Housing_Predictions

April 22, 2018

1 Predicting Housing Prices in Ames, Iowa

1.1 Introduction

When a person is thinking about what house to buy, what are the features that come to mind? Some people want to make sure that they have a basement. Some want to make sure that they have multiple rooms. Some want to make sure that they have multiple bathrooms. Of course, there is the real estate mantra that all that matters is "Location. Location. Location." The objective of this report is to explore what features drive the Sale Price of a house the most.

1.2 Initial Data Exploration

When doing analysis with python, the first step is to load the modules that will be used. Some of the main modules are pandas which is used to manipulate datasets, numpy which is useful for some mathematical computations, matplotlib which is used for graphing and sklearn which is used for predictive modeling after the data is preprocessed.

Of course, no data can be analyzed if there is no data present. So, the first step in analyzing the data is to load the data. The data for this report is split between a train set and a test set. The train and the test set are combined into a data set and stored in a variable called houses_full. The train and the test are combined so that when variables are transformed and engineered, they will be transformed in both the train sets and the test sets. The train set contains the data of 81 different featuress for 1460 houses. The test set contains the data for 1461 houses containing the same features. Some of the features for these houses include the square footage of the entire house, the square footage of each floor including the basement if there's a basement, the number of fireplaces, the neighborhood, and the size of the garage if the house has one. All attributes are available in the Appendix #1c-e.

Further exploration reveals that both the train and test sets have missing values. However, most of these missing value are for features such as pool and fence. The obvious reason that these values are missing for these features is that these houses don't have pools or fences. In Appendix #4 all missing values for categorical variables are replaced with the word "MISSING". Categorical variables are variables that are not represented by numbers. For example, the neighborhood where the house is located is a categorical variable. Unfortunately the test set contains missing numerical data for the Masonry Veneer Area variable. In Appendix #9b all missing numerical entries are replaced with the mean of the feature.

1.3 Transforming the Data

Unfortunately, in order to make accurate predictions on the test dataset, the data cannot be used in its original state. There are some necessary tranformations that need to made in order to give the most accurate predictions. So the first step in the data transformation is to transformed skewed variables. A skew can be seen in the target variable `SalePrice`. In the graph in Appendix #3a the positive skew is evident. The positive skew means that most of the prices for the houses are lower in price while there a smaller amount of home prices being more expensive. For analysis purposes in Appendix #3c, a log+1 transformation is applied to all numeric variables including the `SalePrice` variable. The result is that all numeric variables will be more normally distributed. This means that most home prices will have a middle value with the other prices being equally more expensive or less expensive. Essentially, the new numeric data is more evenly distributed. This effect can be seen on the `SalePrice` variable in Appendix #3d.

The next step in the transformation is to change the categorical variables. So all variables that are not represented as a numeric value, will be converted to a numeric value. For example, the name of the neighborhood where the house is located will no longer be represented by a name. It will be represented as a number. This transformation is shown in Appendix #5. Not only are these variables converted to numbers, but they're labels now include `_E` in order to distinguish them from the original variables. The effect of the transformation is shown in Appendix #5a-3.

Once these transformations are complete, the next step in building a predictive model is to select the correct features from the dataset. The dataset starts with 81 different variables. However, not all of these variables will be helpful when trying to predict the price of a home. So correlations between the `SalePrice` variable and the other variables are checked, in order to discover which features will help predict the value of a home. The correlations between `SalePrice` and the other variables are shown in Appendix #6b - Appendix #6g. The top correlated categorical variables are shown in Appendix #6b, #6d and #6e. The top numerical variables are shown in Appendix #6c, #6f and #6g. These correlation tables show that the top correlated features are the overall quality of the house, the square footage of the living area, the neighborhood, the amount of cars that fit in the garage and lots of other features. The top 25 categorical features and the top 25 numerical features are selected from the full dataset, train set and test set. These are the variables that will be used when building the predictive model.

It would be great if all the variables that are present in the dataset are the only variables that would help predict home prices. Unfortunately some data will need to be "engineered" or created in order to create the most accurate model. Some of the features that can be created are created from some features that are collinear. Collinear features are features that pretty evenly move with the target variable. For example, the square footage of the first floor is generally close to the square footage of the second floor if there is one present. So the square footage of the first and second floor are said to be collinear. However, having a second floor may change the price of a house. Having a basement may change the price of the house as well. Appendix #7b shows the creation of features to show whether the house, has a basement, has a garage, has a second floor, has an open porch, has a screen porch, has a fire place, has a masonry veneer, has a wood deck, has a pool, has a basement bathroom, has an extra bathroom, or is new.

With the data transformed, new data created, and the appropriate features selected, there is only one step left before the predictive models can be created. That is to remove outliers. Since, the square footage of the general living area is an important variable, it would be helpful to remove outliers. There are two obvious outliers, which can be seen in Appendix #8a. These outliers are removed and the data is ready for modeling.

1.4 Predictive Modeling

The first step in creating the predictive model is to get dummy variables for the categorical features. Explaining a dummy variable is best done with an example. For the neighborhood variable, for example, each neighborhood becomes its own column. If the house is in that neighborhood, the dummy variable will show a 1. If the house is not in that neighborhood, the dummy variable will show a 0. This step is shown in Appendix #9a. Once the dummy variables are created, the data is partitioned. The data that is going to be used to build the model is stored in the variable `train_subset`. The data stored in this variable is separated into its own train set and test set. The train set contains 70% of the data in `train_subset` and will be used to build the model. The test set contains the remaining 30% of the data and will be used to test the model.

Next four different machine learning algorithms are used to model the data. These models include a Linear Regression model, a Lasso model, a Ridge model and an ElasticNet model. Each of these models has a graph accompanying it, which compares the predictions with the actual selling price. The Lasso model is the final choice for making predictions on the competition test set.

1.5 Conclusion

After doing this thorough analysis on the housing data in Ames, Iowa, a few conclusions can be made. In the predictive modeling section of this report, the features that have the most effect on the price of a house can be determined. The graphs in Appendix #9 show which variables have the greatest impact. This analysis determined that the selling price of a home in Ames, Iowa is most influenced by the size of the general living area, whether the house has a basement, deck, second floor, extra bathrooms, a garage, a fire place or open porch, the size of additional floors and basements, and the overall quality of the house. Although the real estate agents are right when it comes to "Location. Location. Location," this analysis shows that there are more important criteria when determining the price of a house.

1.6 Appendix

1.6.1 1. Initial Data Exploration

1a. Loading Modules

```
In [119]: import pandas as pd
          import numpy as np
          import matplotlib.pyplot as plt
          import scipy.stats as stats
          import seaborn as sns
          from IPython.display import HTML, display
          from sklearn.manifold import TSNE
          from sklearn.cluster import KMeans
          from sklearn.decomposition import PCA
          from sklearn.model_selection import cross_val_score, train_test_split
          from sklearn.preprocessing import StandardScaler
          from sklearn.linear_model import LinearRegression, RidgeCV, LassoCV, ElasticNetCV, L
          from sklearn.ensemble import RandomForestRegressor
          from sklearn.metrics import mean_squared_error, make_scorer
```

```
from sklearn.preprocessing import StandardScaler
%matplotlib inline
```

1b. Loading Data

```
In [120]: houses_train = pd.read_csv('train.csv')
          houses_test = pd.read_csv('test.csv')
          houses_full = houses_train.append(houses_test, ignore_index = True)
          houses = houses_full[ :1460]
          test = houses_full[1460: ]
```

1c. Inspecting Data

1c-1. Training Data

```
In [121]: houses.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
Data columns (total 81 columns):
1stFlrSF         1460 non-null int64
2ndFlrSF         1460 non-null int64
3SsnPorch        1460 non-null int64
Alley            91 non-null object
BedroomAbvGr     1460 non-null int64
BldgType         1460 non-null object
BsmtCond         1423 non-null object
BsmtExposure     1422 non-null object
BsmtFinSF1       1460 non-null float64
BsmtFinSF2       1460 non-null float64
BsmtFinType1     1423 non-null object
BsmtFinType2     1422 non-null object
BsmtFullBath     1460 non-null float64
BsmtHalfBath     1460 non-null float64
BsmtQual         1423 non-null object
BsmtUnfSF        1460 non-null float64
CentralAir       1460 non-null object
Condition1       1460 non-null object
Condition2       1460 non-null object
Electrical       1459 non-null object
EnclosedPorch    1460 non-null int64
ExterCond        1460 non-null object
ExterQual        1460 non-null object
Exterior1st      1460 non-null object
Exterior2nd      1460 non-null object
Fence            281 non-null object
FireplaceQu      770 non-null object
Fireplaces       1460 non-null int64
```

```
Foundation       1460 non-null object
FullBath         1460 non-null int64
Functional       1460 non-null object
GarageArea       1460 non-null float64
GarageCars       1460 non-null float64
GarageCond       1379 non-null object
GarageFinish     1379 non-null object
GarageQual       1379 non-null object
GarageType       1379 non-null object
GarageYrBlt      1379 non-null float64
GrLivArea        1460 non-null int64
HalfBath         1460 non-null int64
Heating          1460 non-null object
HeatingQC        1460 non-null object
HouseStyle       1460 non-null object
Id               1460 non-null int64
KitchenAbvGr     1460 non-null int64
KitchenQual      1460 non-null object
LandContour      1460 non-null object
LandSlope        1460 non-null object
LotArea          1460 non-null int64
LotConfig        1460 non-null object
LotFrontage      1201 non-null float64
LotShape         1460 non-null object
LowQualFinSF     1460 non-null int64
MSSubClass       1460 non-null int64
MSZoning         1460 non-null object
MasVnrArea       1452 non-null float64
MasVnrType       1452 non-null object
MiscFeature      54 non-null object
MiscVal          1460 non-null int64
MoSold           1460 non-null int64
Neighborhood     1460 non-null object
OpenPorchSF      1460 non-null int64
OverallCond      1460 non-null int64
OverallQual      1460 non-null int64
PavedDrive       1460 non-null object
PoolArea         1460 non-null int64
PoolQC           7 non-null object
RoofMatl         1460 non-null object
RoofStyle        1460 non-null object
SaleCondition    1460 non-null object
SalePrice        1460 non-null float64
SaleType         1460 non-null object
ScreenPorch      1460 non-null int64
Street           1460 non-null object
TotRmsAbvGrd     1460 non-null int64
TotalBsmtSF      1460 non-null float64
```

```
Utilities        1460 non-null object
WoodDeckSF       1460 non-null int64
YearBuilt        1460 non-null int64
YearRemodAdd     1460 non-null int64
YrSold           1460 non-null int64
dtypes: float64(12), int64(26), object(43)
memory usage: 924.0+ KB
```

1c-2. Test Data

```
In [122]: test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1459 entries, 1460 to 2918
Data columns (total 81 columns):
1stFlrSF         1459 non-null int64
2ndFlrSF         1459 non-null int64
3SsnPorch        1459 non-null int64
Alley            107 non-null object
BedroomAbvGr     1459 non-null int64
BldgType         1459 non-null object
BsmtCond         1414 non-null object
BsmtExposure     1415 non-null object
BsmtFinSF1       1458 non-null float64
BsmtFinSF2       1458 non-null float64
BsmtFinType1     1417 non-null object
BsmtFinType2     1417 non-null object
BsmtFullBath     1457 non-null float64
BsmtHalfBath     1457 non-null float64
BsmtQual         1415 non-null object
BsmtUnfSF        1458 non-null float64
CentralAir       1459 non-null object
Condition1       1459 non-null object
Condition2       1459 non-null object
Electrical       1459 non-null object
EnclosedPorch    1459 non-null int64
ExterCond        1459 non-null object
ExterQual        1459 non-null object
Exterior1st      1458 non-null object
Exterior2nd      1458 non-null object
Fence            290 non-null object
FireplaceQu      729 non-null object
Fireplaces       1459 non-null int64
Foundation       1459 non-null object
FullBath         1459 non-null int64
Functional       1457 non-null object
GarageArea       1458 non-null float64
```

```
GarageCars       1458 non-null float64
GarageCond       1381 non-null object
GarageFinish     1381 non-null object
GarageQual       1381 non-null object
GarageType       1383 non-null object
GarageYrBlt      1381 non-null float64
GrLivArea        1459 non-null int64
HalfBath         1459 non-null int64
Heating          1459 non-null object
HeatingQC        1459 non-null object
HouseStyle       1459 non-null object
Id               1459 non-null int64
KitchenAbvGr     1459 non-null int64
KitchenQual      1458 non-null object
LandContour      1459 non-null object
LandSlope        1459 non-null object
LotArea          1459 non-null int64
LotConfig        1459 non-null object
LotFrontage      1232 non-null float64
LotShape         1459 non-null object
LowQualFinSF     1459 non-null int64
MSSubClass       1459 non-null int64
MSZoning         1455 non-null object
MasVnrArea       1444 non-null float64
MasVnrType       1443 non-null object
MiscFeature      51 non-null object
MiscVal          1459 non-null int64
MoSold           1459 non-null int64
Neighborhood     1459 non-null object
OpenPorchSF      1459 non-null int64
OverallCond      1459 non-null int64
OverallQual      1459 non-null int64
PavedDrive       1459 non-null object
PoolArea         1459 non-null int64
PoolQC           3 non-null object
RoofMatl         1459 non-null object
RoofStyle        1459 non-null object
SaleCondition    1459 non-null object
SalePrice        0 non-null float64
SaleType         1458 non-null object
ScreenPorch      1459 non-null int64
Street           1459 non-null object
TotRmsAbvGrd     1459 non-null int64
TotalBsmtSF      1458 non-null float64
Utilities        1457 non-null object
WoodDeckSF       1459 non-null int64
YearBuilt        1459 non-null int64
YearRemodAdd     1459 non-null int64
```

```
YrSold           1459 non-null int64
dtypes: float64(12), int64(26), object(43)
memory usage: 923.4+ KB
```

1c-3. Full Data Set

```
In [123]: houses_full.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2919 entries, 0 to 2918
Data columns (total 81 columns):
1stFlrSF         2919 non-null int64
2ndFlrSF         2919 non-null int64
3SsnPorch        2919 non-null int64
Alley            198 non-null object
BedroomAbvGr     2919 non-null int64
BldgType         2919 non-null object
BsmtCond         2837 non-null object
BsmtExposure     2837 non-null object
BsmtFinSF1       2918 non-null float64
BsmtFinSF2       2918 non-null float64
BsmtFinType1     2840 non-null object
BsmtFinType2     2839 non-null object
BsmtFullBath     2917 non-null float64
BsmtHalfBath     2917 non-null float64
BsmtQual         2838 non-null object
BsmtUnfSF        2918 non-null float64
CentralAir       2919 non-null object
Condition1       2919 non-null object
Condition2       2919 non-null object
Electrical       2918 non-null object
EnclosedPorch    2919 non-null int64
ExterCond        2919 non-null object
ExterQual        2919 non-null object
Exterior1st      2918 non-null object
Exterior2nd      2918 non-null object
Fence            571 non-null object
FireplaceQu      1499 non-null object
Fireplaces       2919 non-null int64
Foundation       2919 non-null object
FullBath         2919 non-null int64
Functional       2917 non-null object
GarageArea       2918 non-null float64
GarageCars       2918 non-null float64
GarageCond       2760 non-null object
GarageFinish     2760 non-null object
GarageQual       2760 non-null object
```

```
GarageType       2762 non-null object
GarageYrBlt      2760 non-null float64
GrLivArea        2919 non-null int64
HalfBath         2919 non-null int64
Heating          2919 non-null object
HeatingQC        2919 non-null object
HouseStyle       2919 non-null object
Id               2919 non-null int64
KitchenAbvGr     2919 non-null int64
KitchenQual      2918 non-null object
LandContour      2919 non-null object
LandSlope        2919 non-null object
LotArea          2919 non-null int64
LotConfig        2919 non-null object
LotFrontage      2433 non-null float64
LotShape         2919 non-null object
LowQualFinSF     2919 non-null int64
MSSubClass       2919 non-null int64
MSZoning         2915 non-null object
MasVnrArea       2896 non-null float64
MasVnrType       2895 non-null object
MiscFeature      105 non-null object
MiscVal          2919 non-null int64
MoSold           2919 non-null int64
Neighborhood     2919 non-null object
OpenPorchSF      2919 non-null int64
OverallCond      2919 non-null int64
OverallQual      2919 non-null int64
PavedDrive       2919 non-null object
PoolArea         2919 non-null int64
PoolQC           10 non-null object
RoofMatl         2919 non-null object
RoofStyle        2919 non-null object
SaleCondition    2919 non-null object
SalePrice        1460 non-null float64
SaleType         2918 non-null object
ScreenPorch      2919 non-null int64
Street           2919 non-null object
TotRmsAbvGrd     2919 non-null int64
TotalBsmtSF      2918 non-null float64
Utilities        2917 non-null object
WoodDeckSF       2919 non-null int64
YearBuilt        2919 non-null int64
YearRemodAdd     2919 non-null int64
YrSold           2919 non-null int64
dtypes: float64(12), int64(26), object(43)
memory usage: 1.8+ MB
```

1d. Viewing Numerical Data

1d-1. Training Data

```
In [124]: houses.describe()
```

```
Out[124]:          1stFlrSF     2ndFlrSF    3SsnPorch  BedroomAbvGr   BsmtFinSF1  \
          count  1460.000000  1460.000000  1460.000000   1460.000000  1460.000000
          mean   1162.626712   346.992466     3.409589      2.866438   443.639726
          std     386.587738   436.528436    29.317331      0.815778   456.098091
          min     334.000000     0.000000     0.000000      0.000000     0.000000
          25%     882.000000     0.000000     0.000000      2.000000     0.000000
          50%    1087.000000     0.000000     0.000000      3.000000   383.500000
          75%    1391.250000   728.000000     0.000000      3.000000   712.250000
          max    4692.000000  2065.000000   508.000000      8.000000  5644.000000

                  BsmtFinSF2  BsmtFullBath  BsmtHalfBath    BsmtUnfSF  EnclosedPorch  \
          count  1460.000000   1460.000000   1460.000000  1460.000000    1460.000000
          mean     46.549315      0.425342      0.057534   567.240411      21.954110
          std     161.319273      0.518911      0.238753   441.866955      61.119149
          min       0.000000      0.000000      0.000000     0.000000       0.000000
          25%       0.000000      0.000000      0.000000   223.000000       0.000000
          50%       0.000000      0.000000      0.000000   477.500000       0.000000
          75%       0.000000      1.000000      0.000000   808.000000       0.000000
          max    1474.000000      3.000000      2.000000  2336.000000     552.000000

                      ...    OverallQual     PoolArea      SalePrice  ScreenPorch  \
          count       ...    1460.000000  1460.000000    1460.000000  1460.000000
          mean        ...       6.099315     2.758904  180921.195890    15.060959
          std         ...       1.382997    40.177307   79442.502883    55.757415
          min         ...       1.000000     0.000000   34900.000000     0.000000
          25%         ...       5.000000     0.000000  129975.000000     0.000000
          50%         ...       6.000000     0.000000  163000.000000     0.000000
          75%         ...       7.000000     0.000000  214000.000000     0.000000
          max         ...      10.000000   738.000000  755000.000000   480.000000

                  TotRmsAbvGrd  TotalBsmtSF   WoodDeckSF    YearBuilt  YearRemodAdd  \
          count    1460.000000  1460.000000  1460.000000  1460.000000   1460.000000
          mean        6.517808  1057.429452    94.244521  1971.267808   1984.865753
          std         1.625393   438.705324   125.338794    30.202904     20.645407
          min         2.000000     0.000000     0.000000  1872.000000   1950.000000
          25%         5.000000   795.750000     0.000000  1954.000000   1967.000000
          50%         6.000000   991.500000     0.000000  1973.000000   1994.000000
          75%         7.000000  1298.250000   168.000000  2000.000000   2004.000000
          max        14.000000  6110.000000   857.000000  2010.000000   2010.000000

                      YrSold
          count  1460.000000
```

```
mean   2007.815753
std       1.328095
min    2006.000000
25%    2007.000000
50%    2008.000000
75%    2009.000000
max    2010.000000

[8 rows x 38 columns]
```

1d-2. Test Data

In [125]: `test.describe()`

Out[125]:

```
          1stFlrSF     2ndFlrSF     3SsnPorch  BedroomAbvGr   BsmtFinSF1  \
count  1459.000000  1459.000000  1459.000000   1459.000000  1458.000000
mean   1156.534613   325.967786     1.794380      2.854010   439.203704
std     398.165820   420.610226    20.207842      0.829788   455.268042
min     407.000000     0.000000     0.000000      0.000000     0.000000
25%     873.500000     0.000000     0.000000      2.000000     0.000000
50%    1079.000000     0.000000     0.000000      3.000000   350.500000
75%    1382.500000   676.000000     0.000000      3.000000   753.500000
max    5095.000000  1862.000000   360.000000      6.000000  4010.000000

        BsmtFinSF2  BsmtFullBath  BsmtHalfBath    BsmtUnfSF  EnclosedPorch  \
count  1458.000000   1457.000000   1457.000000  1458.000000    1459.000000
mean     52.619342      0.434454      0.065202   554.294925      24.243317
std     176.753926      0.530648      0.252468   437.260486      67.227765
min       0.000000      0.000000      0.000000     0.000000       0.000000
25%       0.000000      0.000000      0.000000   219.250000       0.000000
50%       0.000000      0.000000      0.000000   460.000000       0.000000
75%       0.000000      1.000000      0.000000   797.750000       0.000000
max    1526.000000      3.000000      2.000000  2140.000000    1012.000000

           ...      OverallQual     PoolArea  SalePrice  ScreenPorch  \
count      ...      1459.000000  1459.000000        0.0  1459.000000
mean       ...         6.078821     1.744345        NaN    17.064428
std        ...         1.436812    30.491646        NaN    56.609763
min        ...         1.000000     0.000000        NaN     0.000000
25%        ...         5.000000     0.000000        NaN     0.000000
50%        ...         6.000000     0.000000        NaN     0.000000
75%        ...         7.000000     0.000000        NaN     0.000000
max        ...        10.000000   800.000000        NaN   576.000000

       TotRmsAbvGrd  TotalBsmtSF   WoodDeckSF    YearBuilt  YearRemodAdd  \
count   1459.000000  1458.000000  1459.000000  1459.000000   1459.000000
mean       6.385195  1046.117970    93.174777  1971.357779   1983.662783
std        1.508895   442.898624   127.744882    30.390071     21.130467
```

```
min         3.000000     0.000000     0.000000  1879.000000   1950.000000
25%         5.000000   784.000000     0.000000  1953.000000   1963.000000
50%         6.000000   988.000000     0.000000  1973.000000   1992.000000
75%         7.000000  1305.000000   168.000000  2001.000000   2004.000000
max        15.000000  5095.000000  1424.000000  2010.000000   2010.000000

            YrSold
count  1459.000000
mean   2007.769705
std       1.301740
min    2006.000000
25%    2007.000000
50%    2008.000000
75%    2009.000000
max    2010.000000

[8 rows x 38 columns]
```

1d-3. Full Data Set

```
In [126]: houses_full.describe()
```

```
Out[126]:           1stFlrSF     2ndFlrSF    3SsnPorch  BedroomAbvGr   BsmtFinSF1  \
          count  2919.000000  2919.000000  2919.000000   2919.000000  2918.000000
          mean   1159.581706   336.483727     2.602261      2.860226   441.423235
          std     392.362079   428.701456    25.188169      0.822693   455.610826
          min     334.000000     0.000000     0.000000      0.000000     0.000000
          25%     876.000000     0.000000     0.000000      2.000000     0.000000
          50%    1082.000000     0.000000     0.000000      3.000000   368.500000
          75%    1387.500000   704.000000     0.000000      3.000000   733.000000
          max    5095.000000  2065.000000   508.000000      8.000000  5644.000000

                  BsmtFinSF2  BsmtFullBath  BsmtHalfBath    BsmtUnfSF  EnclosedPorch  \
          count  2918.000000   2917.000000   2917.000000  2918.000000    2919.000000
          mean     49.582248      0.429894      0.061364   560.772104      23.098321
          std     169.205611      0.524736      0.245687   439.543659      64.244246
          min       0.000000      0.000000      0.000000     0.000000       0.000000
          25%       0.000000      0.000000      0.000000   220.000000       0.000000
          50%       0.000000      0.000000      0.000000   467.000000       0.000000
          75%       0.000000      1.000000      0.000000   805.500000       0.000000
          max    1526.000000      3.000000      2.000000  2336.000000    1012.000000

                     ...     OverallQual     PoolArea      SalePrice  ScreenPorch  \
          count      ...     2919.000000  2919.000000    1460.000000  2919.000000
          mean       ...        6.089072     2.251799  180921.195890    16.062350
          std        ...        1.409947    35.663946   79442.502883    56.184365
          min        ...        1.000000     0.000000   34900.000000     0.000000
          25%        ...        5.000000     0.000000  129975.000000     0.000000
```

```
50%         ...          6.000000      0.000000  163000.000000      0.000000
75%         ...          7.000000      0.000000  214000.000000      0.000000
max         ...         10.000000    800.000000  755000.000000    576.000000

       TotRmsAbvGrd  TotalBsmtSF   WoodDeckSF    YearBuilt  YearRemodAdd  \
count   2919.000000  2918.000000  2919.000000  2919.000000   2919.000000
mean       6.451524  1051.777587    93.709832  1971.312778   1984.264474
std        1.569379   440.766258   126.526589    30.291442     20.894344
min        2.000000     0.000000     0.000000  1872.000000   1950.000000
25%        5.000000   793.000000     0.000000  1953.500000   1965.000000
50%        6.000000   989.500000     0.000000  1973.000000   1993.000000
75%        7.000000  1302.000000   168.000000  2001.000000   2004.000000
max       15.000000  6110.000000  1424.000000  2010.000000   2010.000000

            YrSold
count  2919.000000
mean   2007.792737
std       1.314964
min    2006.000000
25%    2007.000000
50%    2008.000000
75%    2009.000000
max    2010.000000

[8 rows x 38 columns]
```

1e. Top Rows of Data

```
In [127]: houses.head(10)
```

```
Out[127]:    1stFlrSF  2ndFlrSF  3SsnPorch Alley  BedroomAbvGr BldgType BsmtCond  \
          0       856       854          0   NaN             3     1Fam       TA
          1      1262         0          0   NaN             3     1Fam       TA
          2       920       866          0   NaN             3     1Fam       TA
          3       961       756          0   NaN             3     1Fam       Gd
          4      1145      1053          0   NaN             4     1Fam       TA
          5       796       566        320   NaN             1     1Fam       TA
          6      1694         0          0   NaN             3     1Fam       TA
          7      1107       983          0   NaN             3     1Fam       TA
          8      1022       752          0   NaN             2     1Fam       TA
          9      1077         0          0   NaN             2   2fmCon       TA

            BsmtExposure  BsmtFinSF1  BsmtFinSF2  ...  SaleType ScreenPorch  Street  \
          0           No       706.0         0.0  ...        WD           0    Pave
          1           Gd       978.0         0.0  ...        WD           0    Pave
          2           Mn       486.0         0.0  ...        WD           0    Pave
          3           No       216.0         0.0  ...        WD           0    Pave
          4           Av       655.0         0.0  ...        WD           0    Pave
```

```
5           No       732.0         0.0  ...         WD            0    Pave
6           Av      1369.0         0.0  ...         WD            0    Pave
7           Mn       859.0        32.0  ...         WD            0    Pave
8           No         0.0         0.0  ...         WD            0    Pave
9           No       851.0         0.0  ...         WD            0    Pave

   TotRmsAbvGrd TotalBsmtSF  Utilities WoodDeckSF YearBuilt YearRemodAdd  \
0             8       856.0     AllPub          0      2003         2003
1             6      1262.0     AllPub        298      1976         1976
2             6       920.0     AllPub          0      2001         2002
3             7       756.0     AllPub          0      1915         1970
4             9      1145.0     AllPub        192      2000         2000
5             5       796.0     AllPub         40      1993         1995
6             7      1686.0     AllPub        255      2004         2005
7             7      1107.0     AllPub        235      1973         1973
8             8       952.0     AllPub         90      1931         1950
9             5       991.0     AllPub          0      1939         1950

  YrSold
0   2008
1   2007
2   2008
3   2006
4   2008
5   2009
6   2007
7   2009
8   2008
9   2008

[10 rows x 81 columns]
```

