0.871	-0.023	0.019
a105	-0.0696	0.041	-1.693	0.091	-0.150	0.011
a106	-0.0137	0.009	-1.478	0.140	-0.032	0.004
a107	-0.0602	0.040	-1.521	0.129	-0.138	0.017
a108	-0.0112	0.008	-1.490	0.136	-0.026	0.004
a109	-0.0010	0.003	-0.356	0.722	-0.007	0.005
a110	0.0108	0.003	3.757	0.000	0.005	0.016
a111	-0.0110	0.005	-2.190	0.029	-0.021	-0.001
a112	-6.957e-17	3.35e-17	-2.076	0.038	-1.35e-16	-3.81e-18
a126[0]	0.0024	0.008	0.314	0.753	-0.013	0.017
a126[1]	-0.0112	0.007	-1.561	0.119	-0.025	0.003
a127[0]	-1.054e-16	4.53e-17	-2.328	0.020	-1.94e-16	-1.66e-17
a127[1]	2.32e-16	1.05e-16	2.212	0.027	2.62e-17	4.38e-16
a115	1.191e-16	7.39e-17	1.611	0.108	-2.6e-17	2.64e-16
a142[0]	0.0167	0.007	2.338	0.020	0.003	0.031
a142[1]	-0.0085	0.006	-1.518	0.129	-0.020	0.002
a142[2]	0.0128	0.021	0.622	0.534	-0.028	0.053
a148[0]	1.692e-16	1.24e-16	1.367	0.172	-7.37e-17	4.12e-16
a148[1]	-8.836e-17	2.5e-17	-3.540	0.000	-1.37e-16	-3.94e-17
a148[2]	0.0741	0.037	2.012	0.044	0.002	0.146
a118	-0.0155	0.016	-0.969	0.333	-0.047	0.016
a119	-0.0060	0.004	-1.331	0.184	-0.015	0.003

a133[0]	0.0020	0.013	0.152	0.879	-0.024	0.028
a133[1]	-0.0091	0.012	-0.770	0.442	-0.032	0.014
a135[0]	0.0227	0.018	1.273	0.203	-0.012	0.058
a135[1]	-0.0155	0.017	-0.917	0.359	-0.049	0.018
a136[0]	0.0028	0.009	0.293	0.769	-0.016	0.021
a136[1]	-0.0069	0.010	-0.731	0.465	-0.026	0.012
a138[0]	0.0056	0.006	0.888	0.375	-0.007	0.018
a138[1]	-0.0023	0.006	-0.379	0.705	-0.014	0.010
a139[0]	-0.0074	0.021	-0.361	0.718	-0.048	0.033
a139[1]	0.0090	0.018	0.495	0.621	-0.027	0.045
a140[0]	-0.0148	0.012	-1.255	0.210	-0.038	0.008
a140[1]	0.0132	0.010	1.301	0.193	-0.007	0.033
a128	-1.009e-17	2.34e-17	-0.431	0.667	-5.61e-17	3.59e-17
a131	0.0180	0.015	1.165	0.244	-0.012	0.048
a132	-0.0037	0.005	-0.724	0.469	-0.014	0.006
a134	0.0028	0.004	0.707	0.480	-0.005	0.011
a151[0]	5.363e-17	1.57e-17	3.423	0.001	2.29e-17	8.44e-17
a151[1]	0.0133	0.013	1.038	0.299	-0.012	0.038
a151[2]	0.0164	0.006	2.788	0.005	0.005	0.028
a141	-0.0021	0.006	-0.369	0.712	-0.013	0.009
a143	0.0080	0.022	0.368	0.713	-0.034	0.050
a145	0.0009	0.006	0.146	0.884	-0.011	0.012
a146	-0.0011	0.004	-0.311	0.756	-0.008	0.006
a147	0.0386	0.023	1.706	0.088	-0.006	0.083
a149	0.0795	0.037	2.168	0.030	0.008	0.151
a150	0.0148	0.011	1.349	0.178	-0.007	0.036
a152	0.0080	0.006	1.270	0.204	-0.004	0.020

a153	0.0035	0.003	1.030	0.303	-0.003	0.010
a154	0.0078	0.004	1.812	0.070	-0.001	0.016
a161[0]	-0.0002	0.005	-0.035	0.972	-0.010	0.009
a161[1]	0.0047	0.006	0.839	0.402	-0.006	0.016
a162[0]	-0.0037	0.004	-0.842	0.400	-0.012	0.005
a162[1]	-0.0059	0.006	-0.955	0.340	-0.018	0.006
a163[0]	0.0022	0.006	0.364	0.716	-0.010	0.014
a163[1]	0.0072	0.005	1.397	0.163	-0.003	0.017
a164[0]	-0.0066	0.004	-1.613	0.107	-0.015	0.001
a164[1]	-0.0003	0.007	-0.046	0.963	-0.014	0.013
a165[0]	-0.0046	0.004	-1.048	0.295	-0.013	0.004
a165[1]	-0.0004	0.007	-0.055	0.956	-0.015	0.014
a193[0]	-0.0082	0.006	-1.400	0.162	-0.020	0.003
a193[1]	0.0037	0.012	0.324	0.746	-0.019	0.026
a193[2]	0.0370	0.127	0.292	0.771	-0.212	0.286
a167	-0.0006	0.002	-0.316	0.752	-0.005	0.003
a168	0.0089	0.003	3.240	0.001	0.003	0.014
a169	-9.231e-18	2.5e-18	-3.692	0.000	-1.41e-17	-4.33e-18
a170	-0.0091	0.003	-3.175	0.002	-0.015	-0.003
a171	0.0136	0.004	3.192	0.001	0.005	0.022
a196[0]	-0.0231	0.005	-5.019	0.000	-0.032	-0.014
a196[1]	-0.0058	0.004	-1.434	0.152	-0.014	0.002
a173	-0.0001	0.004	-0.035	0.972	-0.007	0.007
a174	0.0021	0.004	0.589	0.556	-0.005	0.009
a175	-0.0022	0.004	-0.610	0.542	-0.009	0.005
a176	-7.133e-18	7.7e-19	-9.265	0.000	-8.64e-18	-5.62e-18
a177	0.0110	0.005	2.059	0.040	0.001	0.022