1.6.2 2. Finding Missing Values

2a. Train Set

In [128]:

```
train_nan = houses.isnull().sum().sort_values(ascending=False)
percent_nan = (houses.isnull().sum()/houses.isnull().count()).sort_values(ascending=F
missing_table = pd.concat([train_nan, percent_nan], axis=1, keys=['Total', 'Percent']
missing_table.head(25)
```

Out[128]:

	Total	Percent
PoolQC	1453	0.995205
MiscFeature	1406	0.963014
Alley	1369	0.937671
Fence	1179	0.807534
FireplaceQu	690	0.472603
LotFrontage	259	0.177397
GarageFinish	81	0.055479

```
GarageCond        81  0.055479
GarageYrBlt       81  0.055479
GarageQual        81  0.055479
GarageType        81  0.055479
BsmtExposure      38  0.026027
BsmtFinType2      38  0.026027
BsmtCond          37  0.025342
BsmtFinType1      37  0.025342
BsmtQual          37  0.025342
MasVnrArea         8  0.005479
MasVnrType         8  0.005479
Electrical         1  0.000685
Condition1         0  0.000000
Condition2         0  0.000000
2ndFlrSF           0  0.000000
3SsnPorch          0  0.000000
BedroomAbvGr       0  0.000000
GarageCars         0  0.000000
```

2b. Test Set

In [129]:
```
test_nan = test.isnull().sum().sort_values(ascending=False)
percent_nan = (test.isnull().sum()/test.isnull().count()).sort_values(ascending=Fals
missing_table = pd.concat([test_nan, percent_nan], axis=1, keys=['Total', 'Percent']
missing_table.head(25)
```

Out[129]:

	Total	Percent
SalePrice	1459	1.000000
PoolQC	1456	0.997944
MiscFeature	1408	0.965045
Alley	1352	0.926662
Fence	1169	0.801234
FireplaceQu	730	0.500343
LotFrontage	227	0.155586
GarageYrBlt	78	0.053461
GarageQual	78	0.053461
GarageFinish	78	0.053461
GarageCond	78	0.053461
GarageType	76	0.052090
BsmtCond	45	0.030843
BsmtQual	44	0.030158
BsmtExposure	44	0.030158
BsmtFinType2	42	0.028787
BsmtFinType1	42	0.028787
MasVnrType	16	0.010966
MasVnrArea	15	0.010281
MSZoning	4	0.002742
BsmtFullBath	2	0.001371

```
BsmtHalfBath      2  0.001371
Functional        2  0.001371
Utilities         2  0.001371
Exterior2nd       1  0.000685
```

1.6.3 3. Transforming Skewed Data

3a. Sale Price Distribution

```
In [130]: ax = sns.distplot(houses['SalePrice'])
          ax.set_xlabel('Sale Price')
          ax.set_ylabel('Count')
          ax.set_title('Distribution of Sale Price')
          plt.show()
```

3b. Separating Variables

```
In [131]: categorical = houses_full.select_dtypes(include = ['object']).columns
          numerical = houses_full.select_dtypes(exclude = ["object"]).columns
          numerical = numerical.drop('Id')
          print('Categorical: ' + str(len(categorical)))
          print('Numerical: ' + str(len(numerical)))
```

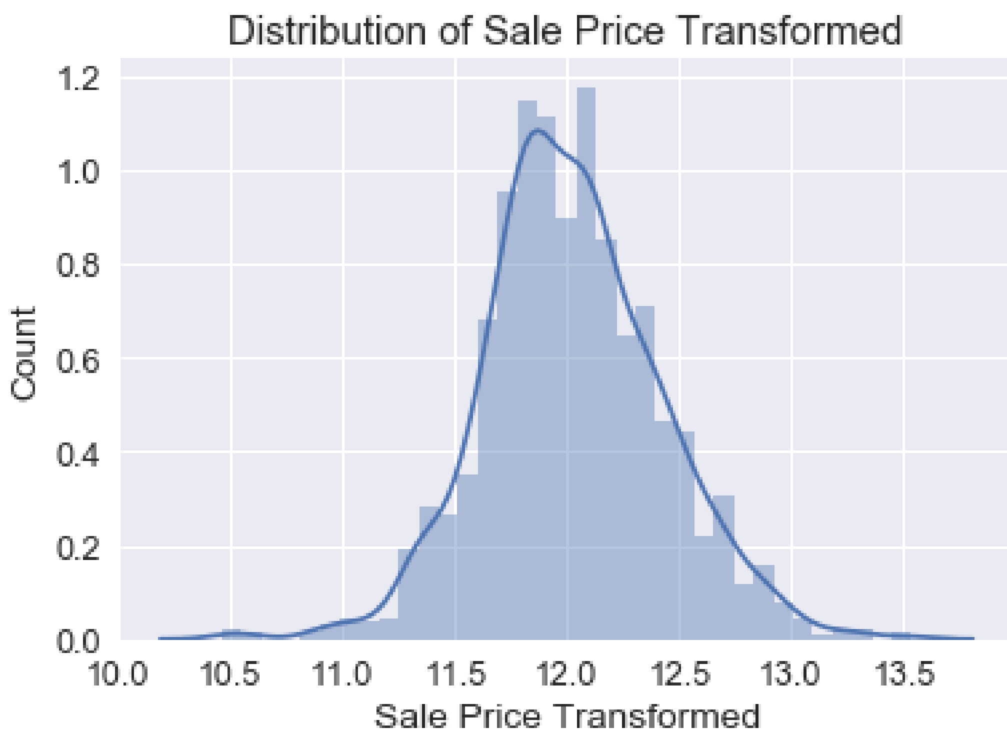
```
Categorical: 43
Numerical: 37
```

3c. Transforming Skewed Features

```
In [132]: skewed = houses_full[numerical].apply(lambda x: stats.skew(x.dropna()))
          skewed = skewed[skewed > 0.75]
          skewed = skewed.index
          houses_full[skewed] = np.log1p(houses_full[skewed])
```

3d. Sale Price Distribution Transformed

```
In [133]: houses = houses_full[ :1460]
          ax = sns.distplot(houses['SalePrice'])
          ax.set_xlabel('Sale Price Transformed')
          ax.set_ylabel('Count')
          ax.set_title('Distribution of Sale Price Transformed')
          plt.show()
```



1.6.4 4. Filling Missing Categorical Variables

```
In [134]: for feature in houses_full[categorical]:
                  houses_full[feature] = houses_full[feature].astype('category')
                  if houses_full[feature].isnull().any():
                      houses_full[feature] = houses_full[feature].cat.add_categories(['MISSING
                      houses_full[feature] = houses_full[feature].fillna('MISSING')

          houses_full.head()
```

```
Out[134]:    1stFlrSF  2ndFlrSF  3SsnPorch    Alley  BedroomAbvGr BldgType BsmtCond  \
          0  6.753438  6.751101        0.0  MISSING             3     1Fam       TA
          1  7.141245  0.000000        0.0  MISSING             3     1Fam       TA
          2  6.825460  6.765039        0.0  MISSING             3     1Fam       TA
          3  6.869014  6.629363        0.0  MISSING             3     1Fam       Gd
          4  7.044033  6.960348        0.0  MISSING             4     1Fam       TA

            BsmtExposure  BsmtFinSF1  BsmtFinSF2  ...   SaleType ScreenPorch  Street  \
          0           No    6.561031         0.0  ...         WD         0.0    Pave
          1           Gd    6.886532         0.0  ...         WD         0.0    Pave
          2           Mn    6.188264         0.0  ...         WD         0.0    Pave
          3           No    5.379897         0.0  ...         WD         0.0    Pave
          4           Av    6.486161         0.0  ...         WD         0.0    Pave

             TotRmsAbvGrd TotalBsmtSF  Utilities WoodDeckSF YearBuilt YearRemodAdd  \
          0      2.197225    6.753438     AllPub   0.000000      2003         2003
          1      1.945910    7.141245     AllPub   5.700444      1976         1976
          2      1.945910    6.825460     AllPub   0.000000      2001         2002
          3      2.079442    6.629363     AllPub   0.000000      1915         1970
          4      2.302585    7.044033     AllPub   5.262690      2000         2000

            YrSold
          0   2008
          1   2007
          2   2008
          3   2006
          4   2008

          [5 rows x 81 columns]
```

1.6.5 5. Encoding Categorical Variables

```
In [135]: def encode(frame, feature):
              ordering = pd.DataFrame()
              ordering['val'] = frame[feature].unique()
              ordering.index = ordering.val
              ordering['spmean'] = frame[[feature, 'SalePrice']].groupby(feature).mean()['SaleI
              ordering = ordering.sort_values('spmean')
              ordering['ordering'] = range(1, ordering.shape[0]+1)
              ordering = ordering['ordering'].to_dict()

              for cat, o in ordering.items():
                  frame.loc[frame[feature] == cat, feature+'_E'] = o

          qual_encoded = []
          for q in categorical:
              encode(houses_full, q)
              qual_encoded.append(q+'_E')
```

```
print(qual_encoded)
```

```
['Alley_E', 'BldgType_E', 'BsmtCond_E', 'BsmtExposure_E', 'BsmtFinType1_E', 'BsmtFinType2_E',
```

5a. Viewing Encoding Transformation

5a-1. Train Set

In [136]:
```
houses = houses_full[ :1460]
houses.describe()
```

Out[136]:
```
          1stFlrSF     2ndFlrSF    3SsnPorch  BedroomAbvGr   BsmtFinSF1  \
count  1460.000000  1460.000000  1460.000000   1460.000000  1460.000000
mean      7.008452     2.864586     0.085679      2.866438     4.229731
std       0.317431     3.293311     0.666876      0.815778     2.992052
min       5.814131     0.000000     0.000000      0.000000     0.000000
25%       6.783325     0.000000     0.000000      2.000000     0.000000
50%       6.992096     0.000000     0.000000      3.000000     5.951943
75%       7.238676     6.591674     0.000000      3.000000     6.569832
max       8.453827     7.633370     6.232448      8.000000     8.638525

        BsmtFinSF2  BsmtFullBath  BsmtHalfBath    BsmtUnfSF  EnclosedPorch  \
count  1460.000000   1460.000000   1460.000000  1460.000000    1460.000000
mean      0.655398      0.425342      0.039486     5.648378       0.698019
std       1.845045      0.518911      0.162599     1.854020       1.727317
min       0.000000      0.000000      0.000000     0.000000       0.000000
25%       0.000000      0.000000      0.000000     5.411646       0.000000
50%       0.000000      0.000000      0.000000     6.170651       0.000000
75%       0.000000      1.000000      0.000000     6.695799       0.000000
max       7.296413      3.000000      1.098612     7.756623       6.315358

          ...     MiscFeature_E  Neighborhood_E  PavedDrive_E     PoolQC_E  \
count     ...       1460.000000     1460.000000   1460.000000  1460.000000
mean      ...          2.966438       12.860274      2.856164     1.008904
std       ...          0.205069        6.409677      0.496592     0.140703
min       ...          1.000000        1.000000      1.000000     1.000000
25%       ...          3.000000        7.000000      3.000000     1.000000
50%       ...          3.000000       13.000000      3.000000     1.000000
75%       ...          3.000000       17.000000      3.000000     1.000000
max       ...          5.000000       25.000000      3.000000     4.000000

        RoofMatl_E  RoofStyle_E  SaleCondition_E   SaleType_E     Street_E  \
count  1460.000000  1460.000000      1460.000000  1460.000000  1460.000000
mean      3.040411     2.608219         4.831507     5.204795     1.995890
std       0.395845     1.209938         0.887253     0.929955     0.063996
min       1.000000     1.000000         1.000000     1.000000     1.000000
25%       3.000000     2.000000         5.000000     5.000000     2.000000
```

```
50%        3.000000     2.000000          5.000000     5.000000     2.000000
75%        3.000000     2.000000          5.000000     5.000000     2.000000
max        8.000000     6.000000          6.000000     9.000000     2.000000

       Utilities_E
count  1460.000000
mean      1.999315
std       0.026171
min       1.000000
25%       2.000000
50%       2.000000
75%       2.000000
max       2.000000

[8 rows x 81 columns]
```

5a-2. Test Set

In [137]:
```python
test = houses_full[1460: ]
test.describe()
```

Out[137]:
```
          1stFlrSF     2ndFlrSF    3SsnPorch  BedroomAbvGr   BsmtFinSF1  \
count  1459.000000  1459.000000  1459.000000   1459.000000  1458.000000
mean      6.999917     2.794559     0.046702      2.854010     4.223071
std       0.327842     3.261396     0.493994      0.829788     2.971567
min       6.011267     0.000000     0.000000      0.000000     0.000000
25%       6.773652     0.000000     0.000000      2.000000     0.000000
50%       6.984716     0.000000     0.000000      3.000000     5.862209
75%       7.232372     6.517671     0.000000      3.000000     6.626049
max       8.536211     7.529943     5.888878      6.000000     8.296796

        BsmtFinSF2  BsmtFullBath  BsmtHalfBath   BsmtUnfSF  EnclosedPorch  \
count  1458.000000   1457.000000   1457.000000  1458.000000    1459.000000
mean      0.707051      0.434454      0.044800     5.605885       0.816893
std       1.912309      0.530648      0.172272     1.879851       1.814052
min       0.000000      0.000000      0.000000     0.000000       0.000000
25%       0.000000      0.000000      0.000000     5.394761       0.000000
50%       0.000000      0.000000      0.000000     6.133398       0.000000
75%       0.000000      1.000000      0.000000     6.683048       0.000000
max       7.331060      3.000000      1.098612     7.669028       6.920672

          ...     MiscFeature_E  Neighborhood_E  PavedDrive_E     PoolQC_E  \
count     ...       1459.000000     1459.000000   1459.000000  1459.000000
mean      ...          2.967786       12.572995      2.805346     1.004798
std       ...          0.195080        6.532969      0.574204     0.114055
min       ...          1.000000        1.000000      1.000000     1.000000
25%       ...          3.000000        7.000000      3.000000     1.000000
50%       ...          3.000000       12.000000      3.000000     1.000000
```

```
75%          ...          3.000000      17.000000      3.000000     1.000000
max          ...          4.000000      25.000000      3.000000     4.000000

        RoofMatl_E  RoofStyle_E  SaleCondition_E  SaleType_E     Street_E  \
count  1459.000000  1459.000000      1459.000000  1459.000000  1459.000000
mean      3.019877     2.557916         4.833448     5.195339     1.995888
std       0.222875     1.177596         0.878226     0.947645     0.064018
min       3.000000     1.000000         1.000000     1.000000     1.000000
25%       3.000000     2.000000         5.000000     5.000000     2.000000
50%       3.000000     2.000000         5.000000     5.000000     2.000000
75%       3.000000     2.000000         5.000000     5.000000     2.000000
max       8.000000     6.000000         6.000000    10.000000     2.000000

       Utilities_E
count  1459.000000
mean      2.001371
std       0.037012
min       2.000000
25%       2.000000
50%       2.000000
75%       2.000000
max       3.000000

[8 rows x 81 columns]
```

5a-3. Full Data

```
In [138]: houses_full.describe()
```

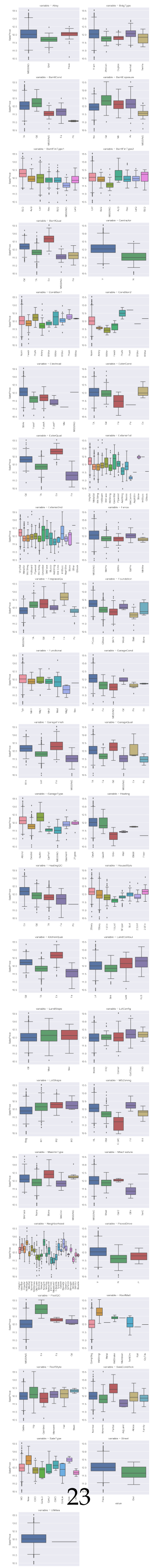
```
Out[138]:
          1stFlrSF     2ndFlrSF    3SsnPorch  BedroomAbvGr   BsmtFinSF1  \
count  2919.000000  2919.000000  2919.000000   2919.000000  2918.000000
mean      7.004186     2.829584     0.066197      2.860226     4.226403
std       0.322650     3.277023     0.587089      0.822693     2.981325
min       5.814131     0.000000     0.000000      0.000000     0.000000
25%       6.776507     0.000000     0.000000      2.000000     0.000000
50%       6.987490     0.000000     0.000000      3.000000     5.912150
75%       7.235979     6.558198     0.000000      3.000000     6.598509
max       8.536211     7.633370     6.232448      8.000000     8.638525

        BsmtFinSF2  BsmtFullBath  BsmtHalfBath    BsmtUnfSF  EnclosedPorch  \
count  2918.000000   2917.000000   2917.000000  2918.000000    2919.000000
mean      0.681207      0.429894      0.042140     5.627146       0.757435
std       1.878810      0.524736      0.167493     1.866773       1.771894
min       0.000000      0.000000      0.000000     0.000000       0.000000
25%       0.000000      0.000000      0.000000     5.398163       0.000000
50%       0.000000      0.000000      0.000000     6.148468       0.000000
75%       0.000000      1.000000      0.000000     6.692703       0.000000
max       7.331060      3.000000      1.098612     7.756623       6.920672
```

```
          ...       MiscFeature_E  Neighborhood_E  PavedDrive_E      PoolQC_E  \
count     ...         2919.000000     2919.000000   2919.000000   2919.000000
mean      ...            2.967112       12.716684      2.830764      1.006852
std       ...            0.200105        6.472081      0.537299      0.128073
min       ...            1.000000        1.000000      1.000000      1.000000
25%       ...            3.000000        7.000000      3.000000      1.000000
50%       ...            3.000000       12.000000      3.000000      1.000000
75%       ...            3.000000       17.000000      3.000000      1.000000
max       ...            5.000000       25.000000      3.000000      4.000000

        RoofMatl_E  RoofStyle_E  SaleCondition_E   SaleType_E     Street_E  \
count  2919.000000  2919.000000      2919.000000  2919.000000  2919.000000
mean      3.030147     2.583076         4.832477     5.200069     1.995889
std       0.321359     1.193942         0.882602     0.938689     0.063996
min       1.000000     1.000000         1.000000     1.000000     1.000000
25%       3.000000     2.000000         5.000000     5.000000     2.000000
50%       3.000000     2.000000         5.000000     5.000000     2.000000
75%       3.000000     2.000000         5.000000     5.000000     2.000000
max       8.000000     6.000000         6.000000    10.000000     2.000000

        Utilities_E
count  2919.000000
mean      2.000343
std       0.032062
min       1.000000
25%       2.000000
50%       2.000000
75%       2.000000
max       3.000000

[8 rows x 81 columns]
```

1.6.6 6. Selecting Features

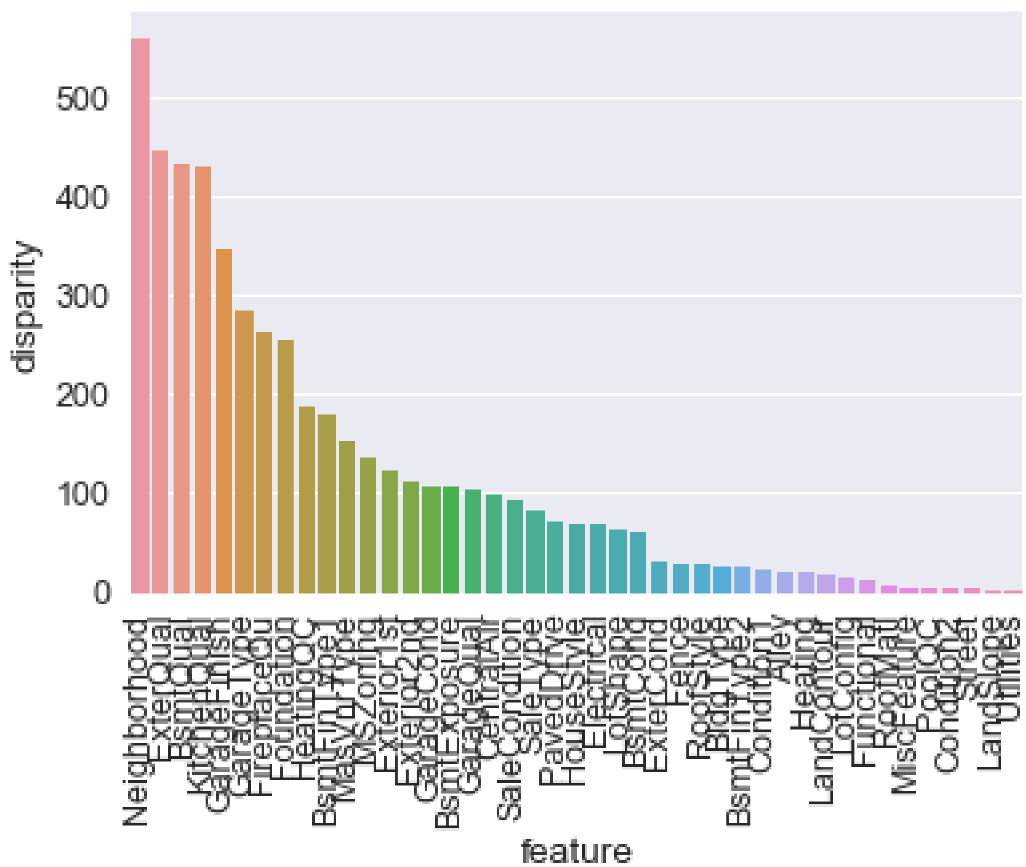
6a. Boxplots of Categorical Variables

```
In [139]: def boxplot(x, y, **kwargs):
              sns.boxplot(x=x, y=y)
              x=plt.xticks(rotation=90)
          f = pd.melt(houses, id_vars=['SalePrice'], value_vars=categorical)
          g = sns.FacetGrid(f, col="variable",  col_wrap=2, sharex=False, sharey=False, size=5)
          g = g.map(boxplot, "value", "SalePrice")
```



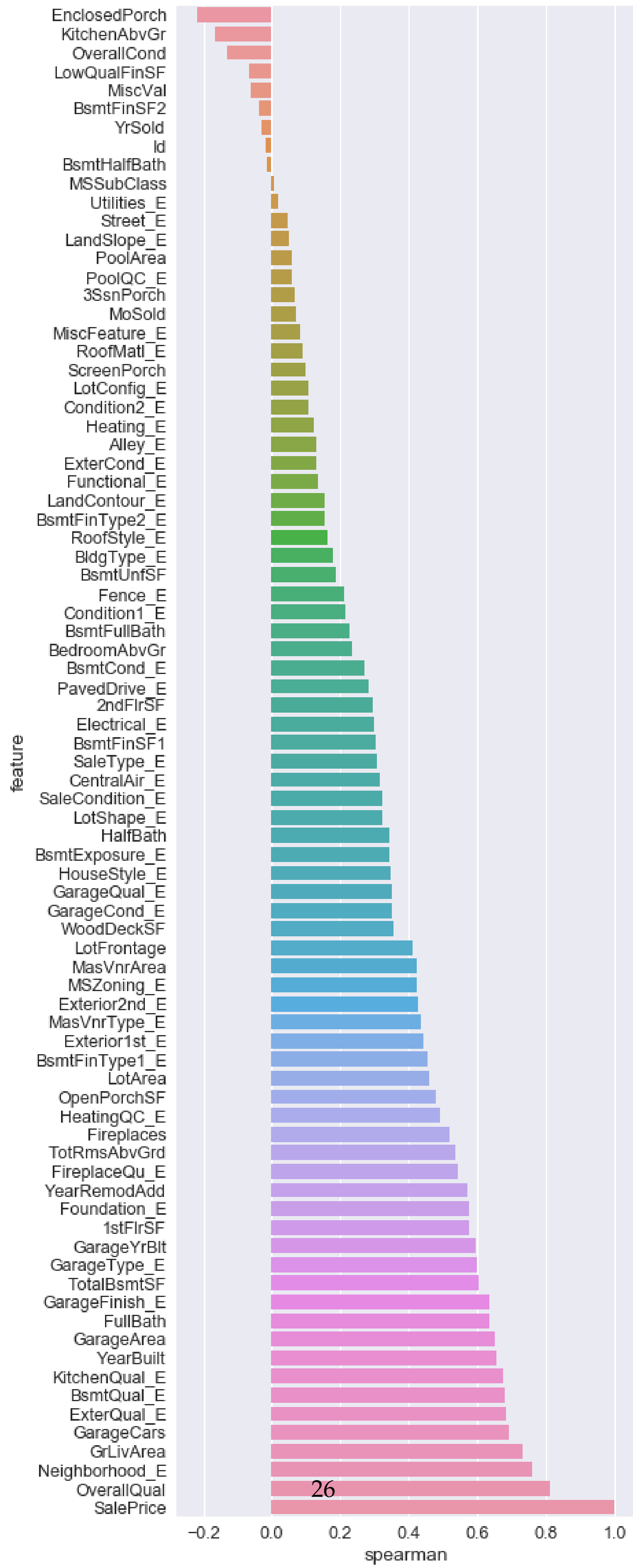
6b. Analysis of Variance (ANOVA)

```
In [140]: def anova(frame):
              anv = pd.DataFrame()
              anv['feature'] = categorical
              pvals = []
              for c in categorical:
                  samples = []
                  for cls in frame[c].unique():
                      s = frame[frame[c] == cls]['SalePrice'].values
                      samples.append(s)
                  pval = stats.f_oneway(*samples)[1]
                  pvals.append(pval)
              anv['pval'] = pvals
              return anv.sort_values('pval')

          a = anova(houses)
          a['disparity'] = np.log(1./a['pval'].values)
          sns.barplot(data=a, x='feature', y='disparity')
          x=plt.xticks(rotation=90)
```



6c. Spearman Correlation

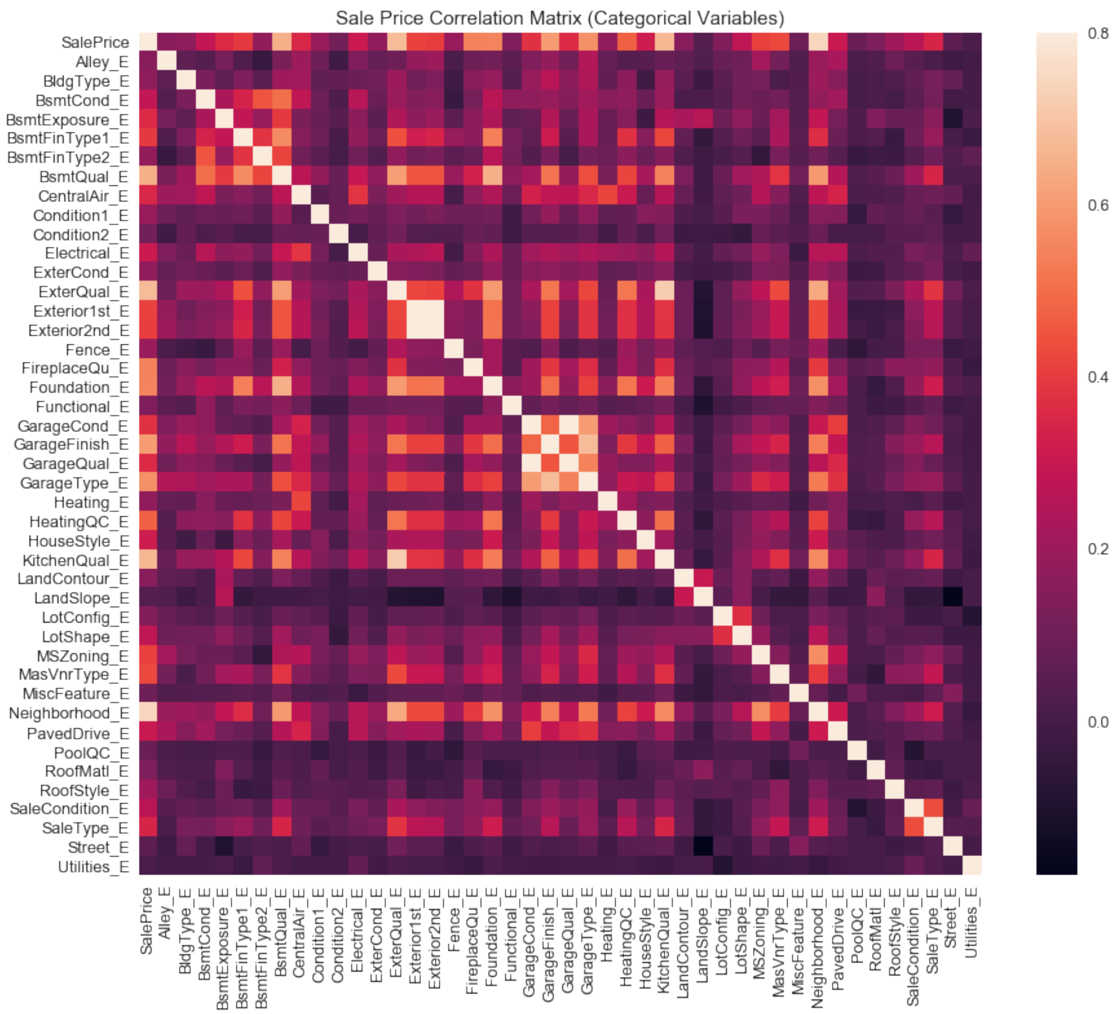
In [141]:
```
numerical_columns = houses.select_dtypes(include = ['int64', 'float64']).columns

def spearman(frame, features):
    spr = pd.DataFrame()
    spr['feature'] = features
    spr['spearman'] = [frame[f].corr(frame['SalePrice'], 'spearman') for f in featur
    spr = spr.sort_values('spearman')
    plt.figure(figsize=(6, 0.25*len(features)))
    sns.barplot(data=spr, y='feature', x='spearman', orient='h')

spearman(houses, numerical_columns)
```