a178	-0.0243	0.003	-7.043	0.000	-0.031	-0.018
a179	-0.0124	0.004	-3.539	0.000	-0.019	-0.006
a180	1.783e-19	1.4e-19	1.271	0.204	-9.69e-20	4.53e-19
a181	-0.0088	0.003	-2.584	0.010	-0.015	-0.002
a182	-0.0122	0.004	-3.472	0.001	-0.019	-0.005
a184	1.755e-18	1.42e-18	1.237	0.216	-1.03e-18	4.54e-18
a185	-0.0021	0.020	-0.102	0.919	-0.042	0.038
a186	0.0551	0.155	0.356	0.722	-0.249	0.359
a187	0.0131	0.036	0.369	0.712	-0.057	0.083
a188	0.0185	0.075	0.245	0.806	-0.129	0.166
a189	0.0076	0.025	0.304	0.761	-0.041	0.056
a190	0.0460	0.139	0.330	0.741	-0.227	0.319
a191	0.0411	0.110	0.372	0.710	-0.175	0.258
a192	0.0394	0.117	0.338	0.736	-0.190	0.268
a194	0.0104	0.004	2.765	0.006	0.003	0.018
a195	-0.0002	0.004	-0.057	0.954	-0.007	0.007
a197	-0.0031	0.003	-0.912	0.362	-0.010	0.004
a198	0.0004	0.004	0.113	0.910	-0.007	0.007
a199	0	0	nan	nan	0	0
a200	0	0	nan	nan	0	0
a201	0	0	nan	nan	0	0
a202	0	0	nan	nan	0	0
a203	0	0	nan	nan	0	0
a204	0.0195	0.021	0.945	0.345	-0.021	0.060
a205	0	0	nan	nan	0	0
a206	0.0101	0.003	3.065	0.002	0.004	0.017
a207	-0.0090	0.019	-0.473	0.636	-0.046	0.028

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a208           0.0039      0.005      0.742      0.458      -0.006
0.014
a209           0.0009      0.008      0.115      0.908      -0.014
0.016
a210          -0.0042      0.009     -0.463      0.643      -0.022
0.014
a211           0.0108      0.028      0.382      0.703      -0.045
0.066
==========================================================================
=====
Omnibus:                      651.210   Durbin-Watson:
1.909
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
11873.407
Skew:                          -1.616   Prob(JB):
0.00
Kurtosis:                      16.601   Cond. No.
1.47e+17
==========================================================================
=====

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The smallest eigenvalue is 9.61e-31. This might indicate that there
are
strong multicollinearity problems or that the design matrix is singular.

                            OLS Regression Results
==========================================================================
=====
Dep. Variable:              SalePrice   R-squared:
0.883
Model:                            OLS   Adj. R-squared:
0.874
Method:                 Least Squares   F-statistic:
92.54
Date:                Wed, 20 Apr 2022   Prob (F-statistic):
0.00
Time:                        23:35:35   Log-Likelihood:
834.56
No. Observations:                1458   AIC:                             -
1447.
Df Residuals:                    1347   BIC:                             -
860.5
Df Model:                         110
Covariance Type:            nonrobust
==========================================================================
=====
                 coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------
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```

Intercept	12.0252	0.004	3232.423	0.000	12.018	12.033
a4	0.0418	0.004	9.380	0.000	0.033	0.051
a5	0.0098	0.004	2.396	0.017	0.002	0.018
a7	0.0469	0.009	5.164	0.000	0.029	0.065
a8	0.0205	0.009	2.184	0.029	0.002	0.039
a9	0.0162	0.006	2.723	0.007	0.005	0.028
a10	0.0225	0.005	4.334	0.000	0.012	0.033
a12	0.0219	0.005	4.287	0.000	0.012	0.032
a14	0.0414	0.006	6.615	0.000	0.029	0.054
a19	0.0447	0.006	7.116	0.000	0.032	0.057
a20	0.0232	0.005	4.864	0.000	0.014	0.033
a21	0.0031	0.006	0.493	0.622	-0.009	0.015
a22	-0.0211	0.007	-2.989	0.003	-0.035	-0.007
a23	0.0703	0.007	9.428	0.000	0.056	0.085
a24	0.0354	0.005	7.395	0.000	0.026	0.045
a25	0.0171	0.004	3.983	0.000	0.009	0.026
a26	0.0125	0.004	2.854	0.004	0.004	0.021
a27	0.0027	0.004	0.622	0.534	-0.006	0.011
a28	0.0061	0.004	1.595	0.111	-0.001	0.014
a29	0.0199	0.004	4.989	0.000	0.012	0.028
a30	0.0058	0.004	1.390	0.165	-0.002	0.014
a31	0.0013	0.004	0.335	0.738	-0.006	0.009
a32	-0.0016	0.004	-0.411	0.681	-0.009	0.006
a33	-0.0054	0.004	-1.362	0.173	-0.013	0.002
a35	-0.0368	0.005	-8.080	0.000	-0.046	-0.028
a36	0.0230	0.005	4.459	0.000	0.013	0.033
a37	0.0068	0.004	1.584	0.113	-0.002	0.015

a38	0.0172	0.006	2.790	0.005	0.005	0.029
a39	-0.0074	0.004	-1.764	0.078	-0.016	0.001
a40	0.0002	0.004	0.038	0.970	-0.008	0.009
a41	0.0041	0.004	0.985	0.325	-0.004	0.012
a42	-0.0005	0.004	-0.119	0.905	-0.009	0.008
a43	-0.0047	0.004	-1.065	0.287	-0.013	0.004
a44	-0.0011	0.004	-0.247	0.805	-0.010	0.007
a45	-0.0058	0.005	-1.175	0.240	-0.015	0.004
a46	0.0085	0.004	2.155	0.031	0.001	0.016
a47	6.361e-05	0.004	0.016	0.987	-0.008	0.008
a48	0.0162	0.004	3.756	0.000	0.008	0.025
a49	-0.0065	0.004	-1.663	0.097	-0.014	0.001
a50	-0.0048	0.004	-1.250	0.212	-0.012	0.003
a183[0]	0.0006	0.005	0.135	0.893	-0.008	0.010
a183[1]	-0.0104	0.004	-2.670	0.008	-0.018	-0.003
a53	0.0014	0.004	0.330	0.742	-0.007	0.010
a54	0.0006	0.004	0.161	0.872	-0.007	0.008
a55	-0.0056	0.005	-1.173	0.241	-0.015	0.004
a56	0.0101	0.004	2.376	0.018	0.002	0.018
a57	0.0130	0.004	2.913	0.004	0.004	0.022
a59	0.0334	0.004	7.719	0.000	0.025	0.042
a62	0.0027	0.005	0.547	0.585	-0.007	0.012
a63	-0.0169	0.004	-3.827	0.000	-0.026	-0.008
a64	0.0001	0.004	0.031	0.975	-0.008	0.008
a66	0.0008	0.005	0.180	0.857	-0.008	0.010
a67	1.496e-05	0.004	0.003	0.997	-0.008	0.008
a68	0.0178	0.004	3.974	0.000	0.009	0.027

a69	0.0278	0.005	5.754	0.000	0.018	0.037
a71	0.0072	0.004	1.618	0.106	-0.002	0.016
a72	0.0006	0.004	0.151	0.880	-0.007	0.009
a73	-0.0005	0.004	-0.126	0.900	-0.009	0.008
a75	0.0245	0.004	5.829	0.000	0.016	0.033
a76	0.0045	0.004	1.042	0.297	-0.004	0.013
a92	-0.0014	0.005	-0.287	0.774	-0.011	0.008
a93	-0.0062	0.007	-0.949	0.343	-0.019	0.007
a94	-0.0100	0.005	-2.049	0.041	-0.020	-0.000
a95	0.0048	0.004	1.076	0.282	-0.004	0.014
a96	0.0040	0.004	0.995	0.320	-0.004	0.012
a98	0.0002	0.004	0.049	0.961	-0.008	0.008
a99	0.0137	0.004	3.352	0.001	0.006	0.022
a101	-0.0078	0.004	-1.781	0.075	-0.016	0.001
a102	-0.0441	0.006	-7.915	0.000	-0.055	-0.033
a103	-0.0041	0.004	-0.936	0.350	-0.013	0.005
a106	0.0019	0.004	0.473	0.637	-0.006	0.010
a108	0.0039	0.004	0.989	0.323	-0.004	0.012
a126[0]	-0.0026	0.008	-0.335	0.738	-0.018	0.013
a126[1]	-0.0035	0.008	-0.454	0.650	-0.018	0.012
a142[0]	0.0298	0.005	5.470	0.000	0.019	0.040
a142[1]	-0.0060	0.005	-1.130	0.259	-0.016	0.004
a142[2]	0.0082	0.006	1.405	0.160	-0.003	0.020
a119	0.0002	0.005	0.050	0.960	-0.009	0.009
a136[0]	0.0098	0.007	1.503	0.133	-0.003	0.023
a136[1]	-0.0085	0.006	-1.331	0.183	-0.021	0.004
a138[0]	0.0071	0.006	1.120	0.263	-0.005	0.020