EnclosedPorch
KitchenAbvGr
OverallCond
LowQualFinSF
MiscVal
BsmtFinSF2
YrSold
Id
BsmtHalfBath
MSSubClass
Utilities_E
Street_E
LandSlope_E
PoolArea
PoolQC_E
3SsnPorch
MoSold
MiscFeature_E
RoofMatl_E
ScreenPorch
LotConfig_E
Condition2_E
Heating_E
Alley_E
ExterCond_E
Functional_E
LandContour_E
BsmtFinType2_E
RoofStyle_E
BldgType_E
BsmtUnfSF
Fence_E
Condition1_E
BsmtFullBath
BedroomAbvGr
BsmtCond_E
PavedDrive_E
2ndFlrSF
Electrical_E
BsmtFinSF1
SaleType_E
CentralAir_E
SaleCondition_E
LotShape_E
HalfBath
BsmtExposure_E
HouseStyle_E
GarageQual_E
GarageCond_E
WoodDeckSF
LotFrontage
MasVnrArea
MSZoning_E
Exterior2nd_E
MasVnrType_E
Exterior1st_E
BsmtFinType1_E
LotArea
OpenPorchSF
HeatingQC_E
Fireplaces
TotRmsAbvGrd
FireplaceQu_E
YearRemodAdd
Foundation_E
1stFlrSF
GarageYrBlt
GarageType_E
TotalBsmtSF
GarageFinish_E
FullBath
GarageArea
YearBuilt
KitchenQual_E
BsmtQual_E
ExterQual_E
GarageCars
GrLivArea
Neighborhood_E
OverallQual
SalePrice
feature
−0.2
0.0
0.2
0.4
0.6
0.8
1.0
spearman

6d. Sale Price Correlation Matrix (Categorical Variables)

```
In [142]: corr_matrix = houses[['SalePrice'] + qual_encoded].corr()
          f, ax = plt.subplots(figsize=(15,12))
          corr_graph = sns.heatmap(corr_matrix, vmax=0.8, square=True)
          corr_graph.set_title('Sale Price Correlation Matrix (Categorical Variables)')
```

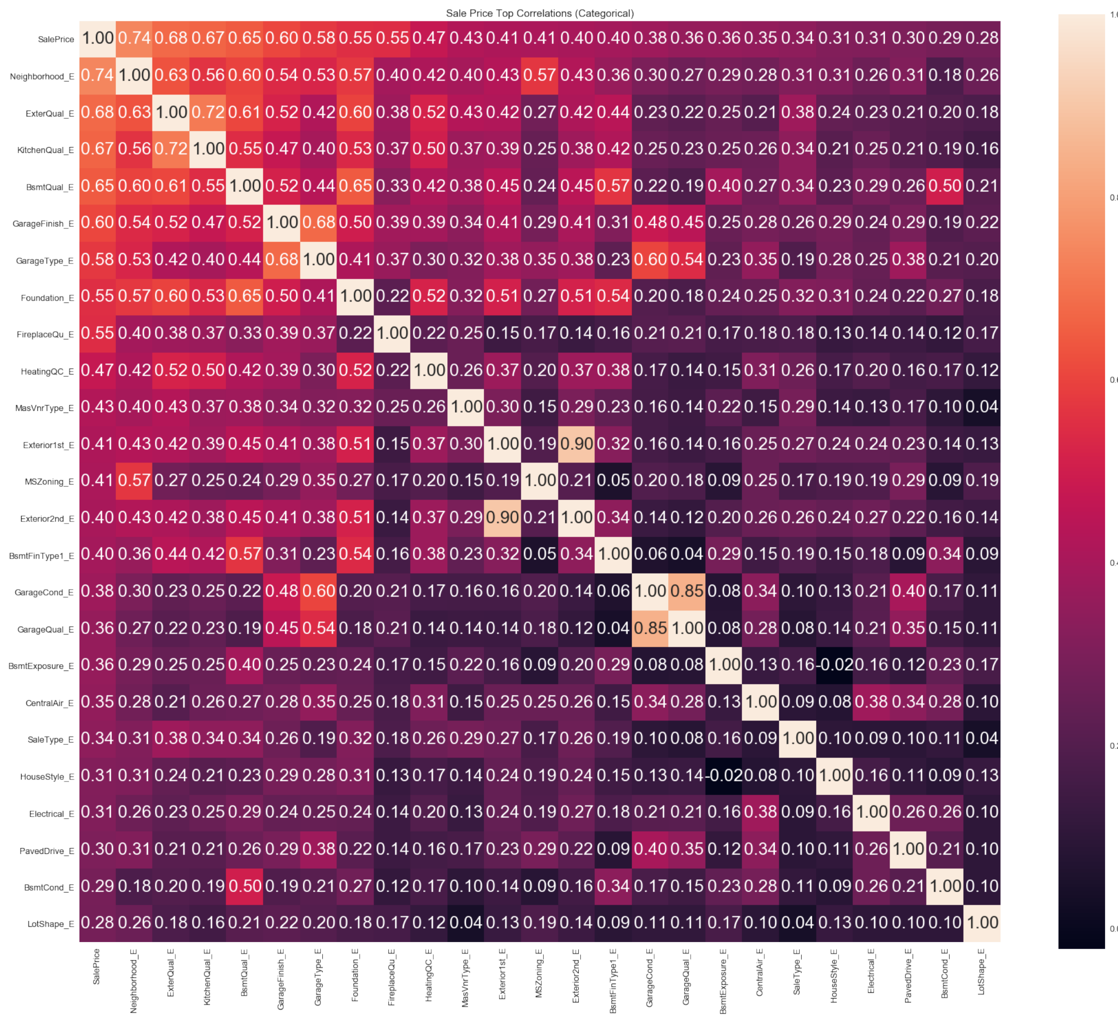
```
Out[142]: Text(0.5,1,'Sale Price Correlation Matrix (Categorical Variables)')
```



6e. Sale Price Top 10 Correlation Matrix (Categorical Variables)

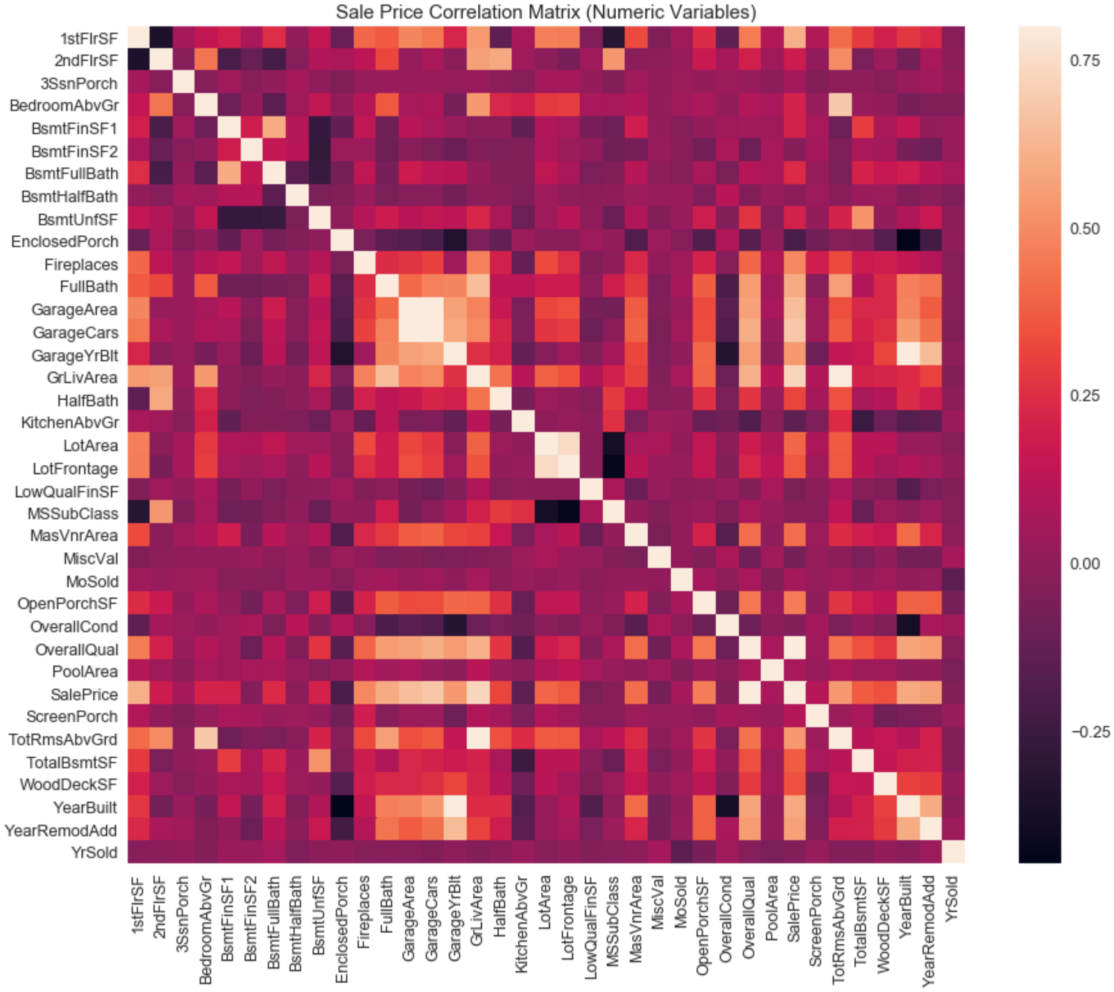
```
In [143]: k = 25
          cols = corr_matrix.nlargest(k, 'SalePrice')['SalePrice'].index
```

```
f, ax = plt.subplots(figsize=(30,25))
cm = np.corrcoef(houses[cols].values.T)
sns.set(font_scale=1.25)
hm = sns.heatmap(cm, cbar=True, annot=True, square=True, fmt='.2f', annot_kws={'size
                 yticklabels=cols.values, xticklabels=cols.values)
hm.set_title('Sale Price Top Correlations (Categorical)')
plt.show()
```



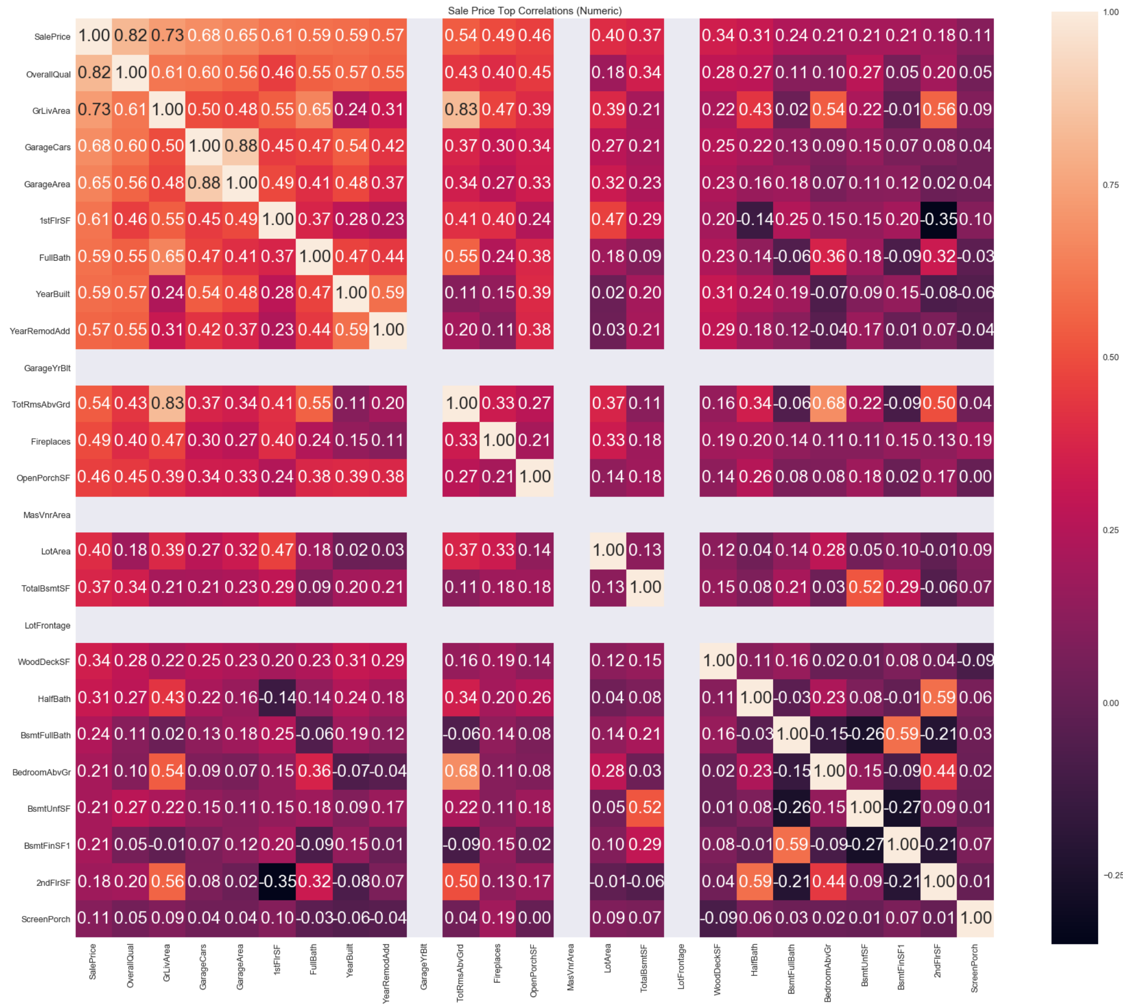
6f. Sale Price Correlation Matrix (Numeric Variables)

```
In [144]: corr_matrix_2 = houses[numerical].corr()
          f, ax = plt.subplots(figsize=(15,12))
          corr_graph = sns.heatmap(corr_matrix_2, vmax=0.8, square=True)
          corr_graph.set_title('Sale Price Correlation Matrix (Numeric Variables)')

Out[144]: Text(0.5,1,'Sale Price Correlation Matrix (Numeric Variables)')
```



6g. Sale Price Top 10 Correlation Matrix (Numeric Variables)

```
In [145]: k = 25
          cols_2 = corr_matrix_2.nlargest(k, 'SalePrice')['SalePrice'].index
          f, ax = plt.subplots(figsize=(30,25))
          cm_2 = np.corrcoef(houses[cols_2].values.T)
          sns.set(font_scale=1.25)
          hm_2 = sns.heatmap(cm_2, cbar=True, annot=True, square=True, fmt='.2f', annot_kws={'s
                           yticklabels=cols_2.values, xticklabels=cols_2.values)
          hm_2.set_title('Sale Price Top Correlations (Numeric)')
          plt.show()
```



6h. Selecting Features Correlated with SalePrice

6h-1 Full Subset

In [146]:
```
cat_subset = houses_full[cols]
cat_subset = cat_subset.drop('SalePrice', axis=1)
num_subset = houses_full[cols_2]
full_subset = pd.concat([num_subset, cat_subset],axis=1)
full_subset.set_index('SalePrice')
full_subset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2919 entries, 0 to 2918
Data columns (total 49 columns):
SalePrice          1460 non-null float64
OverallQual        2919 non-null int64
```

```
GrLivArea         2919 non-null float64
GarageCars        2918 non-null float64
GarageArea        2918 non-null float64
1stFlrSF          2919 non-null float64
FullBath          2919 non-null int64
YearBuilt         2919 non-null int64
YearRemodAdd      2919 non-null int64
GarageYrBlt       2760 non-null float64
TotRmsAbvGrd      2919 non-null float64
Fireplaces        2919 non-null int64
OpenPorchSF       2919 non-null float64
MasVnrArea        2896 non-null float64
LotArea           2919 non-null float64
TotalBsmtSF       2918 non-null float64
LotFrontage       2433 non-null float64
WoodDeckSF        2919 non-null float64
HalfBath          2919 non-null int64
BsmtFullBath      2917 non-null float64
BedroomAbvGr      2919 non-null int64
BsmtUnfSF         2918 non-null float64
BsmtFinSF1        2918 non-null float64
2ndFlrSF          2919 non-null float64
ScreenPorch       2919 non-null float64
Neighborhood_E    2919 non-null float64
ExterQual_E       2919 non-null float64
KitchenQual_E     2919 non-null float64
BsmtQual_E        2919 non-null float64
GarageFinish_E    2919 non-null float64
GarageType_E      2919 non-null float64
Foundation_E      2919 non-null float64
FireplaceQu_E     2919 non-null float64
HeatingQC_E       2919 non-null float64
MasVnrType_E      2919 non-null float64
Exterior1st_E     2919 non-null float64
MSZoning_E        2919 non-null float64
Exterior2nd_E     2919 non-null float64
BsmtFinType1_E    2919 non-null float64
GarageCond_E      2919 non-null float64
GarageQual_E      2919 non-null float64
BsmtExposure_E    2919 non-null float64
CentralAir_E      2919 non-null float64
SaleType_E        2919 non-null float64
HouseStyle_E      2919 non-null float64
Electrical_E      2919 non-null float64
PavedDrive_E      2919 non-null float64
BsmtCond_E        2919 non-null float64
LotShape_E        2919 non-null float64
dtypes: float64(42), int64(7)
```

```
memory usage: 1.1 MB
```

6h-1. Train Subset

```
In [147]: train_subset = full_subset[ :1460]
          train_subset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
Data columns (total 49 columns):
SalePrice          1460 non-null float64
OverallQual        1460 non-null int64
GrLivArea          1460 non-null float64
GarageCars         1460 non-null float64
GarageArea         1460 non-null float64
1stFlrSF           1460 non-null float64
FullBath           1460 non-null int64
YearBuilt          1460 non-null int64
YearRemodAdd       1460 non-null int64
GarageYrBlt        1379 non-null float64
TotRmsAbvGrd       1460 non-null float64
Fireplaces         1460 non-null int64
OpenPorchSF        1460 non-null float64
MasVnrArea         1452 non-null float64
LotArea            1460 non-null float64
TotalBsmtSF        1460 non-null float64
LotFrontage        1201 non-null float64
WoodDeckSF         1460 non-null float64
HalfBath           1460 non-null int64
BsmtFullBath       1460 non-null float64
BedroomAbvGr       1460 non-null int64
BsmtUnfSF          1460 non-null float64
BsmtFinSF1         1460 non-null float64
2ndFlrSF           1460 non-null float64
ScreenPorch        1460 non-null float64
Neighborhood_E     1460 non-null float64
ExterQual_E        1460 non-null float64
KitchenQual_E      1460 non-null float64
BsmtQual_E         1460 non-null float64
GarageFinish_E     1460 non-null float64
GarageType_E       1460 non-null float64
Foundation_E       1460 non-null float64
FireplaceQu_E      1460 non-null float64
HeatingQC_E        1460 non-null float64
MasVnrType_E       1460 non-null float64
Exterior1st_E      1460 non-null float64
MSZoning_E         1460 non-null float64
```

```
Exterior2nd_E     1460 non-null float64
BsmtFinType1_E    1460 non-null float64
GarageCond_E      1460 non-null float64
GarageQual_E      1460 non-null float64
BsmtExposure_E    1460 non-null float64
CentralAir_E      1460 non-null float64
SaleType_E        1460 non-null float64
HouseStyle_E      1460 non-null float64
Electrical_E      1460 non-null float64
PavedDrive_E      1460 non-null float64
BsmtCond_E        1460 non-null float64
LotShape_E        1460 non-null float64
dtypes: float64(42), int64(7)
memory usage: 559.0 KB
```

6h-3. Test Subset

```
In [148]: test_subset = full_subset[1460: ]
          test_subset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1459 entries, 1460 to 2918
Data columns (total 49 columns):
SalePrice         0 non-null float64
OverallQual       1459 non-null int64
GrLivArea         1459 non-null float64
GarageCars        1458 non-null float64
GarageArea        1458 non-null float64
1stFlrSF          1459 non-null float64
FullBath          1459 non-null int64
YearBuilt         1459 non-null int64
YearRemodAdd      1459 non-null int64
GarageYrBlt       1381 non-null float64
TotRmsAbvGrd      1459 non-null float64
Fireplaces        1459 non-null int64
OpenPorchSF       1459 non-null float64
MasVnrArea        1444 non-null float64
LotArea           1459 non-null float64
TotalBsmtSF       1458 non-null float64
LotFrontage       1232 non-null float64
WoodDeckSF        1459 non-null float64
HalfBath          1459 non-null int64
BsmtFullBath      1457 non-null float64
BedroomAbvGr      1459 non-null int64
BsmtUnfSF         1458 non-null float64
BsmtFinSF1        1458 non-null float64
2ndFlrSF          1459 non-null float64
```

```
ScreenPorch       1459 non-null float64
Neighborhood_E    1459 non-null float64
ExterQual_E       1459 non-null float64
KitchenQual_E     1459 non-null float64
BsmtQual_E        1459 non-null float64
GarageFinish_E    1459 non-null float64
GarageType_E      1459 non-null float64
Foundation_E      1459 non-null float64
FireplaceQu_E     1459 non-null float64
HeatingQC_E       1459 non-null float64
MasVnrType_E      1459 non-null float64
Exterior1st_E     1459 non-null float64
MSZoning_E        1459 non-null float64
Exterior2nd_E     1459 non-null float64
BsmtFinType1_E    1459 non-null float64
GarageCond_E      1459 non-null float64
GarageQual_E      1459 non-null float64
BsmtExposure_E    1459 non-null float64
CentralAir_E      1459 non-null float64
SaleType_E        1459 non-null float64
HouseStyle_E      1459 non-null float64
Electrical_E      1459 non-null float64
PavedDrive_E      1459 non-null float64
BsmtCond_E        1459 non-null float64
LotShape_E        1459 non-null float64
dtypes: float64(42), int64(7)
memory usage: 558.6 KB
```

6h-1. Viewing Features for Predictive Model

In [149]:
```
train_subset.head(20)
```

Out[149]:
```
    SalePrice  OverallQual  GrLivArea  GarageCars  GarageArea  1stFlrSF  \
0   12.247699            7   7.444833         2.0       548.0  6.753438
1   12.109016            6   7.141245         2.0       460.0  7.141245
2   12.317171            7   7.488294         2.0       608.0  6.825460
3   11.849405            7   7.448916         3.0       642.0  6.869014
4   12.429220            8   7.695758         3.0       836.0  7.044033
5   11.870607            5   7.217443         2.0       480.0  6.680855
6   12.634606            8   7.435438         2.0       636.0  7.435438
7   12.206078            7   7.645398         2.0       484.0  7.010312
8   11.774528            7   7.481556         2.0       468.0  6.930495
9   11.678448            5   6.982863         1.0       205.0  6.982863
10  11.771444            5   6.947937         1.0       384.0  6.947937
11  12.751303            9   7.751475         3.0       736.0  7.075809
12  11.877576            5   6.816736         1.0       352.0  6.816736
13  12.540761            7   7.309881         3.0       840.0  7.309881
```

```
14  11.964007           6   7.134094         1.0       352.0  7.134094
15  11.790565           7   6.751101         2.0       576.0  6.751101
16  11.911708           6   6.912743         2.0       480.0  6.912743
17  11.407576           4   7.167809         2.0       516.0  7.167809
18  11.976666           5   7.016610         2.0       576.0  7.016610
19  11.842236           5   7.200425         1.0       294.0  7.200425

    FullBath  YearBuilt  YearRemodAdd  GarageYrBlt     ...       GarageCond_E  \
0          2       2003          2003       2003.0     ...                6.0
1          2       1976          1976       1976.0     ...                6.0
2          2       2001          2002       2001.0     ...                6.0
3          1       1915          1970       1998.0     ...                6.0
4          2       2000          2000       2000.0     ...                6.0
5          1       1993          1995       1993.0     ...                6.0
6          2       2004          2005       2004.0     ...                6.0
7          2       1973          1973       1973.0     ...                6.0
8          2       1931          1950       1931.0     ...                6.0
9          1       1939          1950       1939.0     ...                6.0
10         1       1965          1965       1965.0     ...                6.0
11         3       2005          2006       2005.0     ...                6.0
12         1       1962          1962       1962.0     ...                6.0
13         2       2006          2007       2006.0     ...                6.0
14         1       1960          1960       1960.0     ...                6.0
15         1       1929          2001       1991.0     ...                6.0
16         1       1970          1970       1970.0     ...                6.0
17         2       1967          1967       1967.0     ...                6.0
18         1       2004          2004       2004.0     ...                6.0
19         1       1958          1965       1958.0     ...                6.0

    GarageQual_E  BsmtExposure_E  CentralAir_E  SaleType_E  HouseStyle_E  \
0            4.0             2.0           2.0         5.0           7.0
1            4.0             5.0           2.0         5.0           5.0
2            4.0             3.0           2.0         5.0           7.0
3            4.0             2.0           2.0         5.0           7.0
4            4.0             4.0           2.0         5.0           7.0
5            4.0             2.0           2.0         5.0           3.0
6            4.0             4.0           2.0         5.0           5.0
7            4.0             3.0           2.0         5.0           7.0
8            3.0             2.0           2.0         5.0           3.0
9            6.0             2.0           2.0         5.0           1.0
10           4.0             2.0           2.0         5.0           5.0
11           4.0             2.0           2.0         8.0           7.0
12           4.0             2.0           2.0         5.0           5.0
13           4.0             4.0           2.0         8.0           5.0
14           4.0             2.0           2.0         5.0           5.0
15           4.0             2.0           2.0         5.0           1.0
16           4.0             2.0           2.0         5.0           5.0
17           4.0             1.0           2.0         5.0           5.0
```

```
18          4.0            2.0           2.0         5.0           5.0
19          4.0            2.0           2.0         4.0           5.0

    Electrical_E  PavedDrive_E  BsmtCond_E  LotShape_E
0            6.0           3.0         4.0         1.0
1            6.0           3.0         4.0         1.0
2            6.0           3.0         4.0         2.0
3            6.0           3.0         5.0         2.0
4            6.0           3.0         4.0         2.0
5            6.0           3.0         4.0         2.0
6            6.0           3.0         4.0         1.0
7            6.0           3.0         4.0         2.0
8            3.0           3.0         4.0         1.0
9            6.0           3.0         4.0         1.0
10           6.0           3.0         4.0         1.0
11           6.0           3.0         4.0         2.0
12           6.0           3.0         4.0         4.0
13           6.0           3.0         4.0         2.0
14           6.0           3.0         4.0         2.0
15           4.0           3.0         4.0         1.0
16           6.0           3.0         4.0         2.0
17           6.0           3.0         2.0         1.0
18           6.0           3.0         4.0         1.0
19           6.0           3.0         4.0         1.0

[20 rows x 49 columns]
```