a138[1]	-0.0054	0.006	-0.840	0.401	-0.018	0.007
a132	-0.0055	0.005	-1.085	0.278	-0.016	0.004
a134	0.0059	0.004	1.477	0.140	-0.002	0.014
a151[0]	8.138e-18	4.04e-18	2.012	0.044	2.05e-19	1.61e-17
a151[1]	0.0113	0.005	2.265	0.024	0.002	0.021
a151[2]	0.0116	0.004	2.864	0.004	0.004	0.020
a141	-0.0080	0.004	-1.990	0.047	-0.016	-0.000
a145	0.0185	0.007	2.776	0.006	0.005	0.032
a146	-0.0021	0.004	-0.508	0.611	-0.010	0.006
a152	0.0298	0.006	4.722	0.000	0.017	0.042
a153	0.0011	0.004	0.284	0.777	-0.007	0.009
a154	0.0203	0.005	4.308	0.000	0.011	0.030
a171	0.0123	0.005	2.521	0.012	0.003	0.022
a196[0]	-0.0329	0.005	-6.550	0.000	-0.043	-0.023
a196[1]	-0.0180	0.004	-4.016	0.000	-0.027	-0.009
a173	-0.0006	0.004	-0.137	0.891	-0.009	0.008
a174	0.0008	0.004	0.190	0.849	-0.007	0.009
a175	-0.0056	0.004	-1.294	0.196	-0.014	0.003
a177	0.0140	0.006	2.239	0.025	0.002	0.026
a178	-0.0198	0.004	-4.997	0.000	-0.028	-0.012
a179	-0.0130	0.004	-3.290	0.001	-0.021	-0.005
a181	-0.0079	0.004	-2.005	0.045	-0.016	-0.000
a182	-0.0129	0.004	-3.247	0.001	-0.021	-0.005
a194	0.0088	0.004	1.995	0.046	0.000	0.017
a195	-0.0040	0.004	-0.915	0.360	-0.012	0.005
a197	-0.0057	0.004	-1.451	0.147	-0.014	0.002
a198	0.0007	0.004	0.164	0.870	-0.007	0.009

```
a206           0.0071      0.004      1.829      0.068      -0.001
0.015
a208          -0.0002      0.004     -0.053      0.958      -0.009
0.008
a209          -0.0019      0.004     -0.446      0.655      -0.010
0.006
a210          -0.0065      0.004     -1.698      0.090      -0.014
0.001
==========================================================================
=====
Omnibus:                      233.275   Durbin-Watson:
1.940
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
884.988
Skew:                          -0.739   Prob(JB):
6.72e-193
Kurtosis:                       6.519   Cond. No.
5.75e+15
==========================================================================
=====

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The smallest eigenvalue is 3.3e-28. This might indicate that there
are
strong multicollinearity problems or that the design matrix is singular.

                            OLS Regression Results
==========================================================================
=====
Dep. Variable:              SalePrice   R-squared:
0.843
Model:                            OLS   Adj. R-squared:
0.837
Method:                 Least Squares   F-statistic:
130.0
Date:                Wed, 20 Apr 2022   Prob (F-statistic):
0.00
Time:                        23:35:44   Log-Likelihood:
621.70
No. Observations:                1460   AIC:                             -
1125.
Df Residuals:                    1401   BIC:                             -
813.5
Df Model:                          58
Covariance Type:            nonrobust
==========================================================================
=====
                 coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------
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```

Intercept	12.0241	0.004	2847.336	0.000	12.016	12.032
a3	0.0341	0.007	4.686	0.000	0.020	0.048
a4	0.0168	0.006	2.970	0.003	0.006	0.028
a5	0.0056	0.005	1.235	0.217	-0.003	0.015
a6	0.0297	0.006	4.912	0.000	0.018	0.042
a7	0.0539	0.007	7.703	0.000	0.040	0.068
a11	-0.0284	0.010	-2.799	0.005	-0.048	-0.008
a12	0.0110	0.005	2.173	0.030	0.001	0.021
a13	0.0428	0.010	4.492	0.000	0.024	0.061
a14	0.0560	0.006	9.393	0.000	0.044	0.068
a17	0.0020	0.005	0.360	0.719	-0.009	0.013
a18	0.1161	0.011	10.700	0.000	0.095	0.137
a19	0.0146	0.007	2.109	0.035	0.001	0.028
a22	-0.0188	0.006	-3.166	0.002	-0.030	-0.007
a23	0.0390	0.009	4.510	0.000	0.022	0.056
a24	0.0468	0.005	8.878	0.000	0.036	0.057
a25	0.0099	0.005	2.108	0.035	0.001	0.019
a26	0.0008	0.005	0.168	0.866	-0.008	0.010
a27	0.0065	0.005	1.349	0.177	-0.003	0.016
a28	0.0078	0.004	1.803	0.072	-0.001	0.016
a33	-0.0046	0.004	-1.056	0.291	-0.013	0.004
a35	-0.0414	0.004	-9.353	0.000	-0.050	-0.033
a36	0.0093	0.009	1.044	0.297	-0.008	0.027
a37	0.0031	0.004	0.711	0.477	-0.006	0.012
a40	0.0086	0.005	1.879	0.060	-0.000	0.018
a43	-0.0127	0.004	-2.832	0.005	-0.022	-0.004
a45	0.0012	0.005	0.261	0.794	-0.008	0.011

a46	0.0028	0.004	0.644	0.520	-0.006	0.011
a47	-0.0005	0.004	-0.108	0.914	-0.009	0.008
a56	0.0070	0.005	1.522	0.128	-0.002	0.016
a58	-0.0076	0.005	-1.529	0.127	-0.017	0.002
a67	-0.0071	0.005	-1.510	0.131	-0.016	0.002
a68	0.0107	0.005	2.217	0.027	0.001	0.020
a73	-0.0025	0.005	-0.549	0.583	-0.012	0.007
a74	0.0074	0.009	0.812	0.417	-0.010	0.025
a86[0]	-0.0103	0.004	-2.294	0.022	-0.019	-0.001
a86[1]	8.528e-19	4.2e-18	0.203	0.839	-7.38e-18	9.08e-18
a88[0]	-0.0170	0.004	-3.854	0.000	-0.026	-0.008
a88[1]	-1.651e-17	5.3e-18	-3.118	0.002	-2.69e-17	-6.12e-18
a90[0]	-3.065e-18	2.91e-18	-1.054	0.292	-8.77e-18	2.64e-18
a90[1]	-3.71e-18	2.87e-18	-1.294	0.196	-9.34e-18	1.92e-18
a83	-0.0105	0.004	-2.417	0.016	-0.019	-0.002
a91	-0.0017	0.010	-0.166	0.868	-0.022	0.019
a98	-0.0015	0.005	-0.281	0.779	-0.012	0.009
a115	1.057e-17	4.41e-18	2.396	0.017	1.92e-18	1.92e-17
a148[0]	-8.193e-19	2.98e-18	-0.275	0.783	-6.67e-18	5.03e-18
a148[1]	-4.928e-18	2.16e-18	-2.278	0.023	-9.17e-18	-6.84e-19
a148[2]	-0.0089	0.006	-1.462	0.144	-0.021	0.003
a133[0]	-0.0045	0.009	-0.481	0.630	-0.023	0.014
a133[1]	-0.0020	0.009	-0.221	0.825	-0.020	0.016
a151[0]	-3.217e-18	1.19e-18	-2.699	0.007	-5.56e-18	-8.79e-19
a151[1]	0.0094	0.005	1.856	0.064	-0.001	0.019
a151[2]	0.0048	0.004	1.083	0.279	-0.004	0.013
a143	-0.0048	0.005	-0.907	0.365	-0.015	0.006

```
a150          -0.0136      0.005     -2.494      0.013      -0.024      -
0.003
a152           0.0223      0.008      2.916      0.004       0.007
0.037
a153           0.0071      0.004      1.640      0.101      -0.001
0.016
a154           0.0187      0.005      3.648      0.000       0.009
0.029
a162[0]       -0.0055      0.005     -1.191      0.234      -0.015
0.004
a162[1]       -0.0072      0.005     -1.523      0.128      -0.017
0.002
a193[0]       -0.0261      0.006     -4.736      0.000      -0.037      -
0.015
a193[1]        0.0069      0.005      1.297      0.195      -0.004
0.017
a193[2]       -0.0170      0.006     -2.667      0.008      -0.029      -
0.004
a167          -0.0053      0.006     -0.895      0.371      -0.017
0.006
a170          -0.0165      0.006     -2.845      0.005      -0.028      -
0.005
a176                0          0        nan        nan           0
0
a185          -0.0126      0.004     -2.806      0.005      -0.021      -
0.004
a190          -0.0093      0.006     -1.509      0.132      -0.021
0.003
a203                0          0        nan        nan           0
0
a205                0          0        nan        nan           0
0
==========================================================================
=====
Omnibus:                      971.663   Durbin-Watson:
1.937
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
48547.895
Skew:                          -2.463   Prob(JB):
0.00
Kurtosis:                      30.817   Cond. No.
3.91e+16
==========================================================================
=====

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The smallest eigenvalue is 6.15e-30. This might indicate that there
are
strong multicollinearity problems or that the design matrix is singular.