6h-2. Inspecting New DataFrame

```
In [150]: train_subset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
Data columns (total 49 columns):
SalePrice         1460 non-null float64
OverallQual       1460 non-null int64
GrLivArea         1460 non-null float64
GarageCars        1460 non-null float64
GarageArea        1460 non-null float64
1stFlrSF          1460 non-null float64
FullBath          1460 non-null int64
YearBuilt         1460 non-null int64
YearRemodAdd      1460 non-null int64
GarageYrBlt       1379 non-null float64
TotRmsAbvGrd      1460 non-null float64
Fireplaces        1460 non-null int64
OpenPorchSF       1460 non-null float64
MasVnrArea        1452 non-null float64
```

```
LotArea          1460 non-null float64
TotalBsmtSF      1460 non-null float64
LotFrontage      1201 non-null float64
WoodDeckSF       1460 non-null float64
HalfBath         1460 non-null int64
BsmtFullBath     1460 non-null float64
BedroomAbvGr     1460 non-null int64
BsmtUnfSF        1460 non-null float64
BsmtFinSF1       1460 non-null float64
2ndFlrSF         1460 non-null float64
ScreenPorch      1460 non-null float64
Neighborhood_E   1460 non-null float64
ExterQual_E      1460 non-null float64
KitchenQual_E    1460 non-null float64
BsmtQual_E       1460 non-null float64
GarageFinish_E   1460 non-null float64
GarageType_E     1460 non-null float64
Foundation_E     1460 non-null float64
FireplaceQu_E    1460 non-null float64
HeatingQC_E      1460 non-null float64
MasVnrType_E     1460 non-null float64
Exterior1st_E    1460 non-null float64
MSZoning_E       1460 non-null float64
Exterior2nd_E    1460 non-null float64
BsmtFinType1_E   1460 non-null float64
GarageCond_E     1460 non-null float64
GarageQual_E     1460 non-null float64
BsmtExposure_E   1460 non-null float64
CentralAir_E     1460 non-null float64
SaleType_E       1460 non-null float64
HouseStyle_E     1460 non-null float64
Electrical_E     1460 non-null float64
PavedDrive_E     1460 non-null float64
BsmtCond_E       1460 non-null float64
LotShape_E       1460 non-null float64
dtypes: float64(42), int64(7)
memory usage: 559.0 KB
```

1.6.7 7. Feature Engineering

7a. has_feature Function

In [151]:
```
def has_feature(feature):
    if feature > 0:
        return 1
    else:
        return 0
```

7b. Full Data Set Engineering

```
In [152]: full_subset['HasBasement'] = full_subset['TotalBsmtSF'].apply(has_feature)
          full_subset['HasGarage'] = full_subset['GarageArea'].apply(has_feature)
          full_subset['Has2ndFlr'] = full_subset['2ndFlrSF'].apply(has_feature)
          full_subset['HasOpenPorch'] = full_subset['OpenPorchSF'].apply(has_feature)
          full_subset['HasScreenPorch'] = full_subset['ScreenPorch'].apply(has_feature)
          full_subset['HasFirePlace'] = full_subset['Fireplaces'].apply(has_feature)
          full_subset['HasMsVnr'] = full_subset['MasVnrArea'].apply(has_feature)
          full_subset['HasWoodDeck'] = full_subset['WoodDeckSF'].apply(has_feature)
          full_subset['HasPool'] = houses_full['PoolArea'].apply(has_feature)
          full_subset['HasBasementBathroom'] = full_subset['BsmtFullBath'].apply(has_feature)
          full_subset['ExtraBathrooms'] = full_subset['FullBath'].apply(lambda x: 1 if x > 1 el
          full_subset['New'] = full_subset['YearBuilt'].apply(lambda x: 1 if x > 2000 else 0)
          full_subset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2919 entries, 0 to 2918
Data columns (total 61 columns):
SalePrice              1460 non-null float64
OverallQual            2919 non-null int64
GrLivArea              2919 non-null float64
GarageCars             2918 non-null float64
GarageArea             2918 non-null float64
1stFlrSF               2919 non-null float64
FullBath               2919 non-null int64
YearBuilt              2919 non-null int64
YearRemodAdd           2919 non-null int64
GarageYrBlt            2760 non-null float64
TotRmsAbvGrd           2919 non-null float64
Fireplaces             2919 non-null int64
OpenPorchSF            2919 non-null float64
MasVnrArea             2896 non-null float64
LotArea                2919 non-null float64
TotalBsmtSF            2918 non-null float64
LotFrontage            2433 non-null float64
WoodDeckSF             2919 non-null float64
HalfBath               2919 non-null int64
BsmtFullBath           2917 non-null float64
BedroomAbvGr           2919 non-null int64
BsmtUnfSF              2918 non-null float64
BsmtFinSF1             2918 non-null float64
2ndFlrSF               2919 non-null float64
ScreenPorch            2919 non-null float64
Neighborhood_E         2919 non-null float64
ExterQual_E            2919 non-null float64
KitchenQual_E          2919 non-null float64
BsmtQual_E             2919 non-null float64
GarageFinish_E         2919 non-null float64
```

```
GarageType_E          2919 non-null float64
Foundation_E          2919 non-null float64
FireplaceQu_E         2919 non-null float64
HeatingQC_E           2919 non-null float64
MasVnrType_E          2919 non-null float64
Exterior1st_E         2919 non-null float64
MSZoning_E            2919 non-null float64
Exterior2nd_E         2919 non-null float64
BsmtFinType1_E        2919 non-null float64
GarageCond_E          2919 non-null float64
GarageQual_E          2919 non-null float64
BsmtExposure_E        2919 non-null float64
CentralAir_E          2919 non-null float64
SaleType_E            2919 non-null float64
HouseStyle_E          2919 non-null float64
Electrical_E          2919 non-null float64
PavedDrive_E          2919 non-null float64
BsmtCond_E            2919 non-null float64
LotShape_E            2919 non-null float64
HasBasement           2919 non-null int64
HasGarage             2919 non-null int64
Has2ndFlr             2919 non-null int64
HasOpenPorch          2919 non-null int64
HasScreenPorch        2919 non-null int64
HasFirePlace          2919 non-null int64
HasMsVnr              2919 non-null int64
HasWoodDeck           2919 non-null int64
HasPool               2919 non-null int64
HasBasementBathroom   2919 non-null int64
ExtraBathrooms        2919 non-null int64
New                   2919 non-null int64
dtypes: float64(42), int64(19)
memory usage: 1.4 MB
```

7c. Train_subset Engineering

In [153]:
```
train_subset = full_subset[ :1460]
train_subset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
Data columns (total 61 columns):
SalePrice             1460 non-null float64
OverallQual           1460 non-null int64
GrLivArea             1460 non-null float64
GarageCars            1460 non-null float64
GarageArea            1460 non-null float64
```

```
1stFlrSF                1460 non-null float64
FullBath                1460 non-null int64
YearBuilt               1460 non-null int64
YearRemodAdd            1460 non-null int64
GarageYrBlt             1379 non-null float64
TotRmsAbvGrd            1460 non-null float64
Fireplaces              1460 non-null int64
OpenPorchSF             1460 non-null float64
MasVnrArea              1452 non-null float64
LotArea                 1460 non-null float64
TotalBsmtSF             1460 non-null float64
LotFrontage             1201 non-null float64
WoodDeckSF              1460 non-null float64
HalfBath                1460 non-null int64
BsmtFullBath            1460 non-null float64
BedroomAbvGr            1460 non-null int64
BsmtUnfSF               1460 non-null float64
BsmtFinSF1              1460 non-null float64
2ndFlrSF                1460 non-null float64
ScreenPorch             1460 non-null float64
Neighborhood_E          1460 non-null float64
ExterQual_E             1460 non-null float64
KitchenQual_E           1460 non-null float64
BsmtQual_E              1460 non-null float64
GarageFinish_E          1460 non-null float64
GarageType_E            1460 non-null float64
Foundation_E            1460 non-null float64
FireplaceQu_E           1460 non-null float64
HeatingQC_E             1460 non-null float64
MasVnrType_E            1460 non-null float64
Exterior1st_E           1460 non-null float64
MSZoning_E              1460 non-null float64
Exterior2nd_E           1460 non-null float64
BsmtFinType1_E          1460 non-null float64
GarageCond_E            1460 non-null float64
GarageQual_E            1460 non-null float64
BsmtExposure_E          1460 non-null float64
CentralAir_E            1460 non-null float64
SaleType_E              1460 non-null float64
HouseStyle_E            1460 non-null float64
Electrical_E            1460 non-null float64
PavedDrive_E            1460 non-null float64
BsmtCond_E              1460 non-null float64
LotShape_E              1460 non-null float64
HasBasement             1460 non-null int64
HasGarage               1460 non-null int64
Has2ndFlr               1460 non-null int64
HasOpenPorch            1460 non-null int64
```

```
HasScreenPorch         1460 non-null int64
HasFirePlace           1460 non-null int64
HasMsVnr               1460 non-null int64
HasWoodDeck            1460 non-null int64
HasPool                1460 non-null int64
HasBasementBathroom    1460 non-null int64
ExtraBathrooms         1460 non-null int64
New                    1460 non-null int64
dtypes: float64(42), int64(19)
memory usage: 695.9 KB
```

7d. Test Set

```
In [154]: test_subset = full_subset[1460: ]
          test_subset.info()
```