                            OLS Regression Results
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==============================================================================
=====
Dep. Variable:               SalePrice   R-squared:
0.907
Model:                             OLS   Adj. R-squared:
0.900
Method:                  Least Squares   F-statistic:
119.9
Date:                 Wed, 20 Apr 2022   Prob (F-statistic):
0.00
Time:                         23:35:52   Log-Likelihood:
1004.0
No. Observations:                 1460   AIC:                              -
1786.
Df Residuals:                     1349   BIC:                              -
1199.
Df Model:                          110
Covariance Type:             nonrobust
==============================================================================
=====
                 coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
-----
Intercept     12.0241      0.003   3630.329      0.000      12.018
12.031
a4             0.0196      0.005      4.294      0.000       0.011
0.029
a8             0.0429      0.006      7.130      0.000       0.031
0.055
a11           -0.0378      0.006     -6.001      0.000      -0.050      -
0.025
a12            0.0206      0.005      4.160      0.000       0.011
0.030
a14            0.0265      0.006      4.725      0.000       0.015
0.037
a15            0.0348      0.008      4.202      0.000       0.019
0.051
a18            0.0993      0.011      9.053      0.000       0.078
0.121
a19            0.0223      0.006      3.734      0.000       0.011
0.034
a20            0.0152      0.005      2.967      0.003       0.005
0.025
a22           -0.0111      0.005     -2.371      0.018      -0.020      -
0.002
a23            0.0156      0.007      2.229      0.026       0.002
0.029
a24            0.0205      0.004      4.677      0.000       0.012
0.029
a25            0.0141      0.004      3.677      0.000       0.007
0.022
a27            0.0086      0.004      2.242      0.025       0.001
0.016
```

a28	0.0075	0.003	2.172	0.030	0.001	0.014
a29	0.0197	0.004	5.499	0.000	0.013	0.027
a30	-0.0078	0.004	-2.143	0.032	-0.015	-0.001
a35	-0.0378	0.004	-9.583	0.000	-0.046	-0.030
a42	-0.0115	0.004	-3.194	0.001	-0.019	-0.004
a43	-0.0114	0.004	-3.004	0.003	-0.019	-0.004
a44	0.0061	0.004	1.643	0.101	-0.001	0.013
a46	0.0076	0.004	2.165	0.031	0.001	0.015
a48	0.0128	0.004	3.564	0.000	0.006	0.020
a49	-0.0066	0.003	-1.910	0.056	-0.013	0.000
a51	0.0330	0.011	2.959	0.003	0.011	0.055
a183[0]	0.0297	0.010	2.856	0.004	0.009	0.050
a183[1]	-0.0132	0.004	-3.724	0.000	-0.020	-0.006
a53	-0.0062	0.004	-1.598	0.110	-0.014	0.001
a54	-0.0075	0.003	-2.136	0.033	-0.014	-0.001
a55	-0.0187	0.004	-4.624	0.000	-0.027	-0.011
a56	-0.0212	0.005	-4.633	0.000	-0.030	-0.012
a58	-0.0223	0.005	-4.718	0.000	-0.032	-0.013
a60	-0.0501	0.005	-10.833	0.000	-0.059	-0.041
a61	-0.0230	0.004	-5.201	0.000	-0.032	-0.014
a62	-0.0281	0.005	-6.175	0.000	-0.037	-0.019
a63	-0.0373	0.005	-8.259	0.000	-0.046	-0.028
a64	-0.0214	0.004	-5.292	0.000	-0.029	-0.013
a65	-0.0400	0.006	-6.792	0.000	-0.052	-0.028
a67	-0.0205	0.004	-4.642	0.000	-0.029	-0.012
a69	0.0168	0.004	3.882	0.000	0.008	0.025
a70	-0.0526	0.005	-10.069	0.000	-0.063	-0.042

a71	-0.0134	0.004	-3.367	0.001	-0.021	-0.006
a72	-0.0272	0.004	-6.120	0.000	-0.036	-0.018
a73	-0.0162	0.004	-4.110	0.000	-0.024	-0.008
a75	0.0109	0.004	2.897	0.004	0.004	0.018
a76	-0.0097	0.004	-2.486	0.013	-0.017	-0.002
a78	0.0068	0.004	1.871	0.062	-0.000	0.014
a89[0]	0.0257	0.004	6.233	0.000	0.018	0.034
a89[1]	0.0095	0.004	2.550	0.011	0.002	0.017
a84	0.0110	0.004	2.857	0.004	0.003	0.019
a92	0.0156	0.005	3.370	0.001	0.007	0.025
a97	-0.0192	0.007	-2.632	0.009	-0.033	-0.005
a99	0.0132	0.004	3.641	0.000	0.006	0.020
a102	-0.0331	0.005	-6.613	0.000	-0.043	-0.023
a103	-0.0120	0.004	-3.122	0.002	-0.020	-0.004
a105	-0.0688	0.025	-2.782	0.005	-0.117	-0.020
a106	-0.0125	0.006	-1.990	0.047	-0.025	-0.000
a107	-0.0574	0.024	-2.393	0.017	-0.105	-0.010
a108	-0.0104	0.005	-1.917	0.055	-0.021	0.000
a111	-0.0101	0.006	-1.773	0.076	-0.021	0.001
a142[0]	0.0155	0.005	2.915	0.004	0.005	0.026
a142[1]	-0.0028	0.005	-0.572	0.568	-0.013	0.007
a142[2]	0.0044	0.004	1.041	0.298	-0.004	0.013
a119	-0.0068	0.004	-1.878	0.061	-0.014	0.000
a135[0]	0.0134	0.015	0.864	0.388	-0.017	0.044
a135[1]	-0.0004	0.015	-0.028	0.977	-0.031	0.030
a140[0]	-0.0184	0.008	-2.331	0.020	-0.034	-0.003
a140[1]	0.0220	0.008	2.901	0.004	0.007	0.037

a126[0]	0.0028	0.007	0.408	0.684	-0.011	0.016
a126[1]	-0.0108	0.007	-1.613	0.107	-0.024	0.002
a131	0.0117	0.005	2.566	0.010	0.003	0.021
a134	0.0075	0.004	2.121	0.034	0.001	0.014
a139[0]	-0.0116	0.017	-0.672	0.502	-0.045	0.022
a139[1]	0.0227	0.017	1.340	0.180	-0.011	0.056
a148[0]	-1.351e-18	6.38e-18	-0.212	0.832	-1.39e-17	1.12e-17
a148[1]	2.633e-17	4.43e-18	5.949	0.000	1.76e-17	3.5e-17
a148[2]	0.0193	0.007	2.675	0.008	0.005	0.033
a149	0.0253	0.008	3.163	0.002	0.010	0.041
a151[0]	-8.508e-18	3.35e-18	-2.540	0.011	-1.51e-17	-1.94e-18
a151[1]	0.0051	0.004	1.211	0.226	-0.003	0.013
a151[2]	0.0089	0.004	2.480	0.013	0.002	0.016
a152	0.0143	0.006	2.290	0.022	0.002	0.027
a154	0.0123	0.004	2.826	0.005	0.004	0.021
a161[0]	0.0378	0.047	0.805	0.421	-0.054	0.130
a161[1]	0.0071	0.015	0.470	0.638	-0.022	0.036
a162[0]	0.0267	0.040	0.672	0.502	-0.051	0.104
a162[1]	-0.0056	0.019	-0.287	0.774	-0.044	0.033
a163[0]	0.0507	0.059	0.854	0.393	-0.066	0.167
a163[1]	0.0087	0.013	0.665	0.506	-0.017	0.034
a165[0]	0.0254	0.038	0.673	0.501	-0.049	0.100
a165[1]	0.0012	0.025	0.050	0.960	-0.047	0.049
a164[0]	0.0150	0.029	0.519	0.604	-0.042	0.072
a164[1]	0.0044	0.023	0.196	0.845	-0.040	0.049
a193[0]	0.0254	0.060	0.424	0.671	-0.092	0.143
a193[1]	0.0054	0.045	0.122	0.903	-0.082	0.093

a193[2]	0.0156	0.010	1.524	0.128	-0.004	0.036
a167	0.0134	0.006	2.355	0.019	0.002	0.025
a168	0.0225	0.005	4.245	0.000	0.012	0.033
a171	0.0129	0.004	2.945	0.003	0.004	0.022
a196[0]	-0.0255	0.005	-5.540	0.000	-0.035	-0.016
a196[1]	-0.0074	0.004	-1.797	0.073	-0.015	0.001
a177	0.0142	0.005	2.692	0.007	0.004	0.025
a178	-0.0248	0.003	-7.095	0.000	-0.032	-0.018
a179	-0.0120	0.004	-3.396	0.001	-0.019	-0.005
a181	-0.0111	0.004	-3.143	0.002	-0.018	-0.004
a182	-0.0150	0.004	-4.202	0.000	-0.022	-0.008
a185	-0.0092	0.004	-2.560	0.011	-0.016	-0.002
a191	0.0257	0.010	2.595	0.010	0.006	0.045
a192	0.0234	0.010	2.295	0.022	0.003	0.043
a194	0.0112	0.003	3.198	0.001	0.004	0.018
a204	0.0112	0.004	2.823	0.005	0.003	0.019
a206	0.0103	0.003	2.957	0.003	0.003	0.017
a207	-0.0139	0.004	-3.866	0.000	-0.021	-0.007

==

Omnibus:	699.187	Durbin-Watson:	1.910
Prob(Omnibus):	0.000	Jarque-Bera (JB):	14799.157
Skew:	-1.731	Prob(JB):	0.00
Kurtosis:	18.208	Cond. No.	1.42e+16

==

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 6.81e-29. This might indicate that there are

strong multicollinearity problems or that the design matrix is singular.

```
                            OLS Regression Results
==============================================================================
=====
Dep. Variable:              SalePrice   R-squared:
0.856
Model:                            OLS   Adj. R-squared:
0.853
Method:                 Least Squares   F-statistic:
256.8
Date:                Wed, 20 Apr 2022   Prob (F-statistic):
0.00
Time:                        23:36:01   Log-Likelihood:
683.13
No. Observations:                1460   AIC:                             -
1298.
Df Residuals:                    1426   BIC:                             -
1119.
Df Model:                          33
Covariance Type:            nonrobust
==============================================================================
=====
                 coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
-----
Intercept     12.0241      0.004   2996.071      0.000      12.016
12.032
a8             0.0673      0.007     10.145      0.000       0.054
0.080
a14            0.0504      0.006      8.643      0.000       0.039
0.062
a15            0.0162      0.009      1.882      0.060      -0.001
0.033
a16            0.0315      0.004      8.698      0.000       0.024
0.039
a17            0.0088      0.004      2.080      0.038       0.001
0.017
a18            0.0389      0.008      5.129      0.000       0.024
0.054
a24            0.0394      0.005      8.139      0.000       0.030
0.049
a34            0.0934      0.015      6.337      0.000       0.064
0.122
a35           -0.0372      0.004     -8.861      0.000      -0.045      -
0.029
a63           -0.0291      0.004     -7.008      0.000      -0.037      -
0.021
a70           -0.0243      0.004     -5.442      0.000      -0.033      -
0.016
a87           -0.0042      0.002     -1.981      0.048      -0.008   -
4.14e-05
```

a89[0]	0.0189	0.004	4.400	0.000	0.010	0.027
a89[1]	0.0042	0.002	1.981	0.048	4.14e-05	0.008
a102	-0.0575	0.005	-10.936	0.000	-0.068	-0.047
a109	-0.0003	0.002	-0.149	0.881	-0.004	0.004
a110	-0.0023	0.003	-0.745	0.456	-0.008	0.004
a111	0.0032	0.003	0.938	0.348	-0.003	0.010
a163[0]	0.0208	0.006	3.762	0.000	0.010	0.032
a163[1]	0.0059	0.004	1.400	0.162	-0.002	0.014
a167	-0.0031	0.002	-1.329	0.184	-0.008	0.001
a168	0.0136	0.003	4.277	0.000	0.007	0.020
a170	-0.0108	0.003	-3.092	0.002	-0.018	-0.004
a196[0]	-0.0328	0.005	-6.462	0.000	-0.043	-0.023
a196[1]	-0.0116	0.005	-2.488	0.013	-0.021	-0.002
a177	0.0294	0.006	5.031	0.000	0.018	0.041
a178	-0.0243	0.004	-5.866	0.000	-0.032	-0.016
a185	-0.0092	0.004	-2.152	0.032	-0.018	-0.001
a186	0.0277	0.007	3.899	0.000	0.014	0.042
a187	-0.0022	0.004	-0.510	0.610	-0.011	0.006
a188	0.0118	0.005	2.188	0.029	0.001	0.022
a189	-0.0038	0.004	-0.900	0.368	-0.012	0.005
a190	0.0060	0.007	0.883	0.377	-0.007	0.019
a191	0.0212	0.006	3.415	0.001	0.009	0.033
a192	0.0211	0.006	3.442	0.001	0.009	0.033
a193[0]	-0.0162	0.005	-3.160	0.002	-0.026	-0.006
a193[1]	0.0060	0.005	1.287	0.198	-0.003	0.015
a193[2]	-0.0014	0.006	-0.237	0.813	-0.013	0.010

==