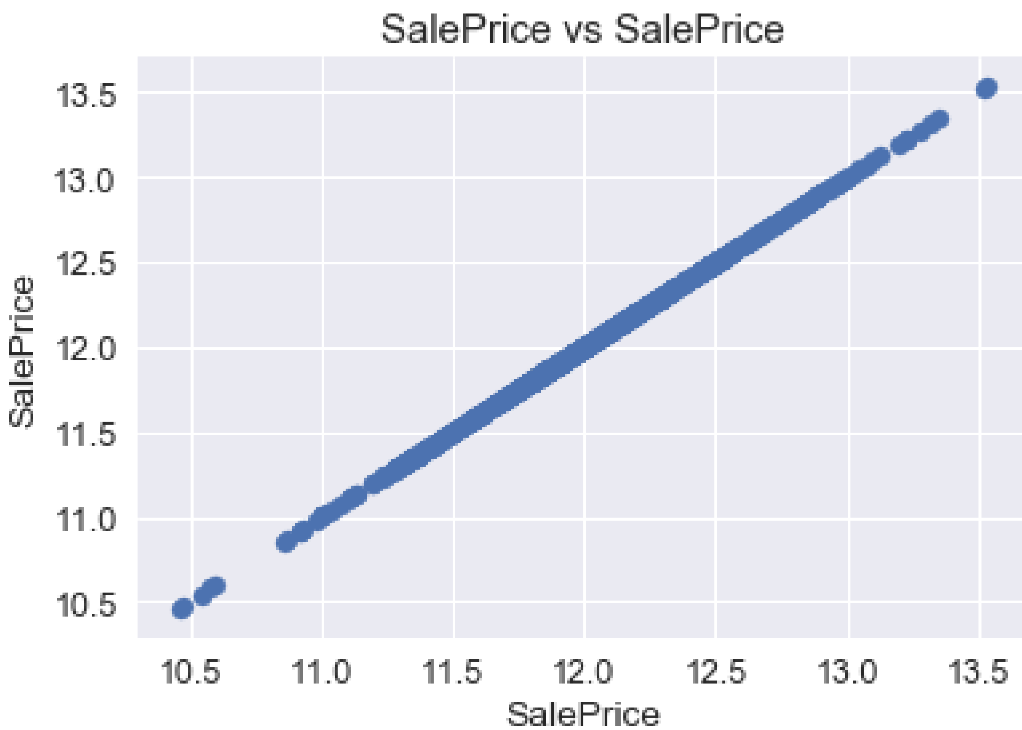
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1459 entries, 1460 to 2918
Data columns (total 61 columns):
SalePrice              0 non-null float64
OverallQual            1459 non-null int64
GrLivArea              1459 non-null float64
GarageCars             1458 non-null float64
GarageArea             1458 non-null float64
1stFlrSF               1459 non-null float64
FullBath               1459 non-null int64
YearBuilt              1459 non-null int64
YearRemodAdd           1459 non-null int64
GarageYrBlt            1381 non-null float64
TotRmsAbvGrd           1459 non-null float64
Fireplaces             1459 non-null int64
OpenPorchSF            1459 non-null float64
MasVnrArea             1444 non-null float64
LotArea                1459 non-null float64
TotalBsmtSF            1458 non-null float64
LotFrontage            1232 non-null float64
WoodDeckSF             1459 non-null float64
HalfBath               1459 non-null int64
BsmtFullBath           1457 non-null float64
BedroomAbvGr           1459 non-null int64
BsmtUnfSF              1458 non-null float64
BsmtFinSF1             1458 non-null float64
2ndFlrSF               1459 non-null float64
ScreenPorch            1459 non-null float64
Neighborhood_E         1459 non-null float64
ExterQual_E            1459 non-null float64
KitchenQual_E          1459 non-null float64
```

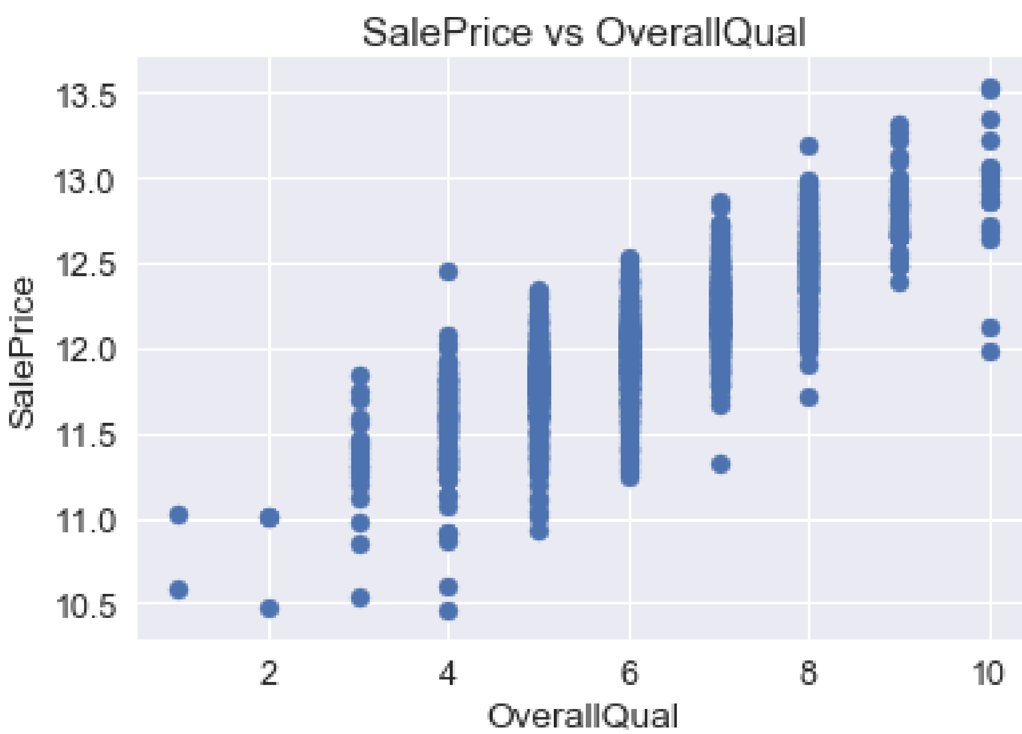
```
BsmtQual_E             1459 non-null float64
GarageFinish_E         1459 non-null float64
GarageType_E           1459 non-null float64
Foundation_E           1459 non-null float64
FireplaceQu_E          1459 non-null float64
HeatingQC_E            1459 non-null float64
MasVnrType_E           1459 non-null float64
Exterior1st_E          1459 non-null float64
MSZoning_E             1459 non-null float64
Exterior2nd_E          1459 non-null float64
BsmtFinType1_E         1459 non-null float64
GarageCond_E           1459 non-null float64
GarageQual_E           1459 non-null float64
BsmtExposure_E         1459 non-null float64
CentralAir_E           1459 non-null float64
SaleType_E             1459 non-null float64
HouseStyle_E           1459 non-null float64
Electrical_E           1459 non-null float64
PavedDrive_E           1459 non-null float64
BsmtCond_E             1459 non-null float64
LotShape_E             1459 non-null float64
HasBasement            1459 non-null int64
HasGarage              1459 non-null int64
Has2ndFlr              1459 non-null int64
HasOpenPorch           1459 non-null int64
HasScreenPorch         1459 non-null int64