```
Omnibus:                      914.363   Durbin-Watson:
1.951
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
39448.779
Skew:                          -2.287   Prob(JB):
0.00
Kurtosis:                      28.051   Cond. No.
2.18e+16
==========================================================================
=====

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The smallest eigenvalue is 1.82e-29. This might indicate that there
are
strong multicollinearity problems or that the design matrix is singular.
```

New Column Name	Old Column Name
a0	BsmtFinSF1
a1	BsmtFinSF2
a2	BsmtUnfSF
a3	TotalBsmtSF
a4	BsmtFullBath
a5	BsmtHalfBath
a6	GarageYrBlt
a7	GarageArea
a8	GarageCars
a9	MasVnrArea
a10	MSSubClass
a11	LotFrontage
a12	LotArea
a13	YearBuilt
a14	YearRemodAdd
a15	1stFlrSF
a16	2ndFlrSF
a17	LowQualFinSF
a18	GrLivArea
a19	FullBath
a20	HalfBath
a21	BedroomAbvGr
a22	KitchenAbvGr
a23	TotRmsAbvGrd
a24	Fireplaces
a25	WoodDeckSF
a26	OpenPorchSF
a27	EnclosedPorch

a28	3SsnPorch
a29	ScreenPorch
a30	PoolArea
a31	MiscVal
a32	MoSold
a33	YrSold
a34	TotalSF
a35	C (all)
a36	FV
a37	RH
a38	RL
a39	Grvl
a40	IR1
a41	IR2
a42	IR3
a43	Bnk
a44	HLS
a45	Low
a46	AllPub
a47	Corner
a48	CulDSac
a49	FR2
a50	FR3
a51	Gtl
a183	Mod
a53	Blmngtn
a54	Blueste
a55	BrDale
a56	BrkSide
a57	ClearCr
a58	CollgCr
a59	Crawfor
a60	Edwards
a61	Gilbert
a62	IDOTRR
a63	MeadowV
a64	Mitchel
a65	NAmes
a66	NPkVill
a67	NWAmes
a68	NoRidge
a69	NridgHt
a70	OldTown
a71	SWISU
a72	Sawyer

a73	SawyerW
a74	Somerst
a75	StoneBr
a76	Timber
a86	Artery
a78	Condition1_Other
a88	Feedr
a89	Norm
a90	PosA
a82	PosN
a83	RRAe
a84	RRAn
a85	RRNe
a87	Condition2_Other
a91	1Fam
a92	2fmCon
a93	Duplex
a94	Twnhs
a95	1.5Fin
a96	1.5Unf
a97	1Story
a98	2.5Fin
a99	2.5Unf
a100	2Story
a101	SFoyer
a102	OQ_Bad
a103	OC_Bad
a104	Flat
a105	Gable
a106	Gambrel
a107	Hip
a108	Mansard
a109	CompShg
a110	RoofMatl_Other
a111	Tar&Grv
a112	WdShake
a126	AsbShng
a127	AsphShn
a115	BrkComm
a142	BrkFace
a148	CBlock
a118	CemntBd
a119	Exterior1st_Other
a133	HdBoard
a135	MetalSd

a136	Plywood
a138	Stucco
a139	VinylSd
a140	Wd Sdng
a128	Brk Cmn
a131	CmentBd
a132	Exterior2nd_Other
a134	ImStucc
a151	Stone
a141	BrkCmn
a143	None
a145	ExterQualGood
a146	ExterCondGood
a147	BrkTil
a149	PConc
a150	Slab
a152	BsmtQualGood
a153	BsmtCondGood
a154	BsmtExposureGood
a161	ALQ
a162	BLQ
a163	GLQ
a164	LwQ
a165	Rec
a193	Unf
a167	GasA
a168	GasW
a169	Grav
a170	Heating_Other
a171	HeatingQCGood
a196	N
a173	Electrical_Other
a174	FuseA
a175	FuseF
a176	FuseP
a177	KitchenQualGood
a178	Functional_Other
a179	Maj1
a180	Maj2
a181	Min1
a182	Min2
a184	Sev
a185	2Types
a186	Attchd
a187	Basment

a188	BuiltIn
a189	CarPort
a190	Detchd
a191	Fin
a192	RFn
a194	GarageQualGood
a195	GarageCondGood
a197	P
a198	COD
a199	CWD
a200	Con
a201	ConLD
a202	ConLI
a203	ConLw
a204	New
a205	Oth
a206	SaleType_Other
a207	Abnorml
a208	AdjLand
a209	Alloca
a210	Family
a211	Normal