HasFirePlace           1459 non-null int64
HasMsVnr               1459 non-null int64
HasWoodDeck            1459 non-null int64
HasPool                1459 non-null int64
HasBasementBathroom    1459 non-null int64
ExtraBathrooms         1459 non-null int64
New                    1459 non-null int64
dtypes: float64(42), int64(19)
memory usage: 695.4 KB
```

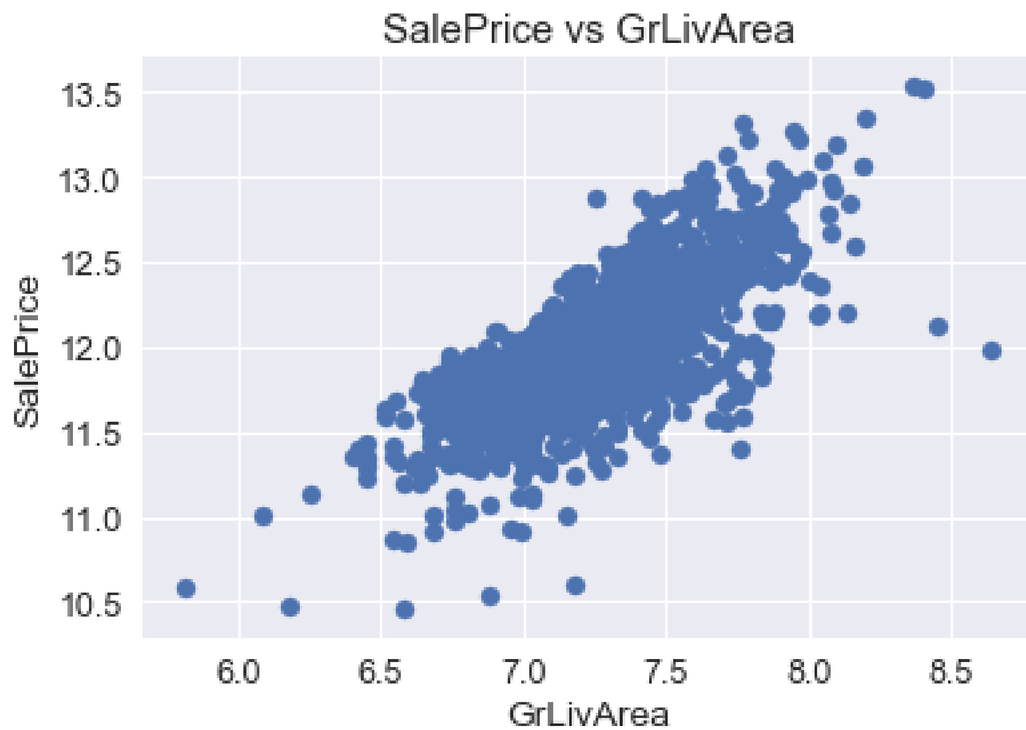
1.6.8 8. Visualizing Data

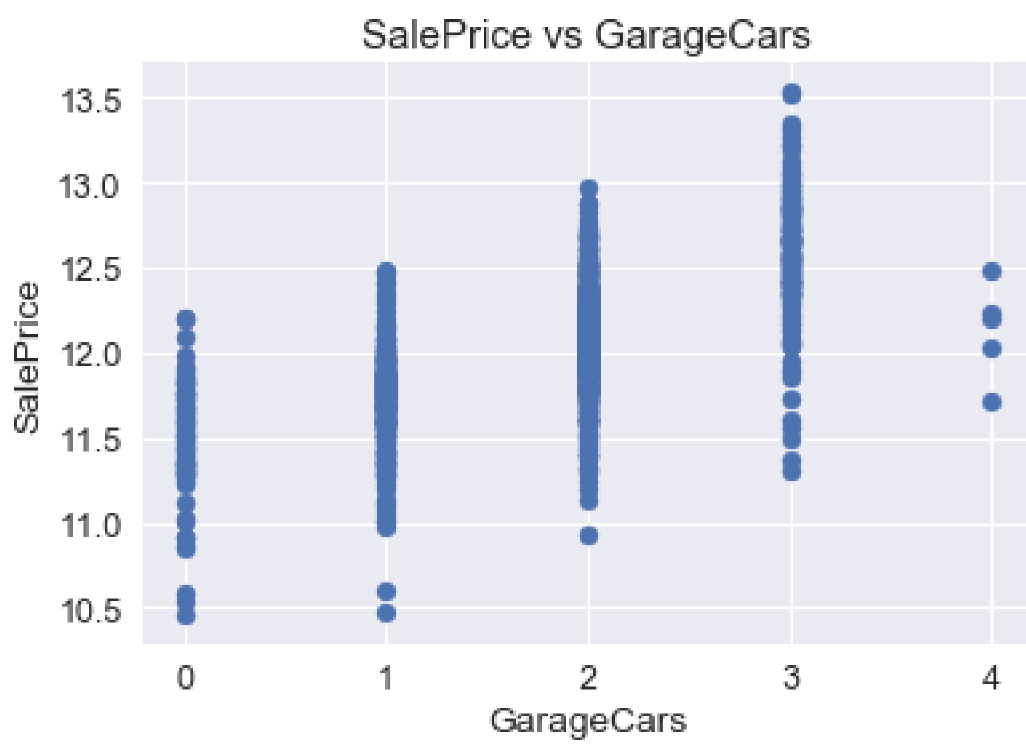
8a. Scatter Plots of Selected Features

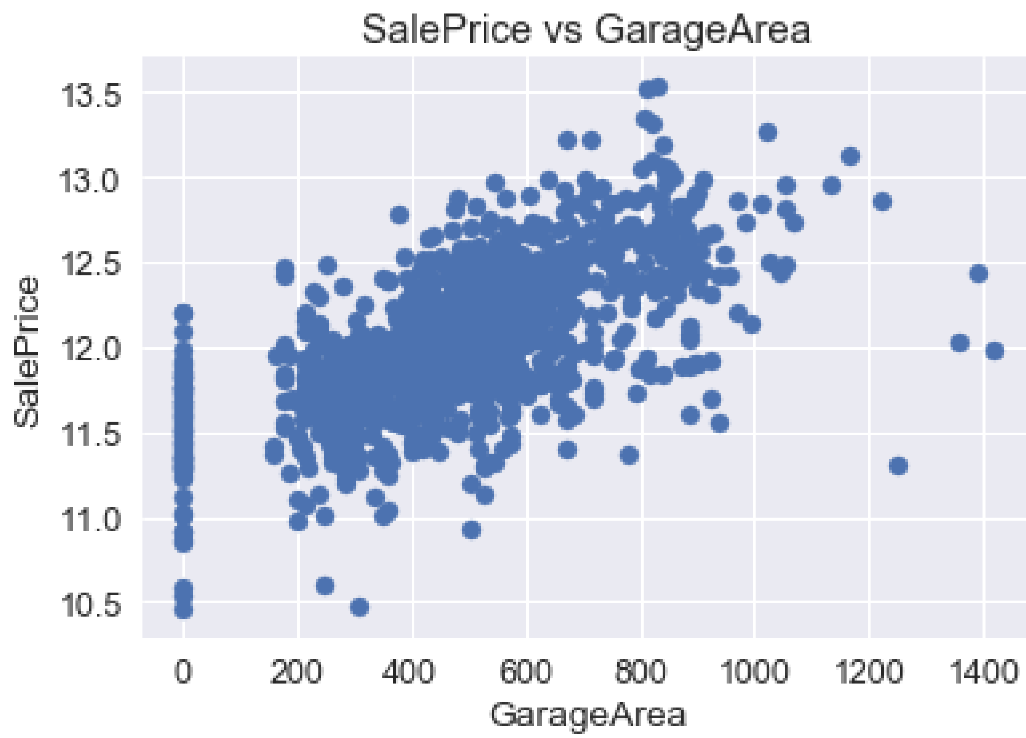
```
In [155]: for feature in train_subset:
              plt.scatter(train_subset[feature], train_subset['SalePrice'])
              plt.title('SalePrice vs ' + feature)
              plt.ylabel('SalePrice')
              plt.xlabel(feature)
              plt.show()
```

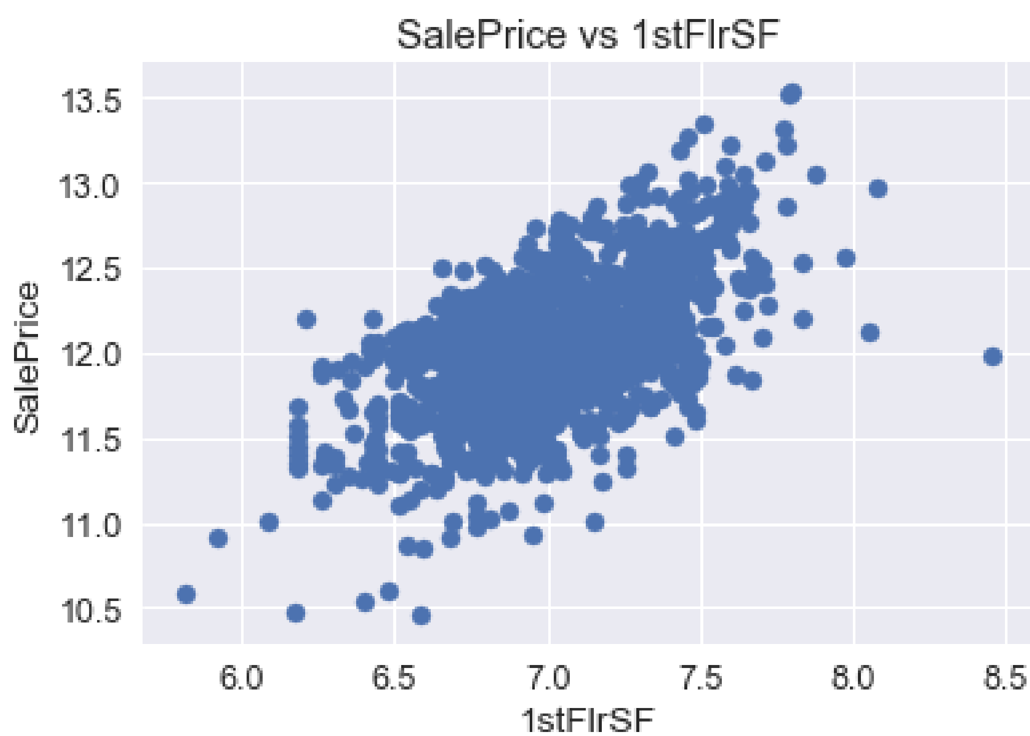

SalePrice vs SalePrice
13.5
13.0
12.5
12.0
11.5
11.0
10.5
SalePrice
10.5
11.0
11.5
12.0
12.5
13.0
13.5
SalePrice

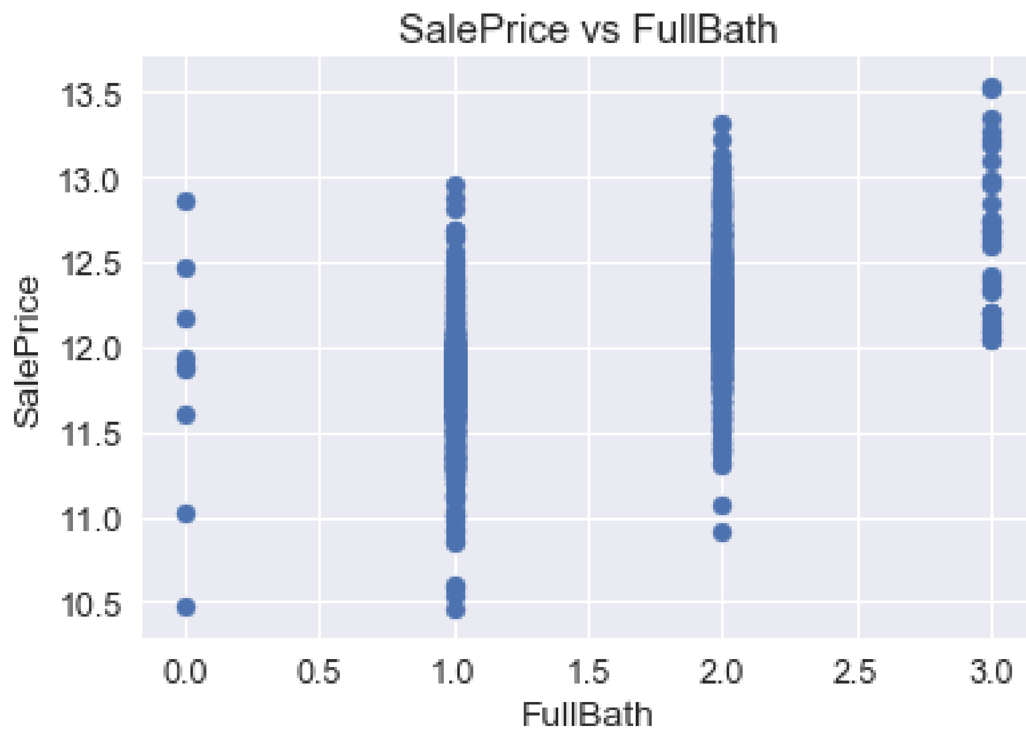

SalePrice vs OverallQual
13.5
13.0
12.5
12.0
11.5
11.0
10.5
SalePrice
2
4
6
8
10
OverallQual

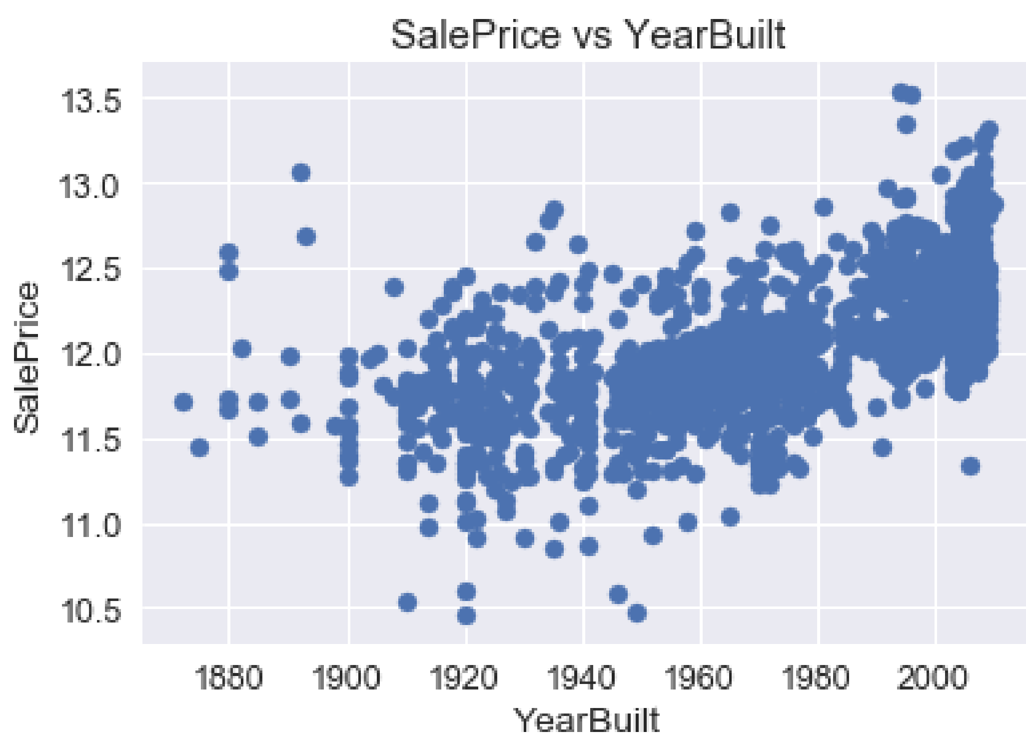

SalePrice vs GrLivArea
SalePrice
GrLivArea
13.5
13.0
12.5
12.0
11.5
11.0
10.5
6.0
6.5
7.0
7.5
8.0
8.5

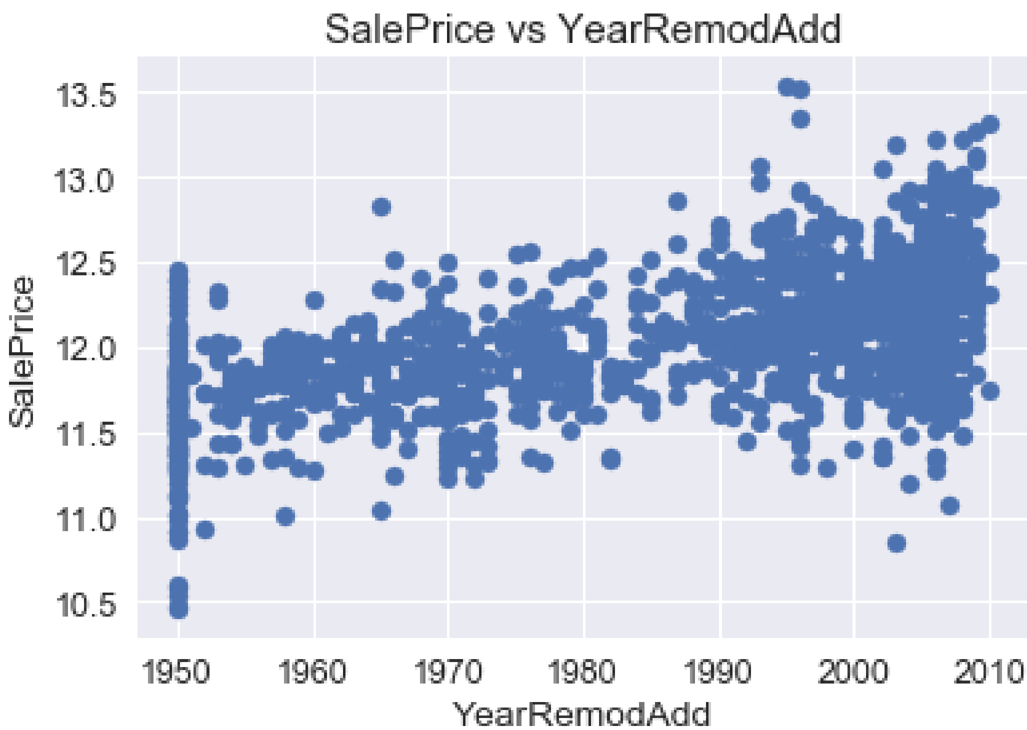

SalePrice vs GarageCars
SalePrice
GarageCars
13.5
13.0
12.5
12.0
11.5
11.0
10.5
0
1
2
3
4

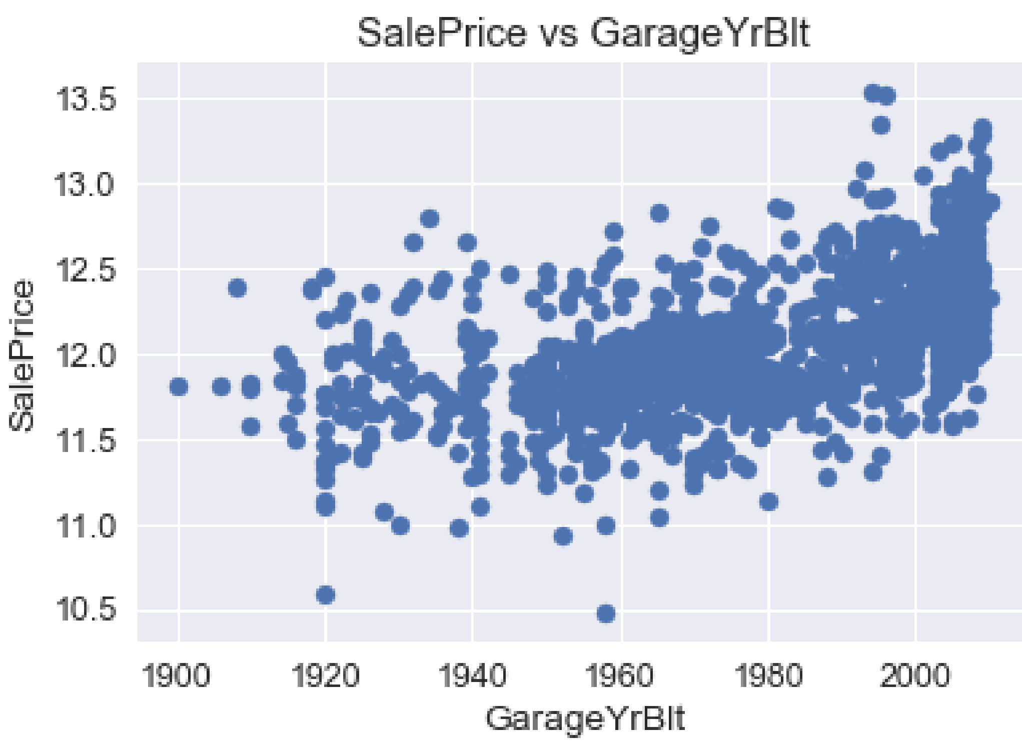

SalePrice vs GarageArea
SalePrice
GarageArea
13.5
13.0
12.5
12.0
11.5
11.0
10.5
0
200
400
600
800
1000
1200
1400

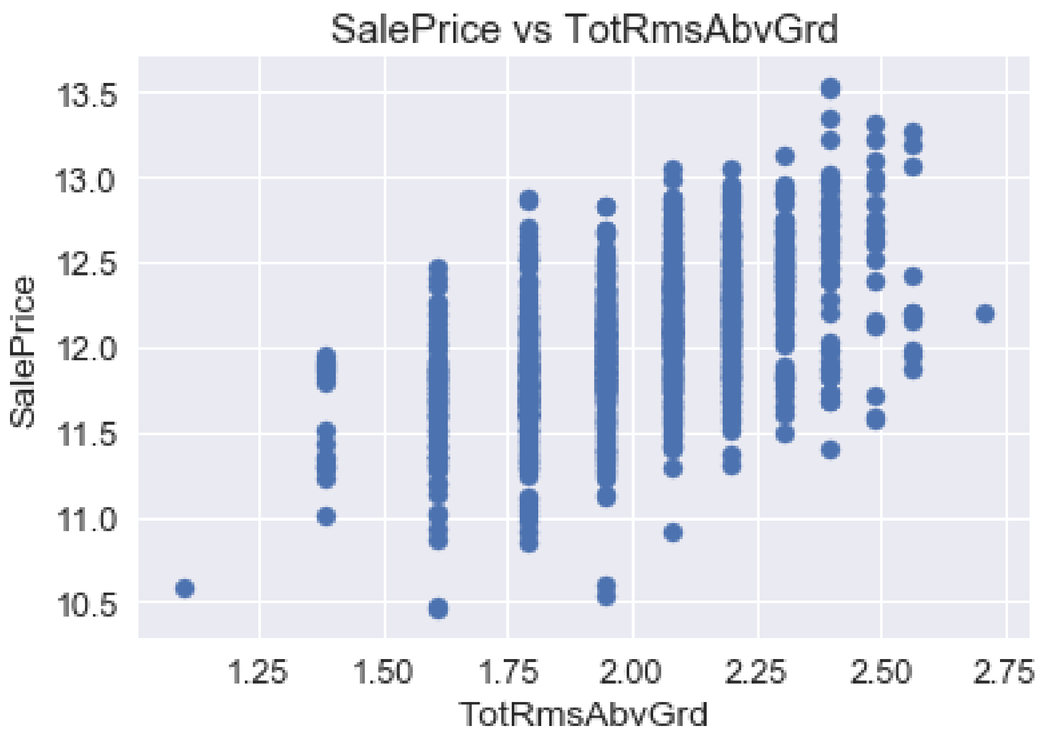

SalePrice vs 1stFlrSF
SalePrice
1stFlrSF
13.5
13.0
12.5
12.0
11.5
11.0
10.5
6.0
6.5
7.0
7.5
8.0
8.5

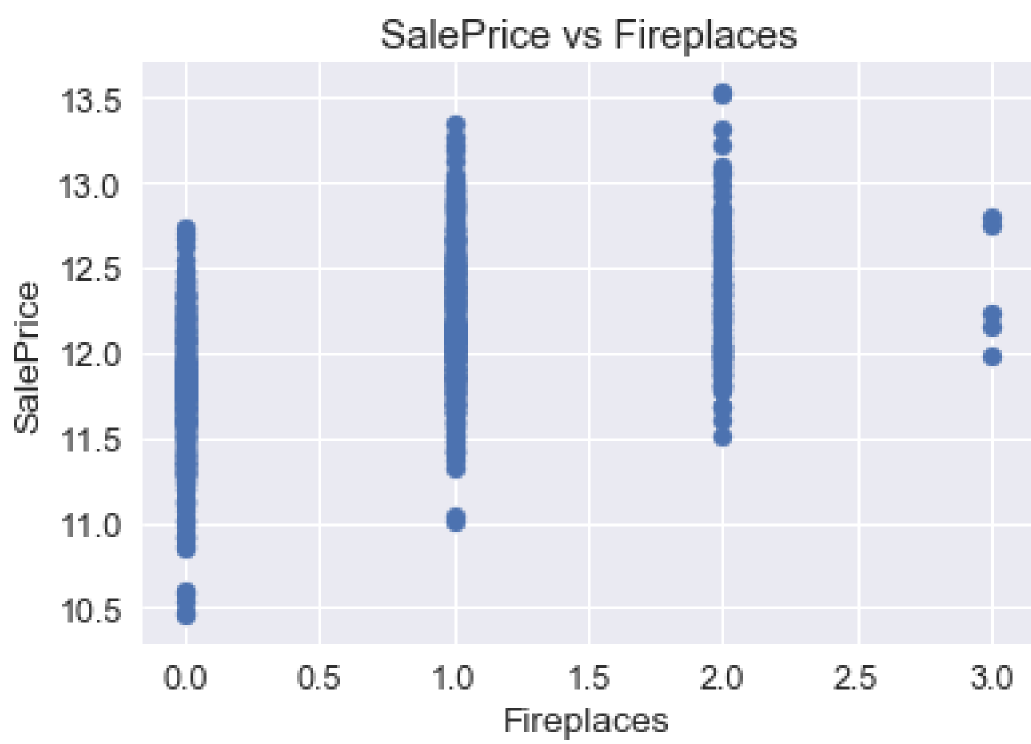

SalePrice vs FullBath
SalePrice
13.5
13.0
12.5
12.0
11.5
11.0
10.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
FullBath

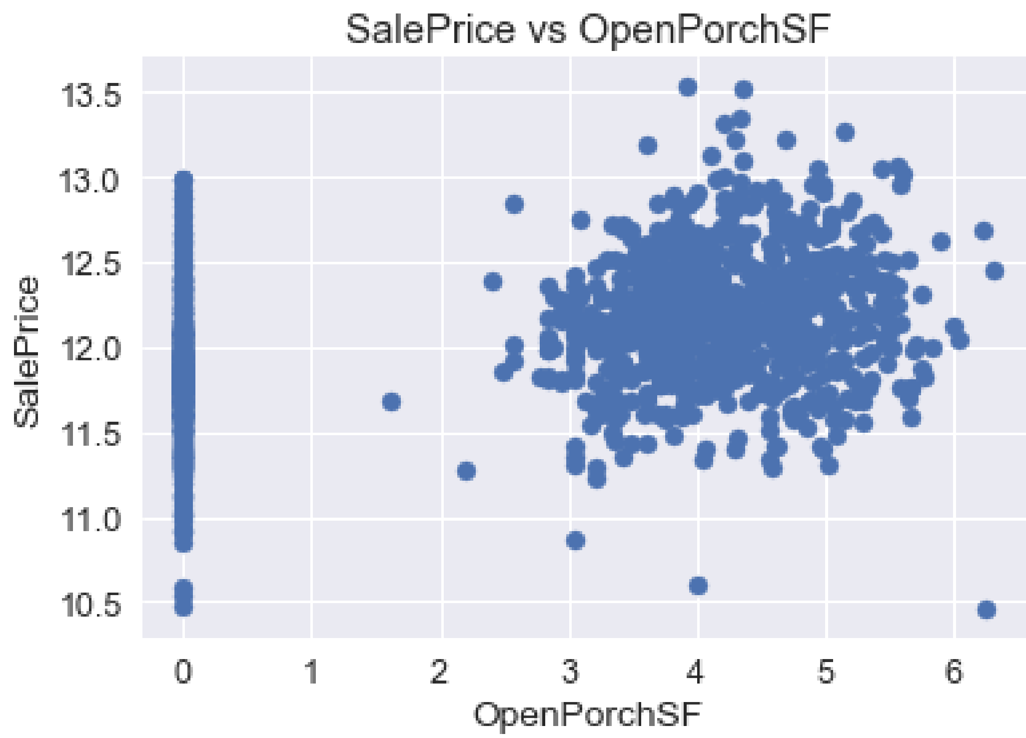

SalePrice vs YearBuilt
SalePrice
13.5
13.0
12.5
12.0
11.5
11.0
10.5
1880
1900
1920
1940
1960
1980
2000
YearBuilt

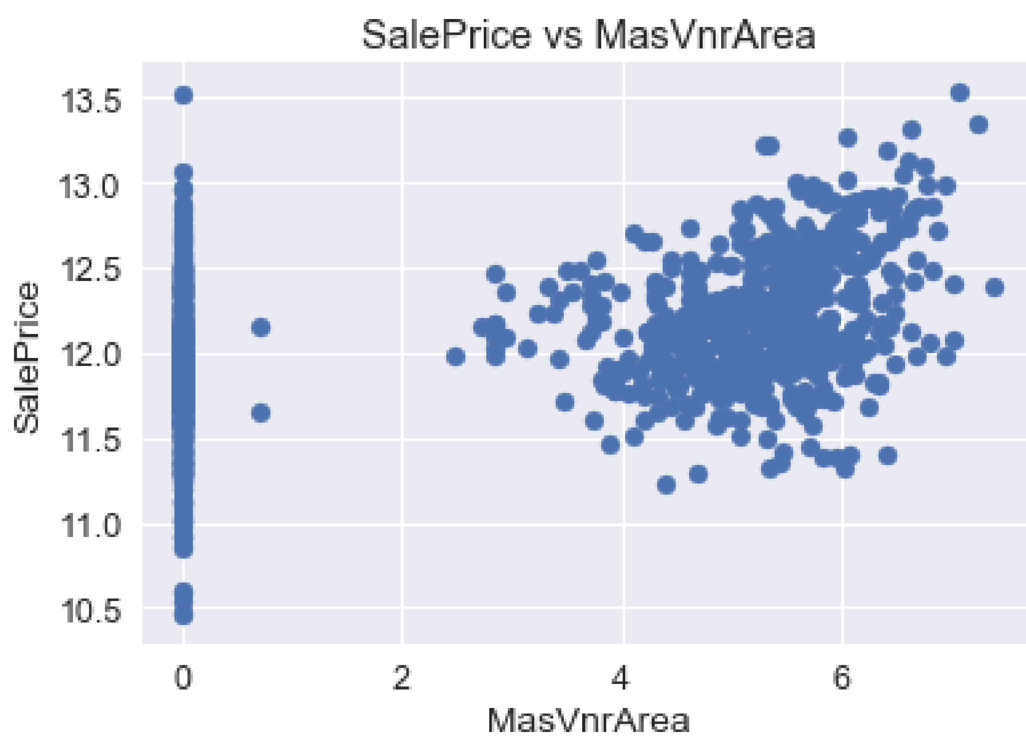

SalePrice vs YearRemodAdd
SalePrice
13.5
13.0
12.5
12.0
11.5
11.0
10.5
1950
1960
1970
1980
1990
2000
2010
YearRemodAdd

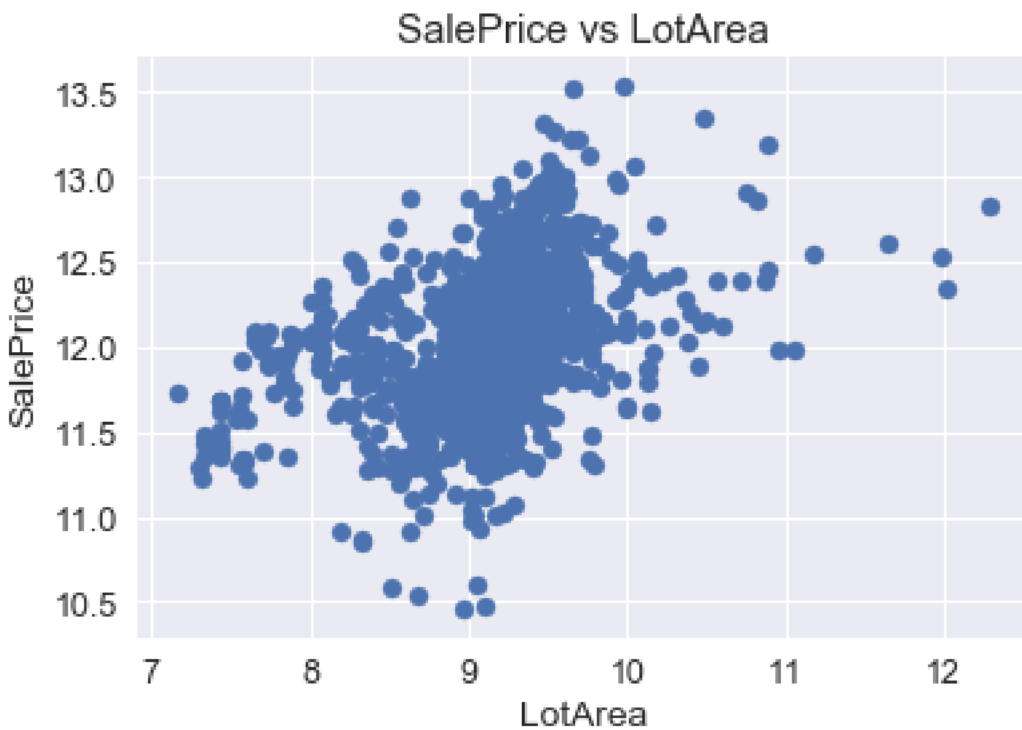

SalePrice vs GarageYrBlt
SalePrice
13.5
13.0
12.5
12.0
11.5
11.0
10.5
1900
1920
1940
1960
1980
2000
GarageYrBlt

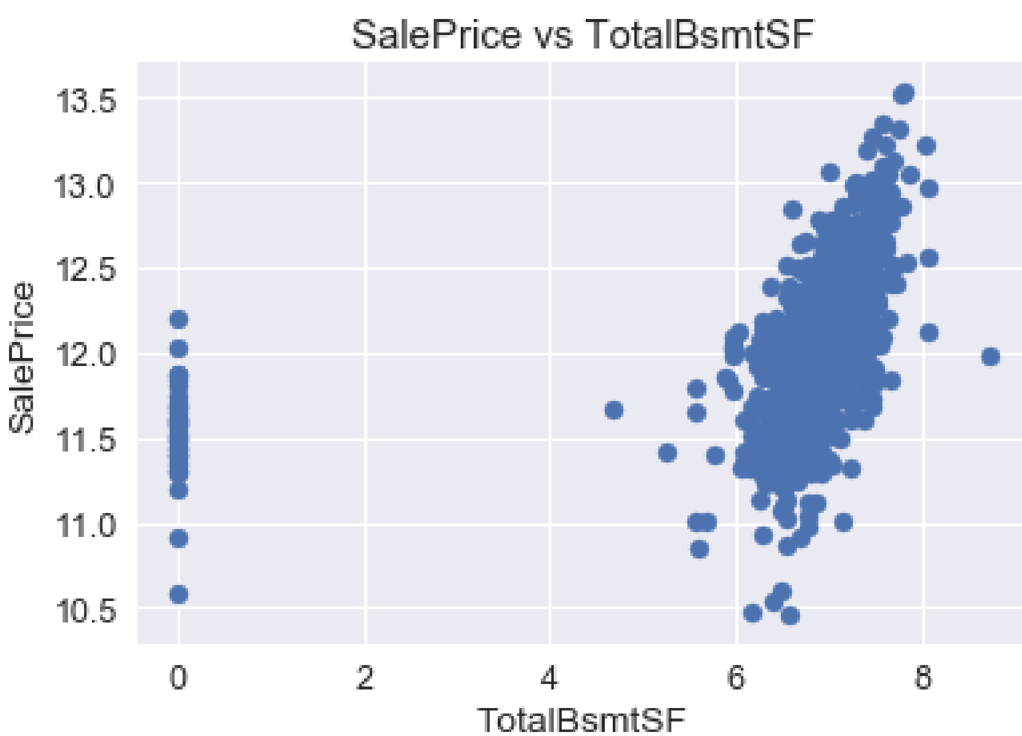

SalePrice vs TotRmsAbvGrd
SalePrice
TotRmsAbvGrd
13.5
13.0
12.5
12.0
11.5
11.0
10.5
1.25
1.50
1.75
2.00
2.25
2.50
2.75

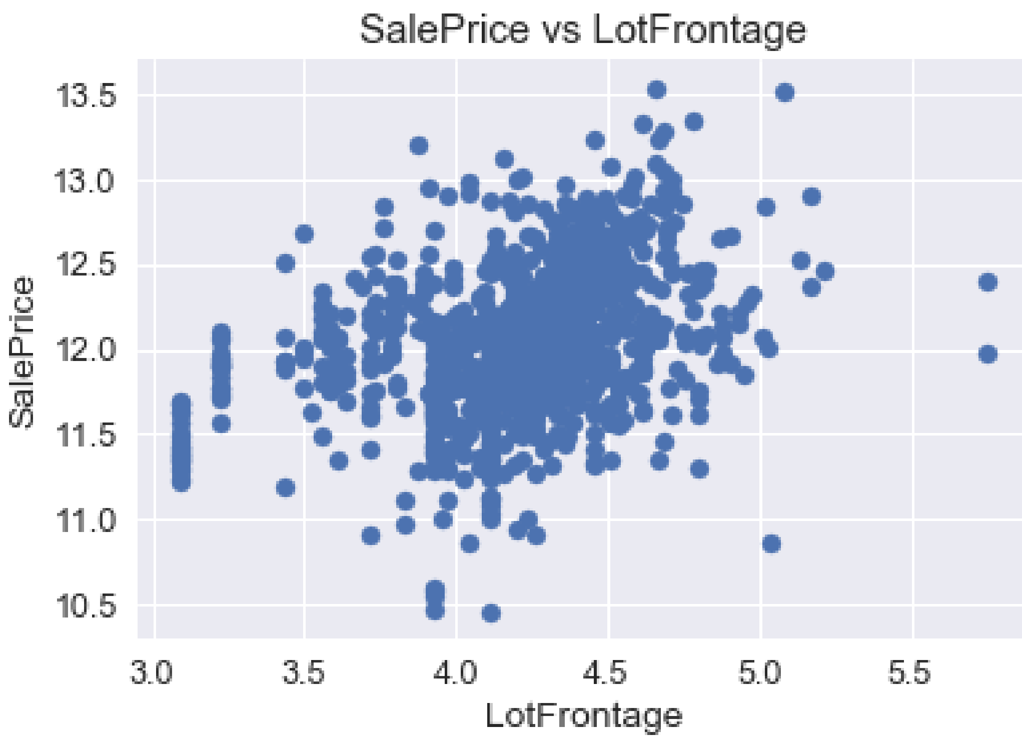

SalePrice vs Fireplaces
SalePrice
Fireplaces
13.5
13.0
12.5
12.0
11.5
11.0
10.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0

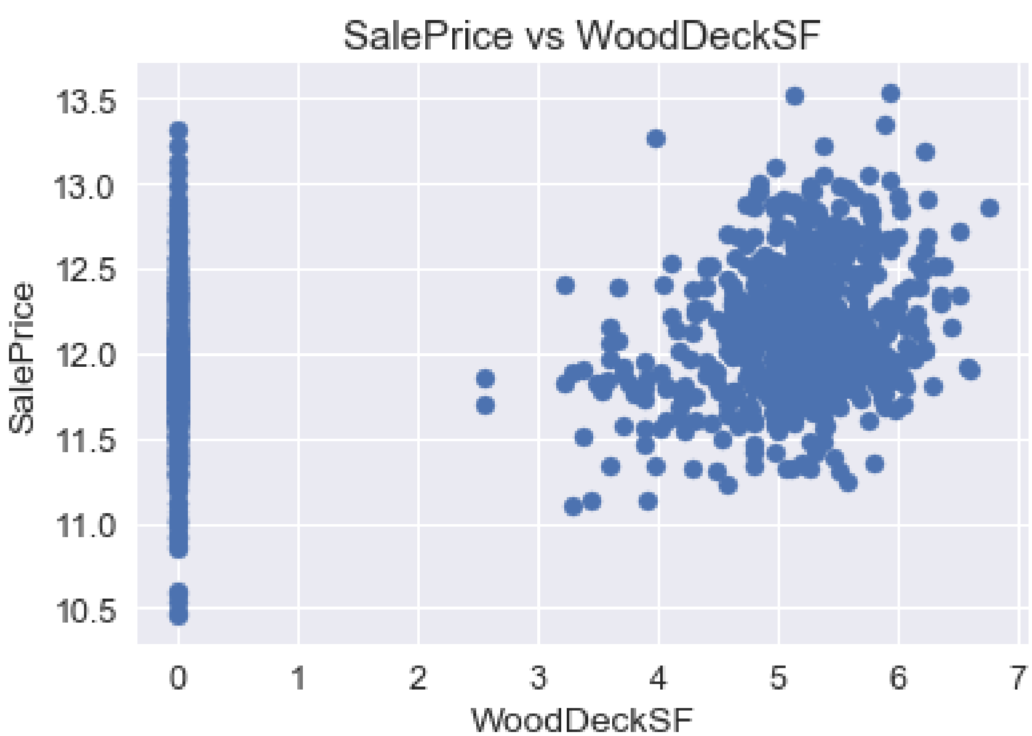

SalePrice vs OpenPorchSF
13.5
13.0
12.5
12.0
11.5
11.0
10.5
SalePrice
0
1
2
3
4
5
6
OpenPorchSF

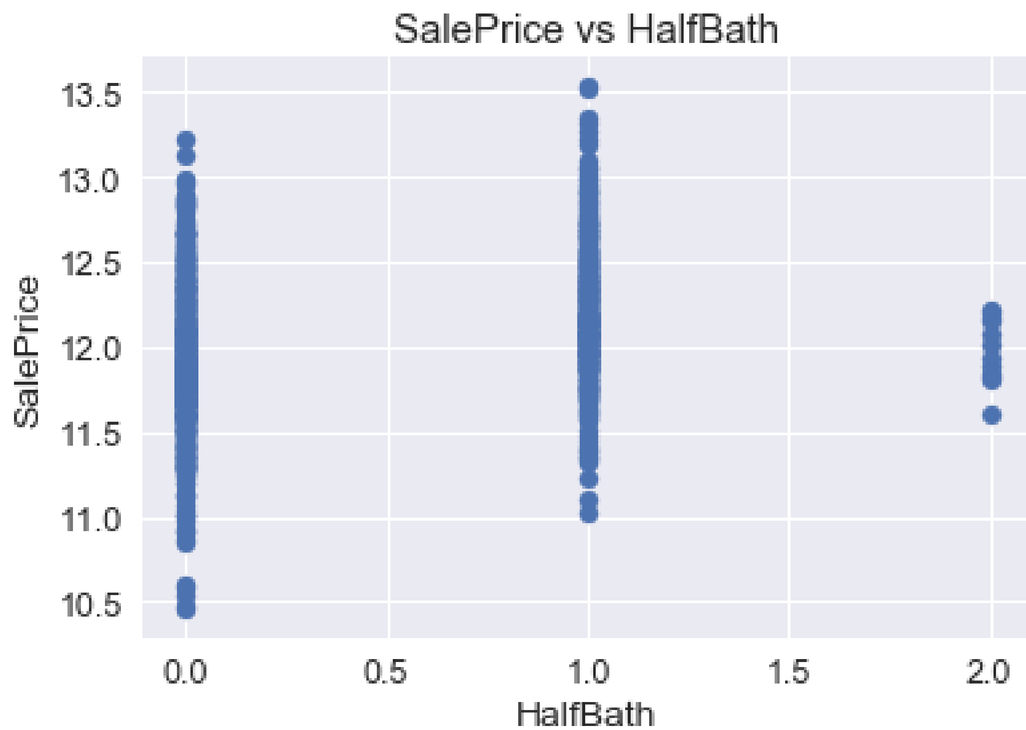

SalePrice vs MasVnrArea
13.5
13.0
12.5
12.0
11.5
11.0
10.5
SalePrice
0
2
4
6
MasVnrArea

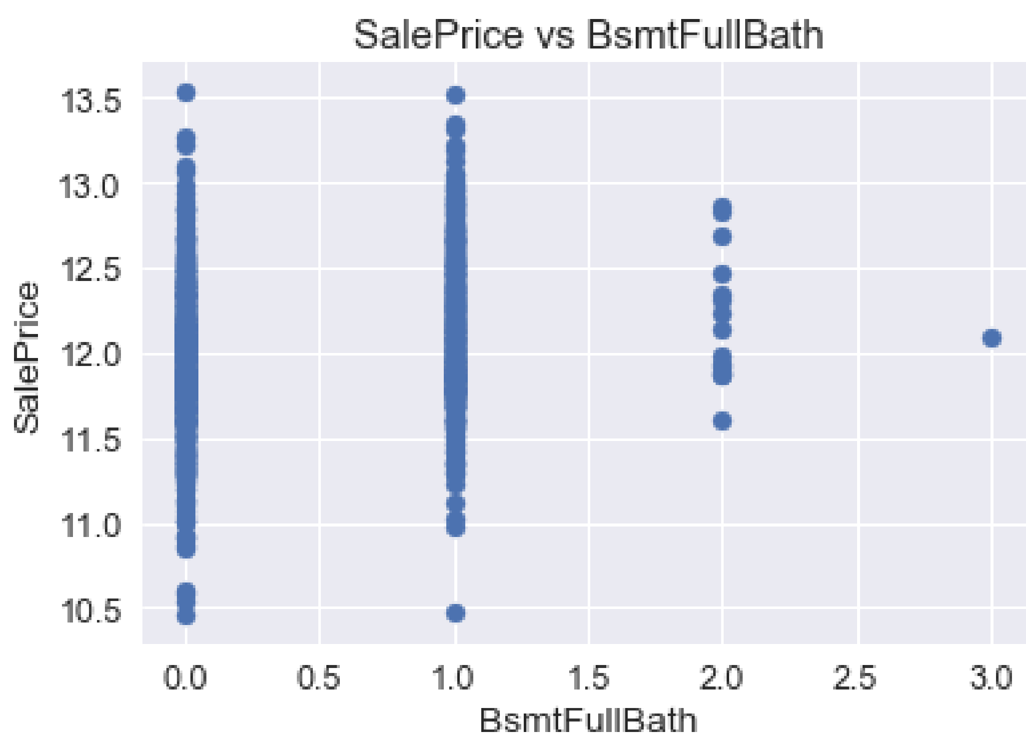

SalePrice vs LotArea
SalePrice
13.5
13.0
12.5
12.0
11.5
11.0
10.5
7
8
9
10
11
12
LotArea


SalePrice vs TotalBsmtSF
SalePrice
13.5
13.0
12.5
12.0
11.5
11.0
10.5
0
2
4
6
8
TotalBsmtSF

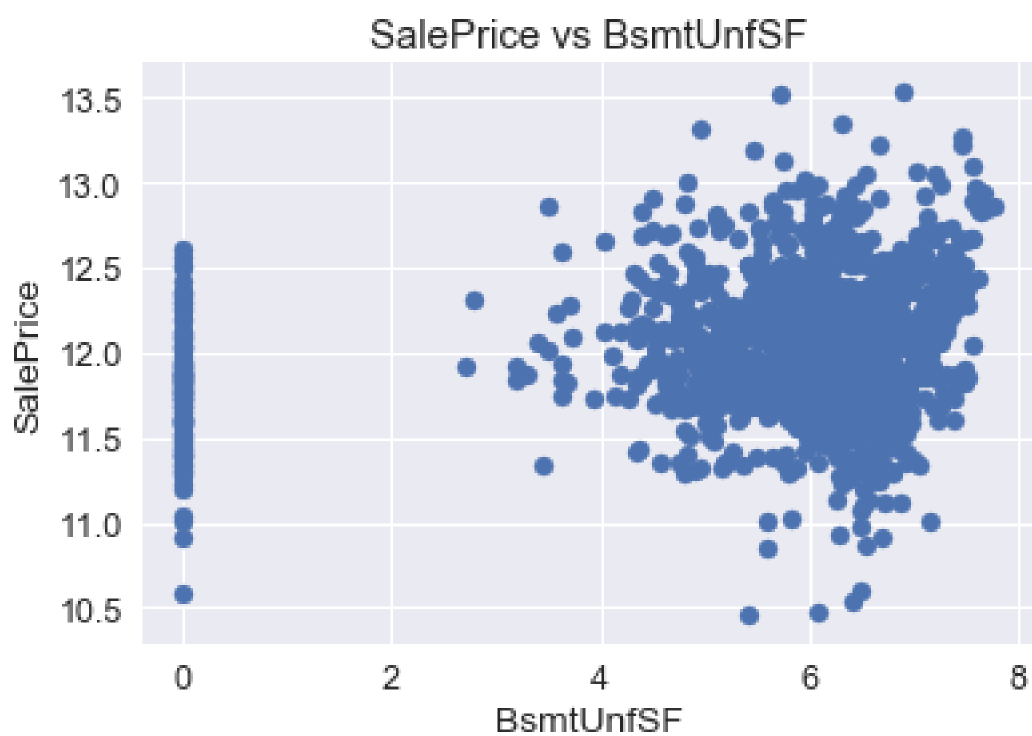

SalePrice vs LotFrontage
SalePrice
13.5
13.0
12.5
12.0
11.5
11.0
10.5
3.0
3.5
4.0
4.5
5.0
5.5
LotFrontage

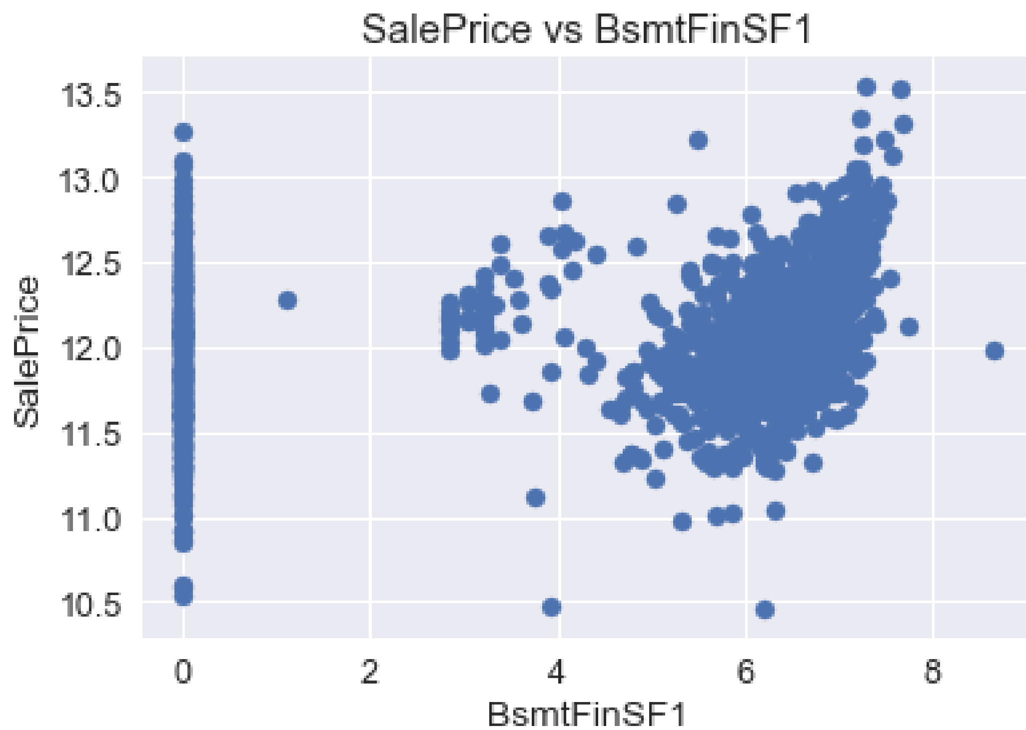

SalePrice vs WoodDeckSF
SalePrice
13.5
13.0
12.5
12.0
11.5
11.0
10.5
0
1
2
3
4
5
6
7
WoodDeckSF


SalePrice vs HalfBath
13.5
13.0
12.5
12.0
11.5
11.0
10.5
SalePrice
0.0
0.5
1.0
1.5
2.0
HalfBath

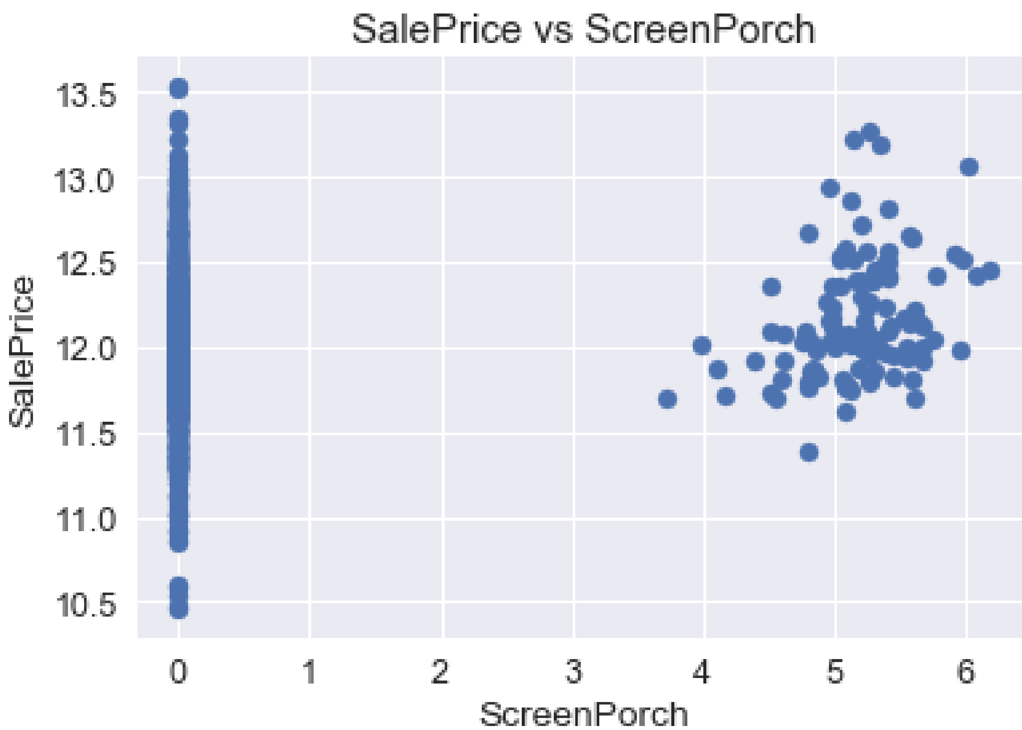

SalePrice vs BsmtFullBath
13.5
13.0
12.5
12.0
11.5
11.0
10.5
SalePrice
0.0
0.5
1.0
1.5
2.0
2.5
3.0
BsmtFullBath

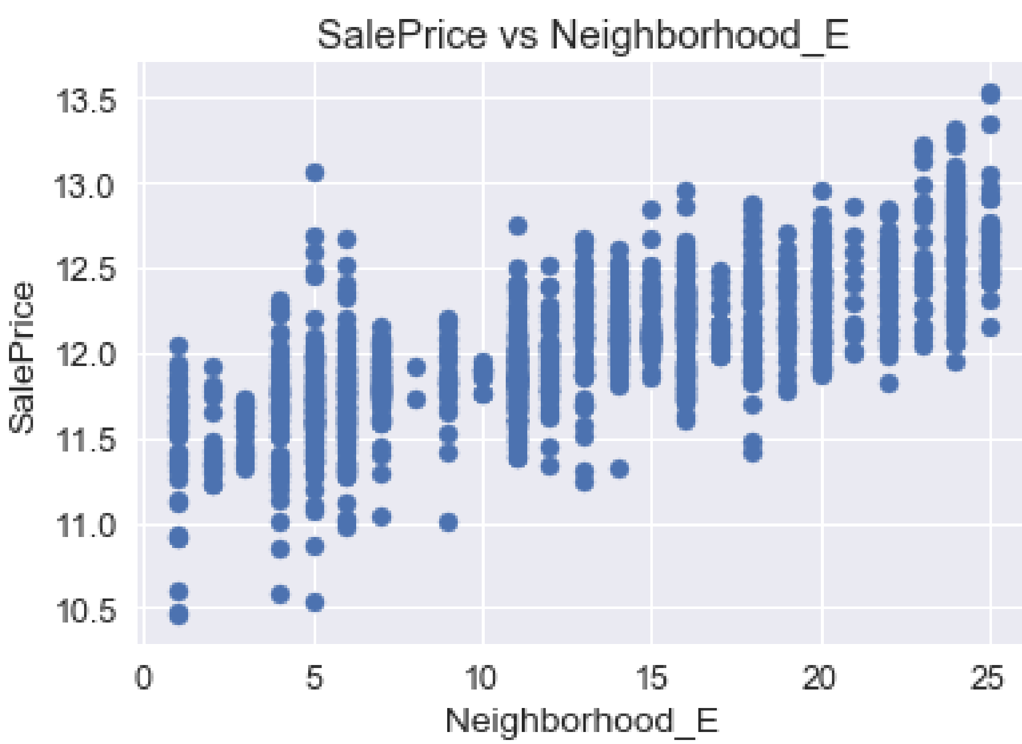

SalePrice vs BedroomAbvGr
13.5
13.0
12.5
12.0
11.5
11.0
10.5
SalePrice
0
2
4
6
8
BedroomAbvGr

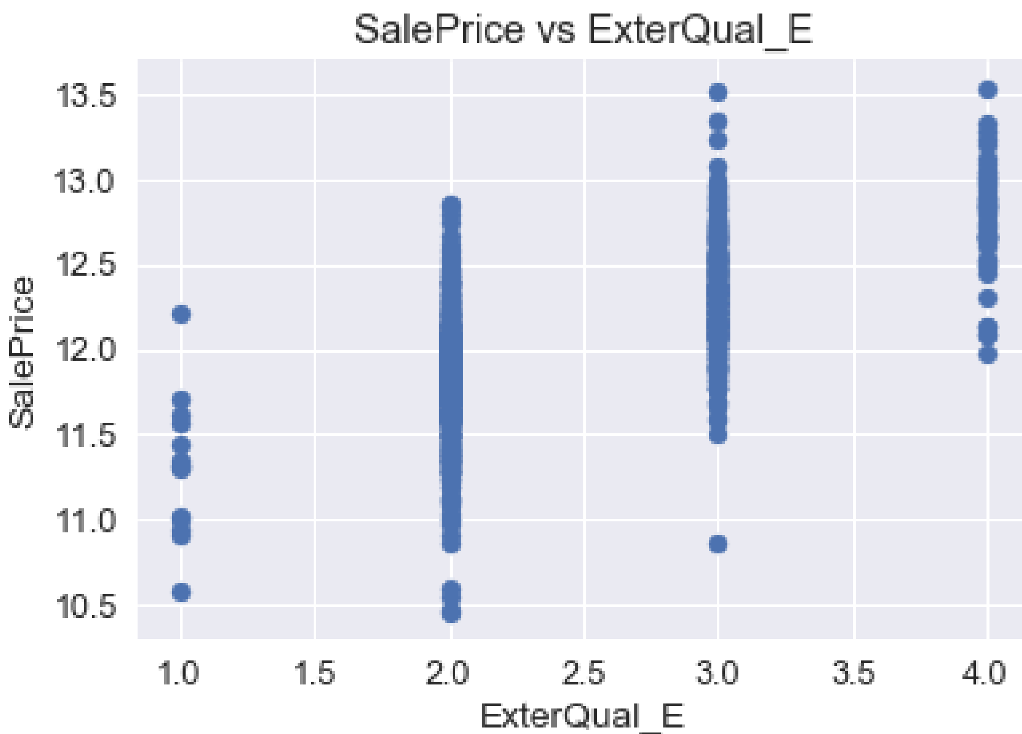

SalePrice vs BsmtUnfSF
13.5
13.0
12.5
12.0
11.5
11.0
10.5
SalePrice
0
2
4
6
8
BsmtUnfSF

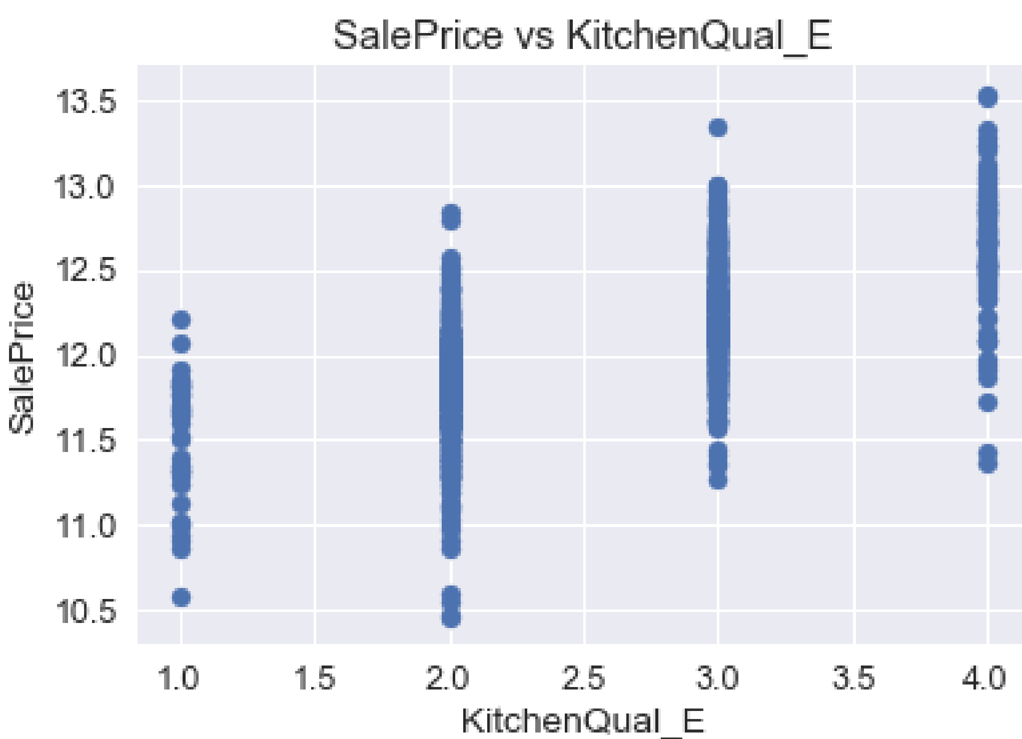

SalePrice vs BsmtFinSF1
SalePrice
13.5
13.0
12.5
12.0
11.5
11.0
10.5
0
2
4
6
8
BsmtFinSF1

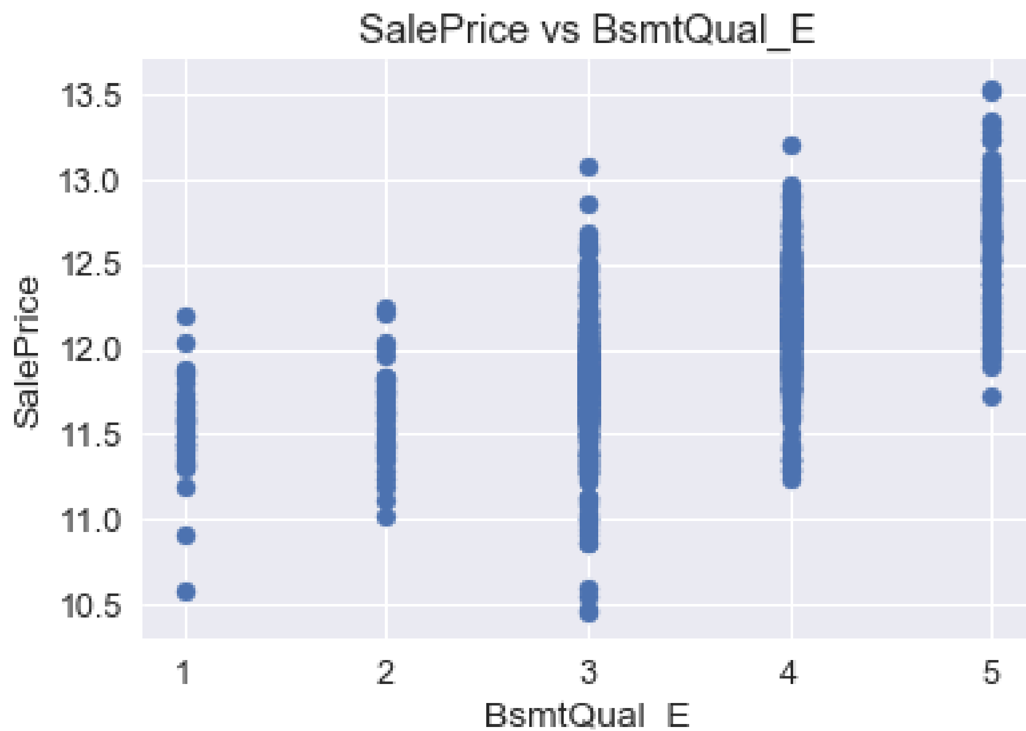

SalePrice vs 2ndFlrSF
SalePrice
13.5
13.0
12.5
12.0
11.5
11.0
10.5
0
2
4
6
8
2ndFlrSF

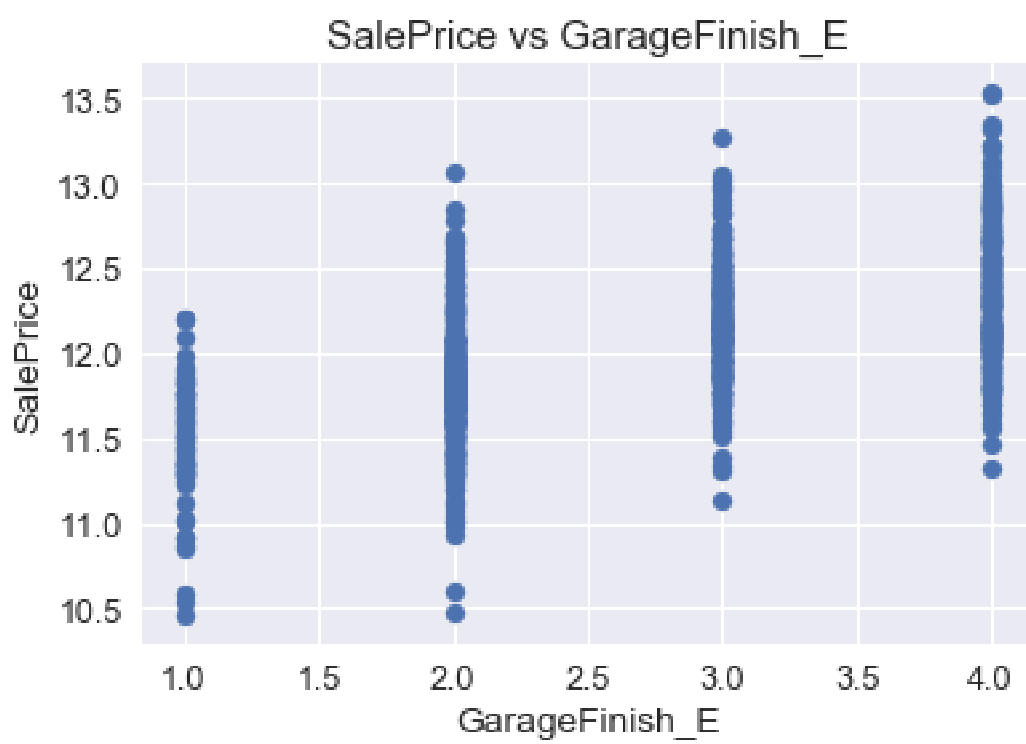

SalePrice vs ScreenPorch
SalePrice
13.5
13.0
12.5
12.0
11.5
11.0
10.5
0
1
2
3
4
5
6
ScreenPorch

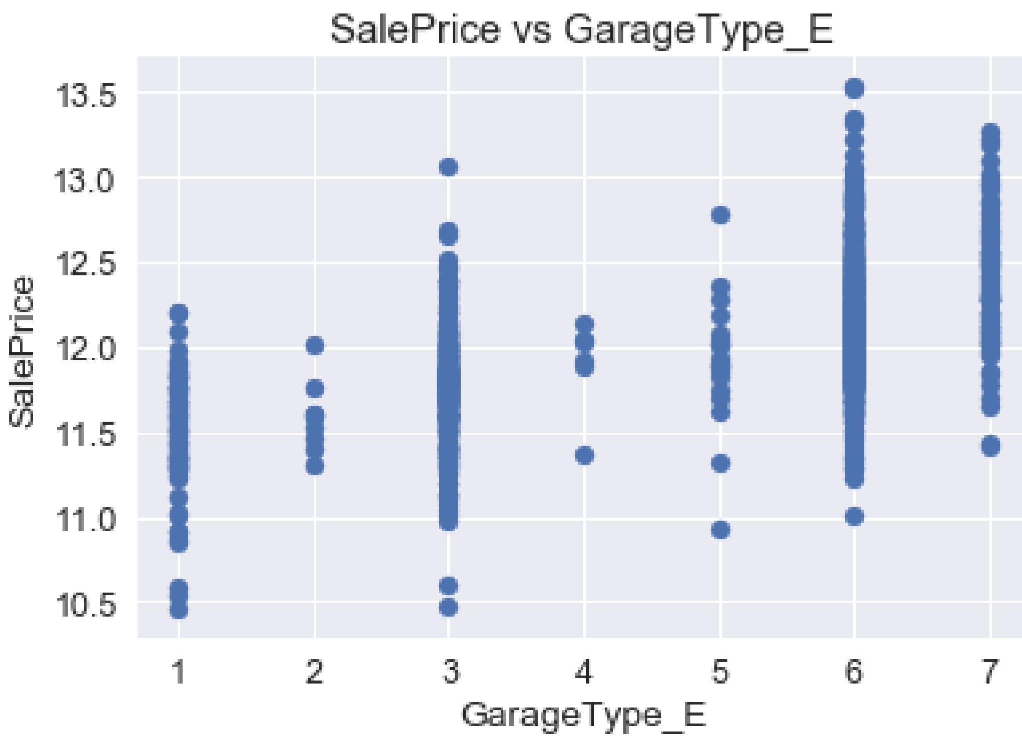

SalePrice vs Neighborhood_E
SalePrice
13.5
13.0
12.5
12.0
11.5
11.0
10.5
0
5
10
15
20
25
Neighborhood_E


SalePrice vs ExterQual_E
13.5
13.0
12.5
12.0
11.5
11.0
10.5
SalePrice
1.0
1.5
2.0
2.5
3.0
3.5
4.0
ExterQual_E

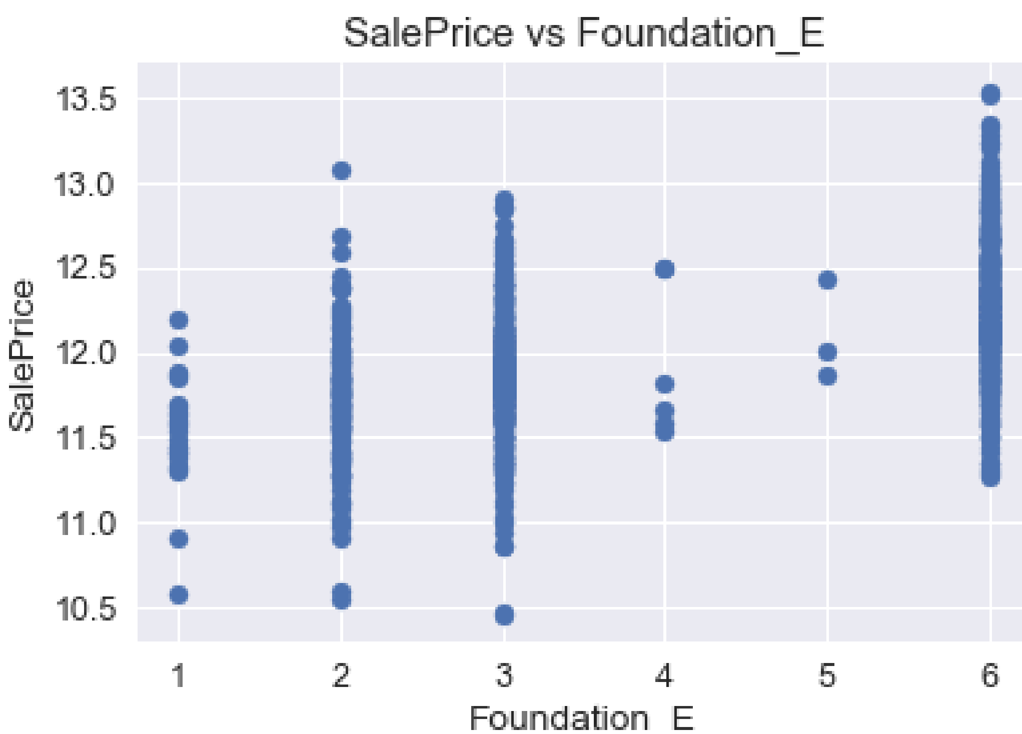

SalePrice vs KitchenQual_E
13.5
13.0
12.5
12.0
11.5
11.0
10.5
SalePrice
1.0
1.5
2.0
2.5
3.0
3.5
4.0
KitchenQual_E


SalePrice vs BsmtQual_E
SalePrice
13.5
13.0
12.5
12.0
11.5
11.0
10.5
1
2
3
4
5
BsmtQual_E


SalePrice vs GarageFinish_E
SalePrice
13.5
13.0
12.5
12.0
11.5
11.0
10.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
GarageFinish_E

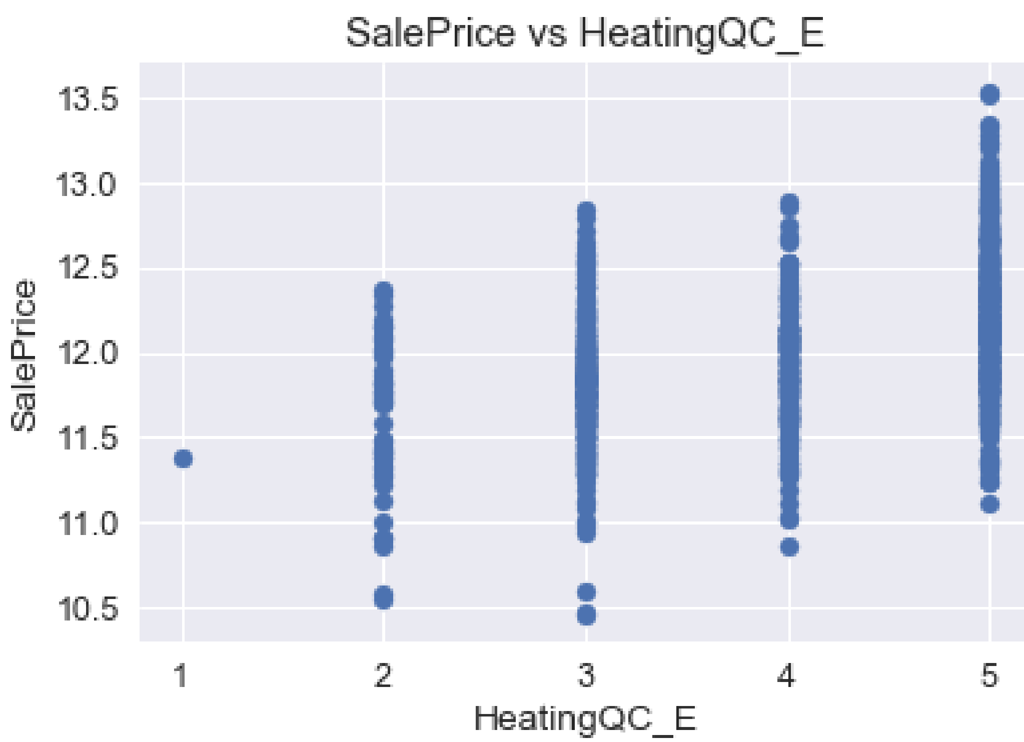


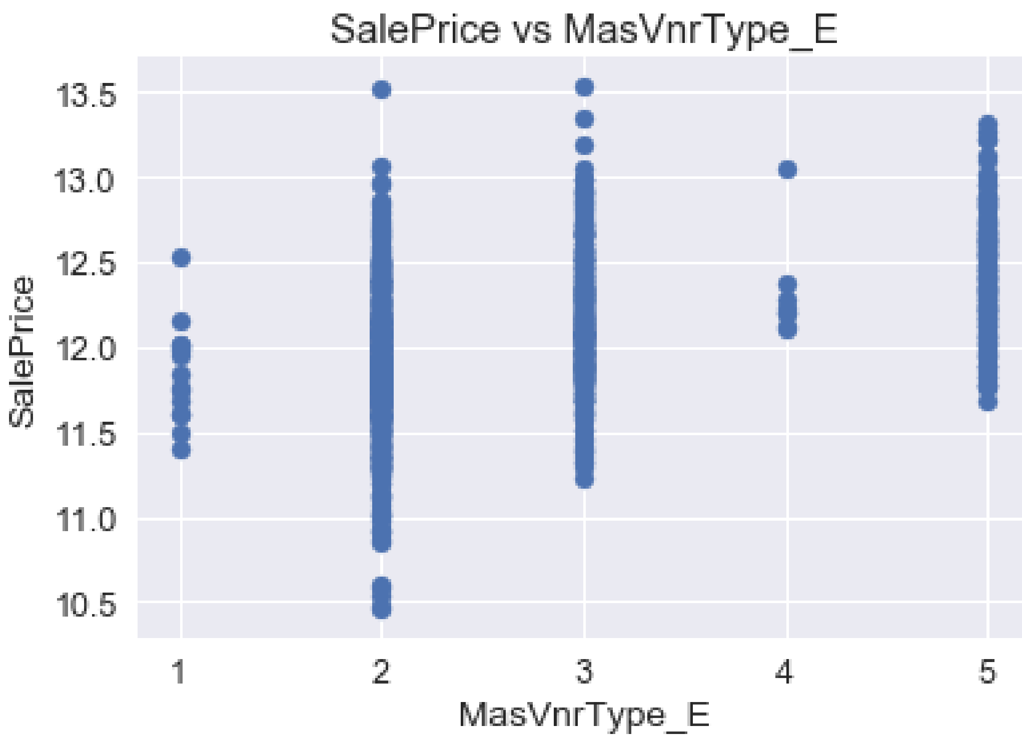
SalePrice vs GarageType_E
13.5
13.0
12.5
12.0
11.5
11.0
10.5
SalePrice
1
2
3
4
5
6
7
GarageType_E



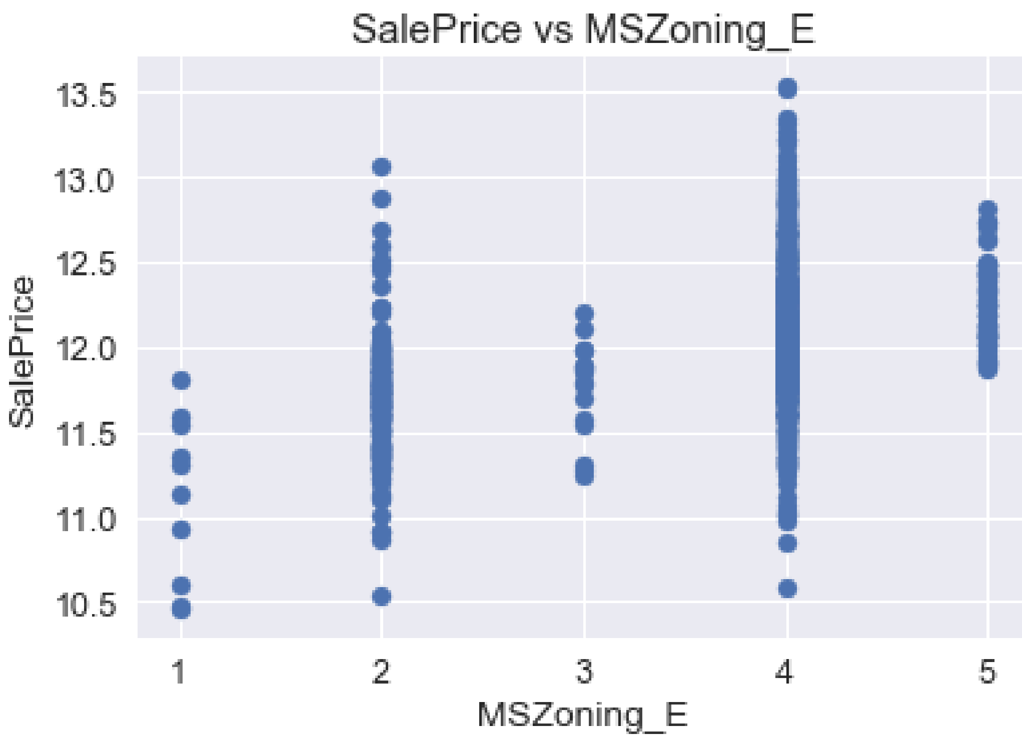
SalePrice vs Foundation_E
13.5
13.0
12.5
12.0
11.5
11.0
10.5
SalePrice
1
2
3
4
5
6
Foundation_E

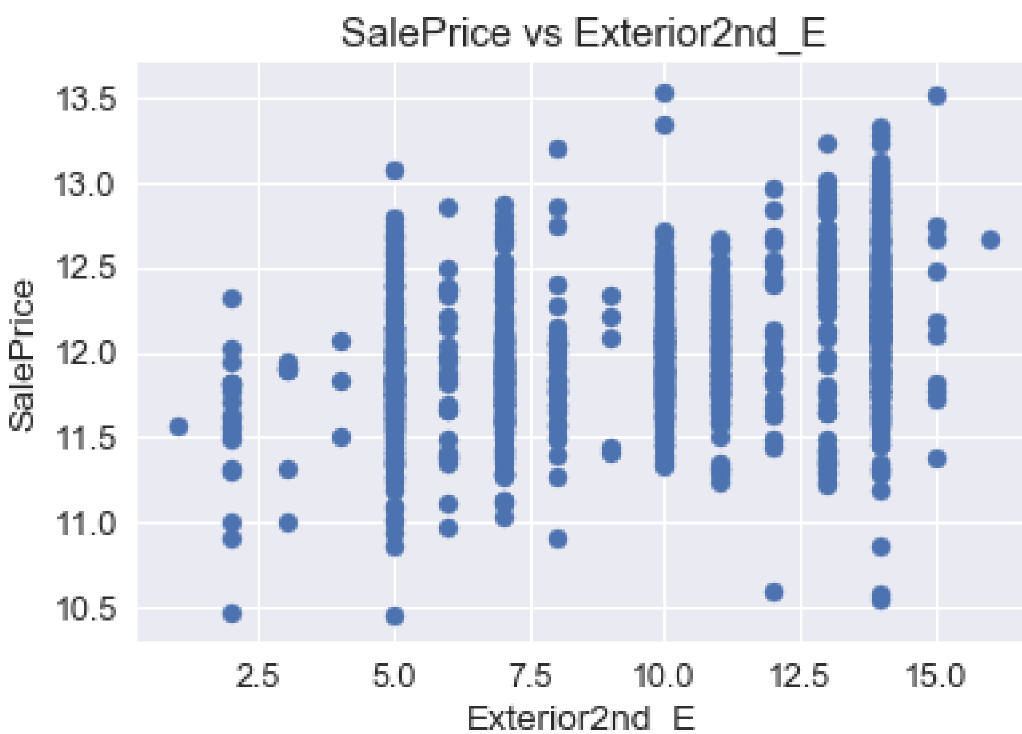

SalePrice vs FireplaceQu_E
13.5
13.0
12.5
12.0
11.5
11.0
10.5
SalePrice
1
2
3
4
5
6
FireplaceQu_E

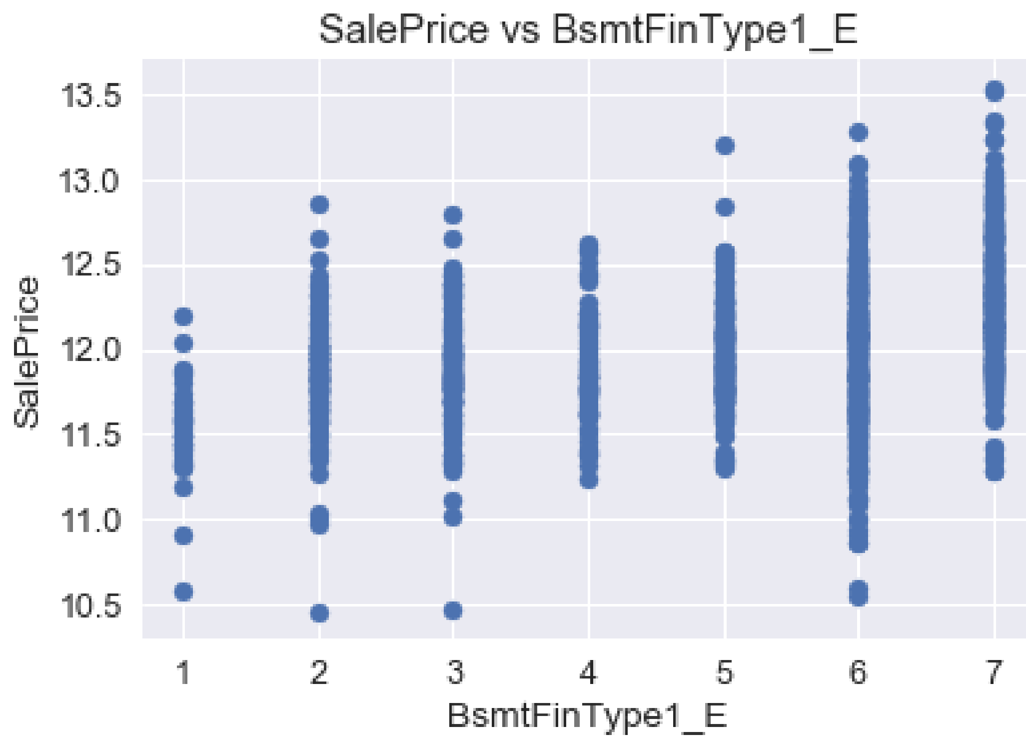

SalePrice vs HeatingQC_E
13.5
13.0
12.5
12.0
11.5
11.0
10.5
SalePrice
1
2
3
4
5
HeatingQC_E

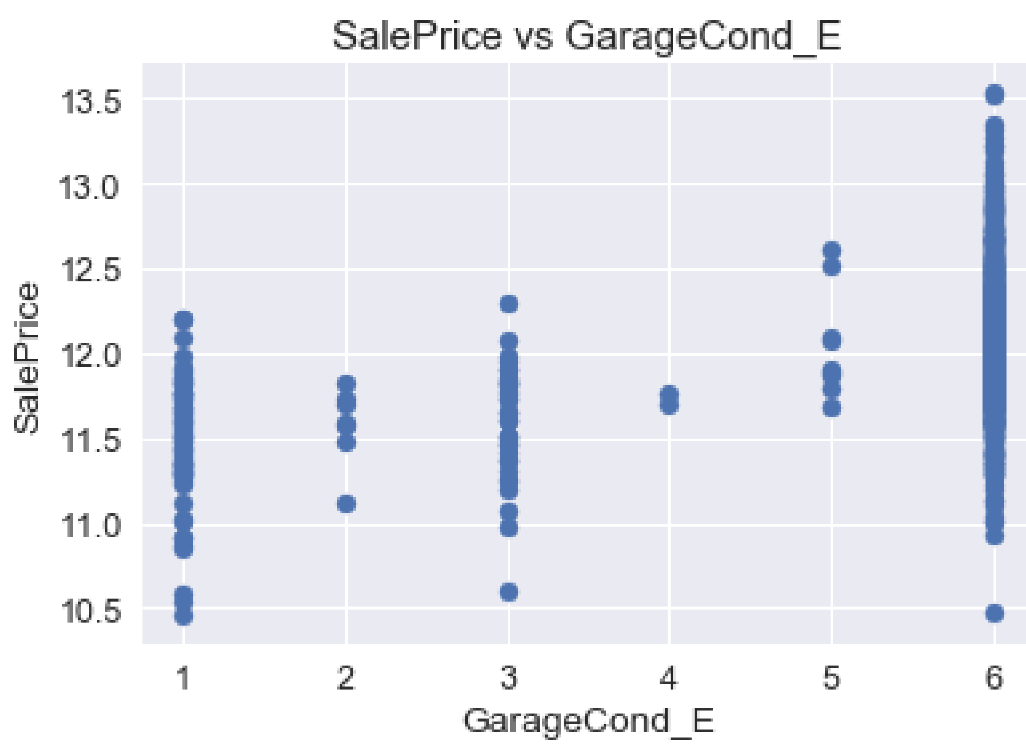

SalePrice vs MasVnrType_E
SalePrice
13.5
13.0
12.5
12.0
11.5
11.0
10.5
1
2
3
4
5
MasVnrType_E

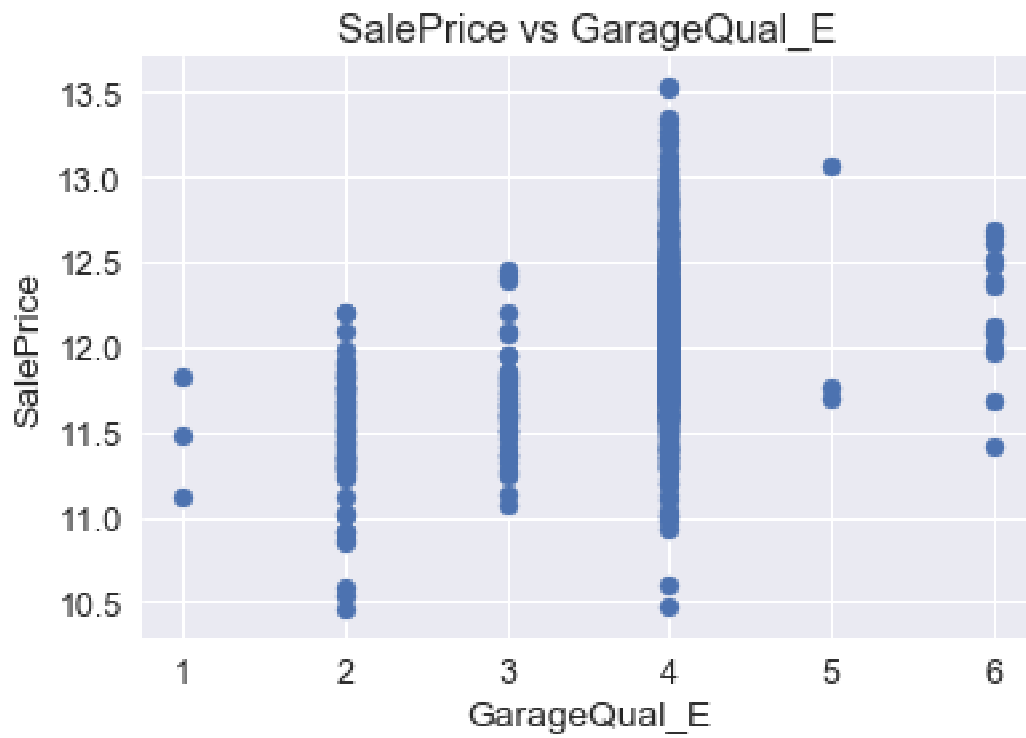

SalePrice vs Exterior1st_E
SalePrice
13.5
13.0
12.5
12.0
11.5
11.0
10.5
2
4
6
8
10
12
14
Exterior1st_E

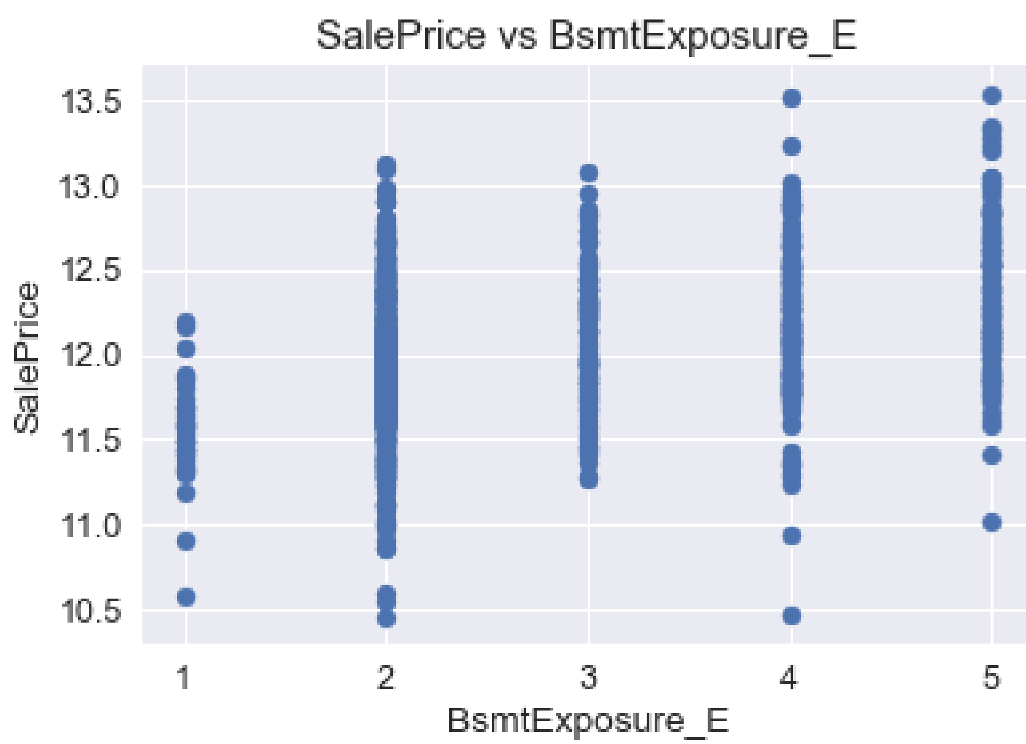

SalePrice vs MSZoning_E
SalePrice
MSZoning_E
13.5
13.0
12.5
12.0
11.5
11.0
10.5
1
2
3
4
5

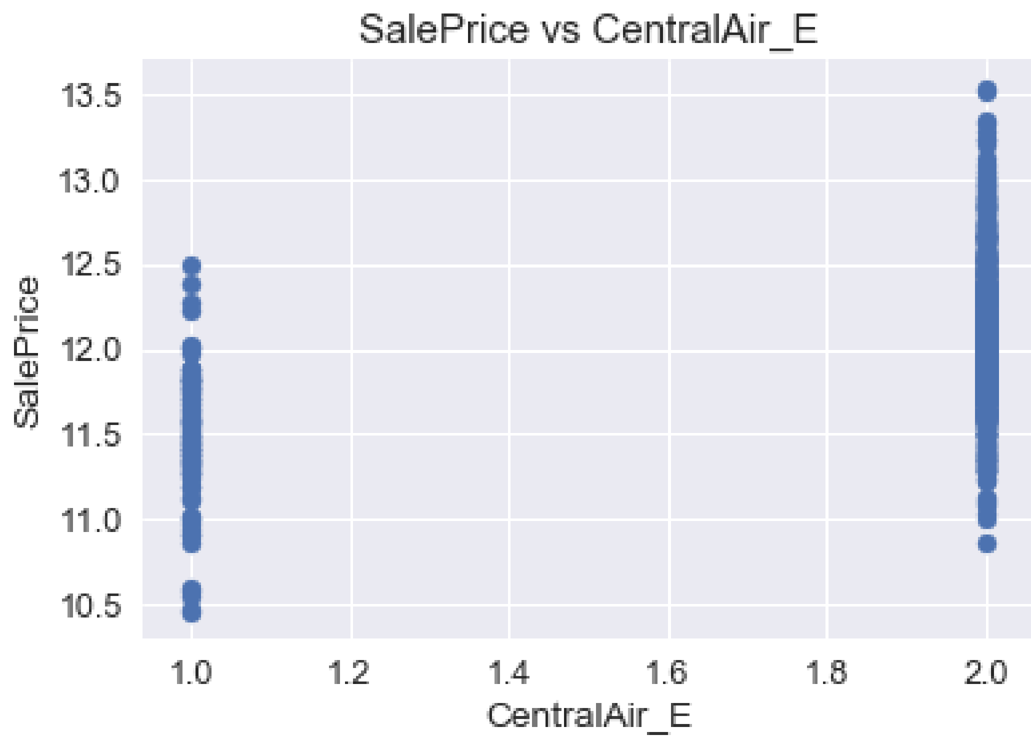

SalePrice vs Exterior2nd_E
SalePrice
Exterior2nd_E
13.5
13.0
12.5
12.0
11.5
11.0
10.5
2.5
5.0
7.5
10.0
12.5
15.0

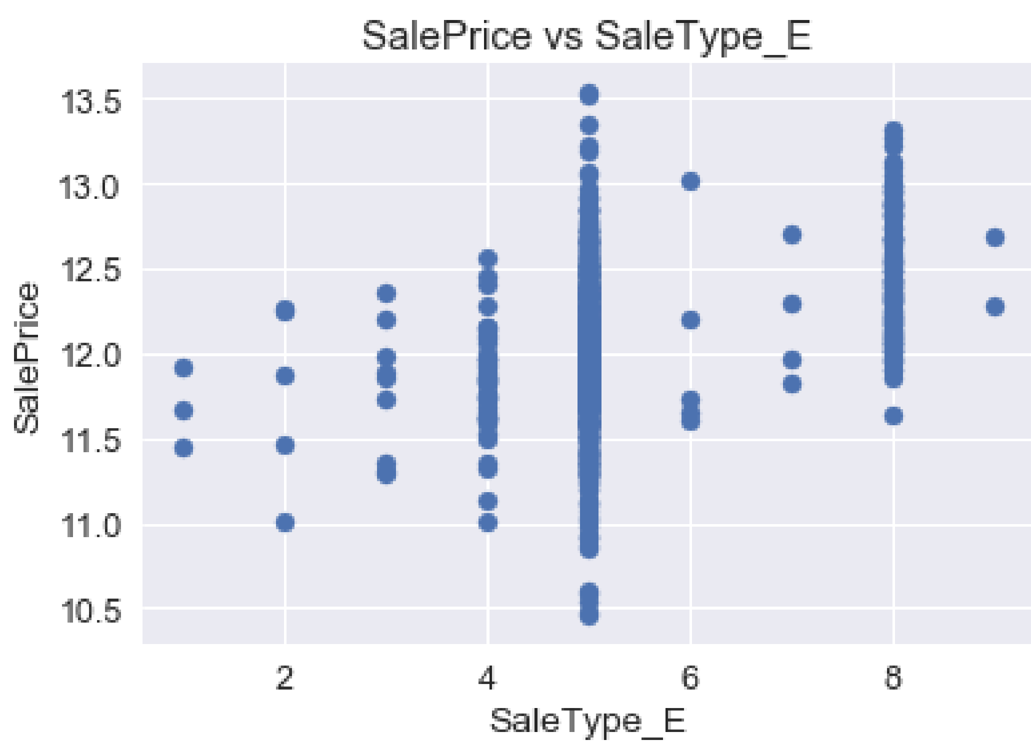

SalePrice vs BsmtFinType1_E
13.5
13.0
12.5
12.0
11.5
11.0
10.5
SalePrice
1
2
3
4
5
6
7
BsmtFinType1_E

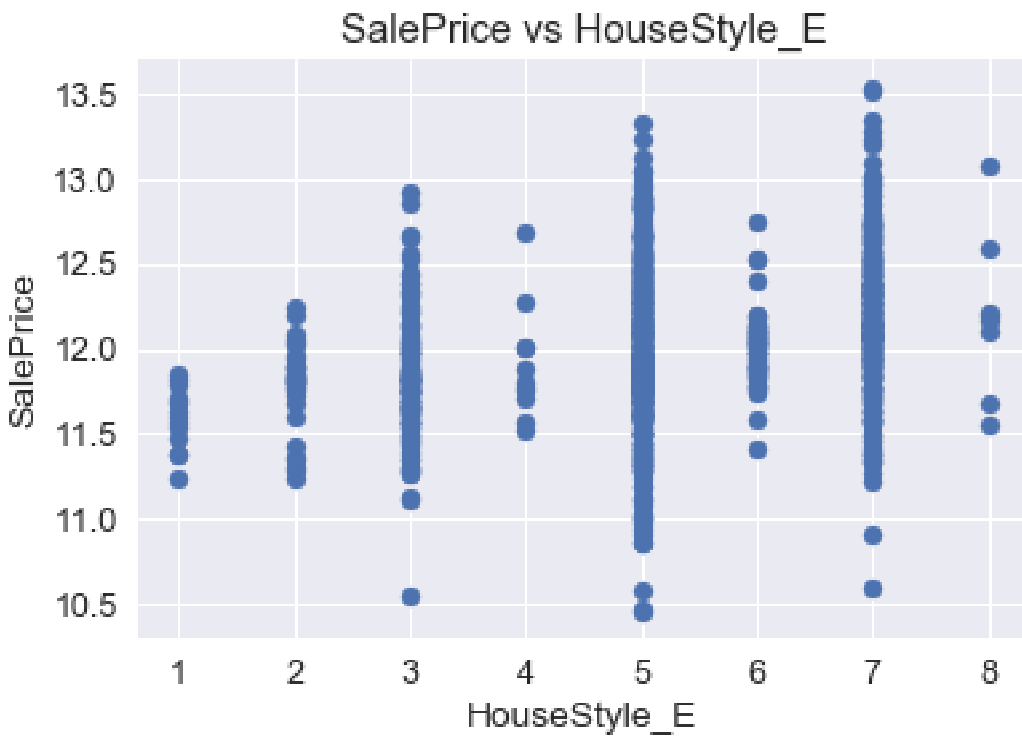

SalePrice vs GarageCond_E
13.5
13.0
12.5
12.0
11.5
11.0
10.5
SalePrice
1
2
3
4
5
6
GarageCond_E

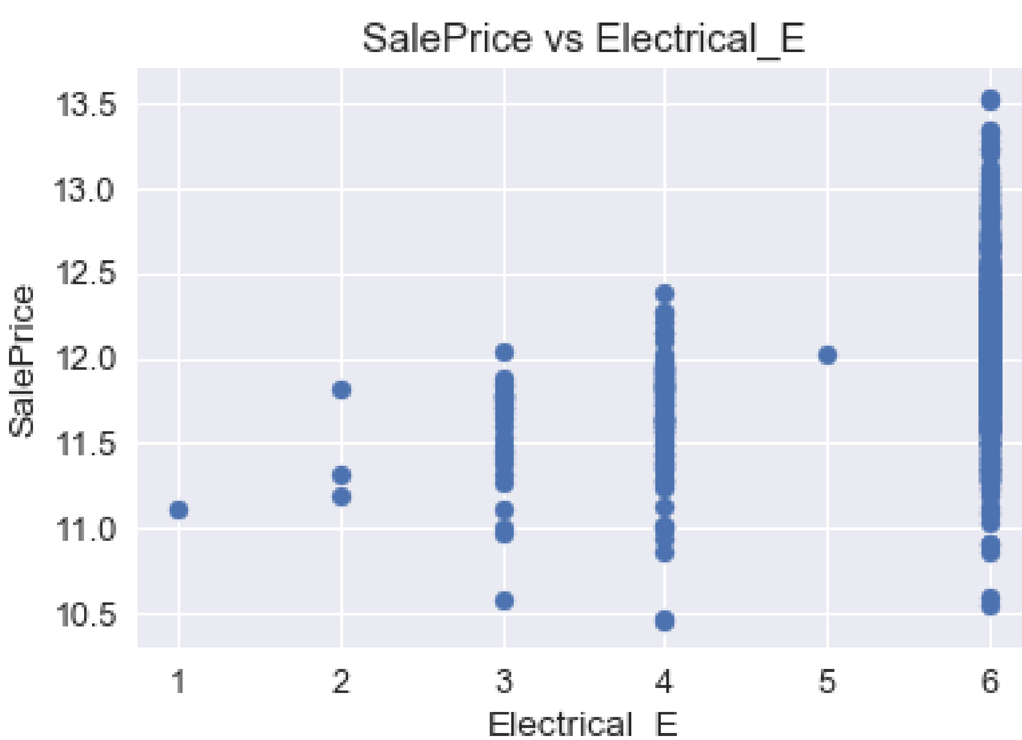

SalePrice vs GarageQual_E
SalePrice
13.5
13.0
12.5
12.0
11.5
11.0
10.5
1
2
3
4
5
6
GarageQual_E

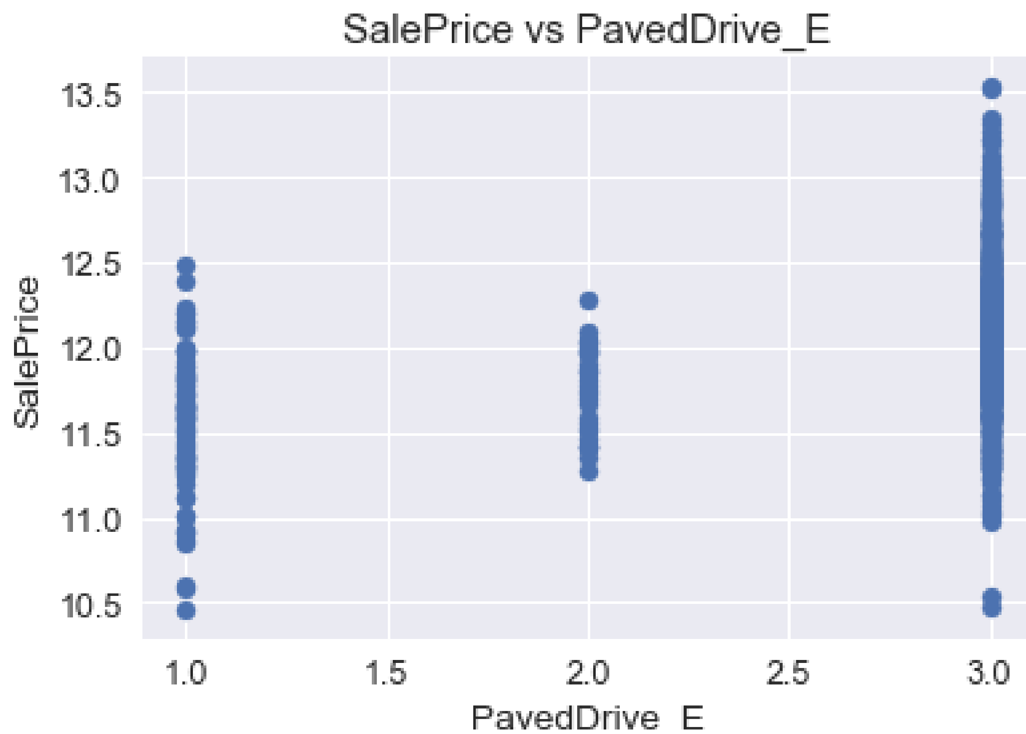

SalePrice vs BsmtExposure_E
SalePrice
13.5
13.0
12.5
12.0
11.5
11.0
10.5
1
2
3
4
5
BsmtExposure_E

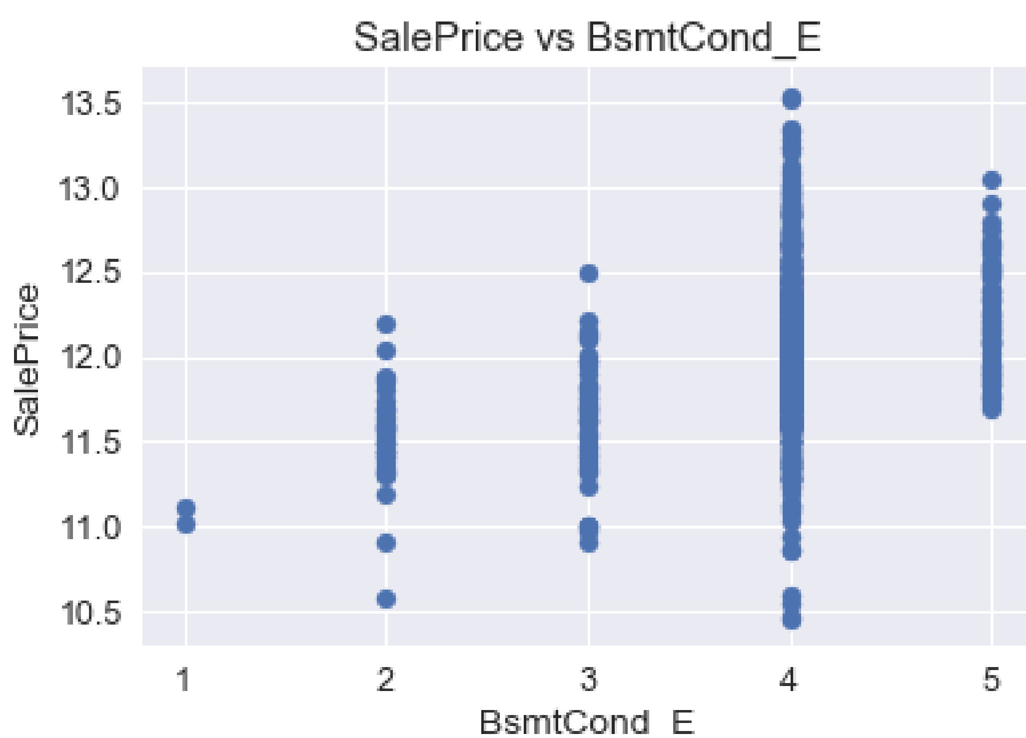

SalePrice vs CentralAir_E
SalePrice
13.5
13.0
12.5
12.0
11.5
11.0
10.5
1.0
1.2
1.4
1.6
1.8
2.0
CentralAir_E

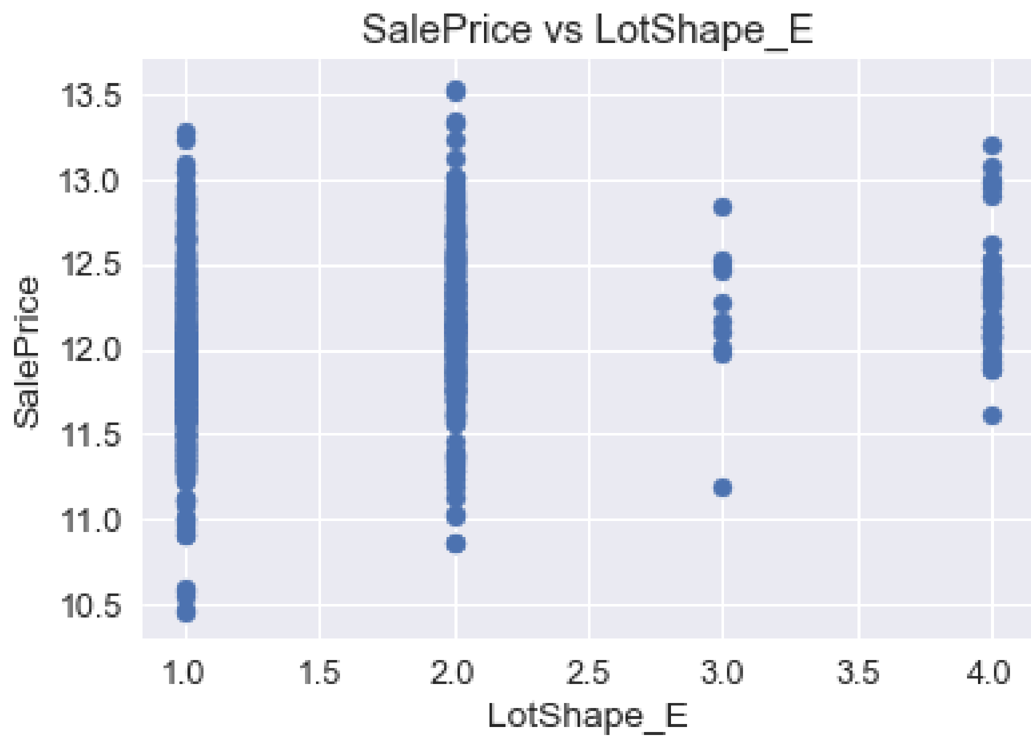

SalePrice vs SaleType_E
SalePrice
13.5
13.0
12.5
12.0
11.5
11.0
10.5
2
4
6
8
SaleType_E

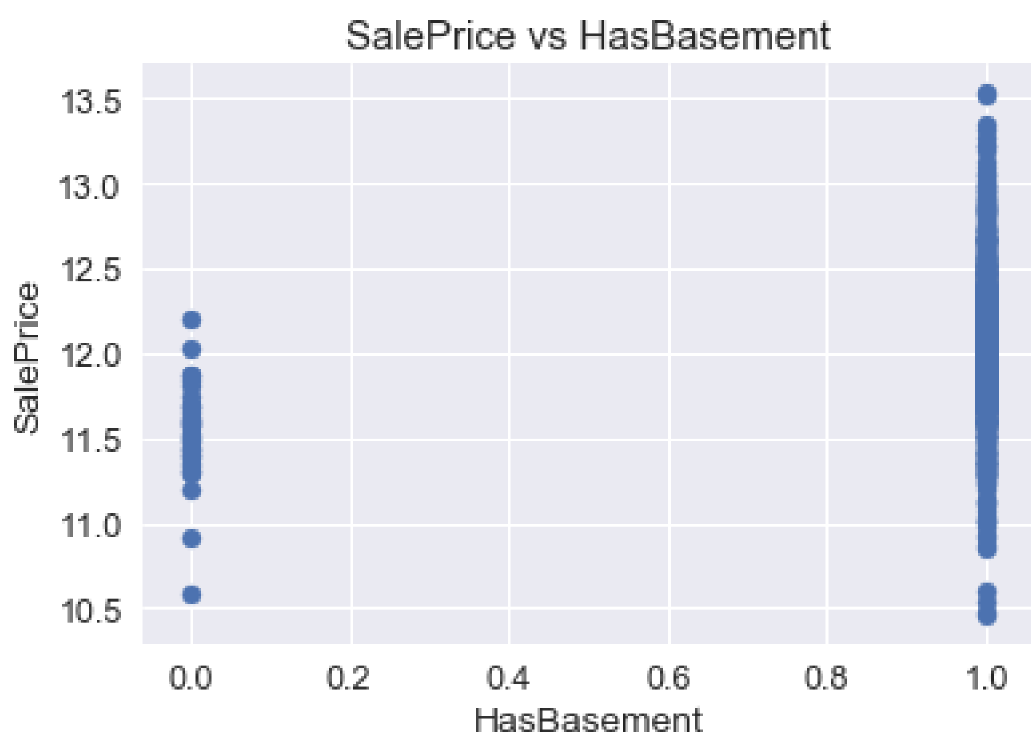

SalePrice vs HouseStyle_E
SalePrice
13.5
13.0
12.5
12.0
11.5
11.0
10.5
1
2
3
4
5
6
7
8
HouseStyle_E

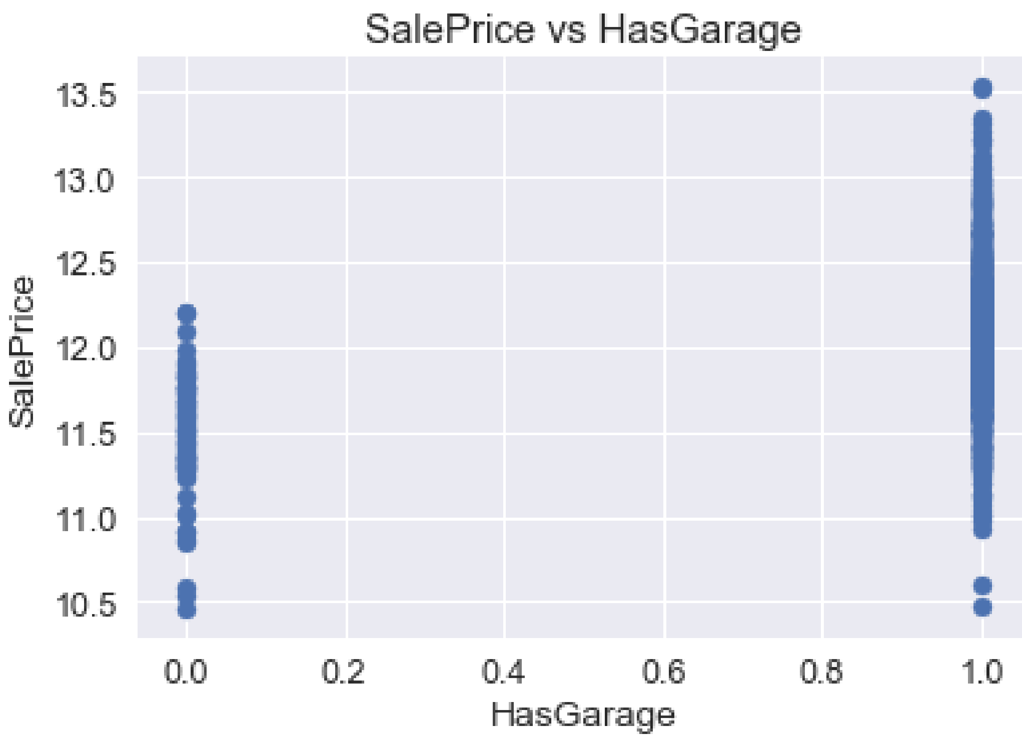

SalePrice vs Electrical_E
SalePrice
13.5
13.0
12.5
12.0
11.5
11.0
10.5
1
2
3
4
5
6
Electrical_E


SalePrice vs PavedDrive_E
SalePrice
13.5
13.0
12.5
12.0
11.5
11.0
10.5
1.0
1.5
2.0
2.5
3.0
PavedDrive_E

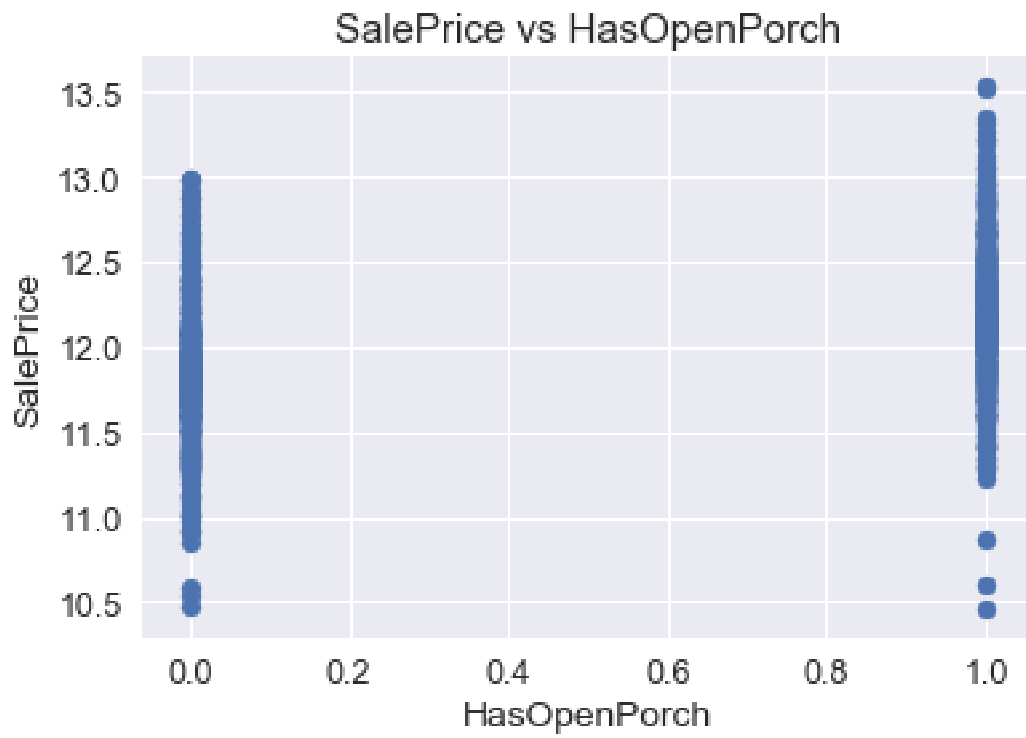

SalePrice vs BsmtCond_E
SalePrice
13.5
13.0
12.5
12.0
11.5
11.0
10.5
1
2
3
4
5
BsmtCond_E

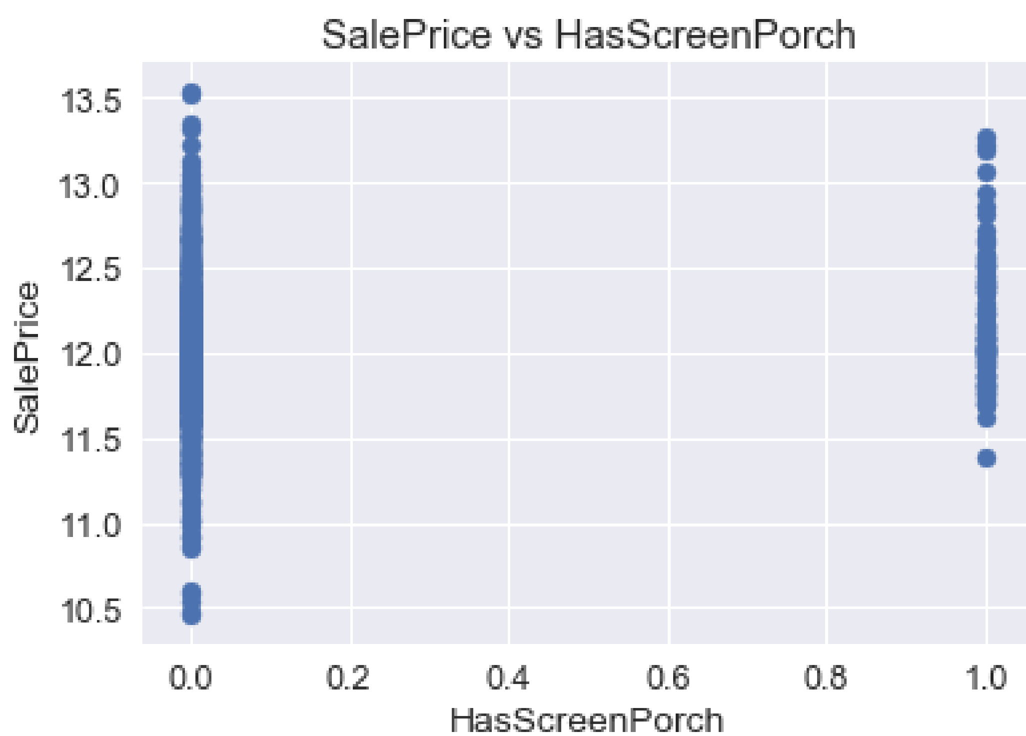

SalePrice vs LotShape_E
SalePrice
LotShape_E
13.5
13.0
12.5
12.0
11.5
11.0
10.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0

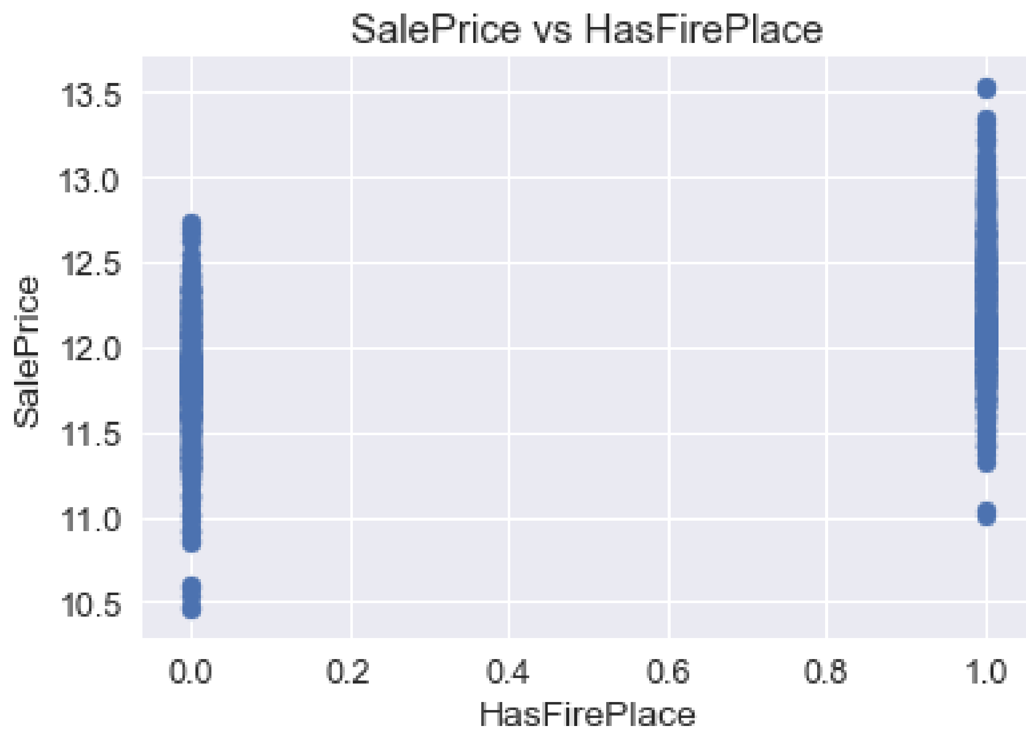

SalePrice vs HasBasement
SalePrice
HasBasement
13.5
13.0
12.5
12.0
11.5
11.0
10.5
0.0
0.2
0.4
0.6
0.8
1.0

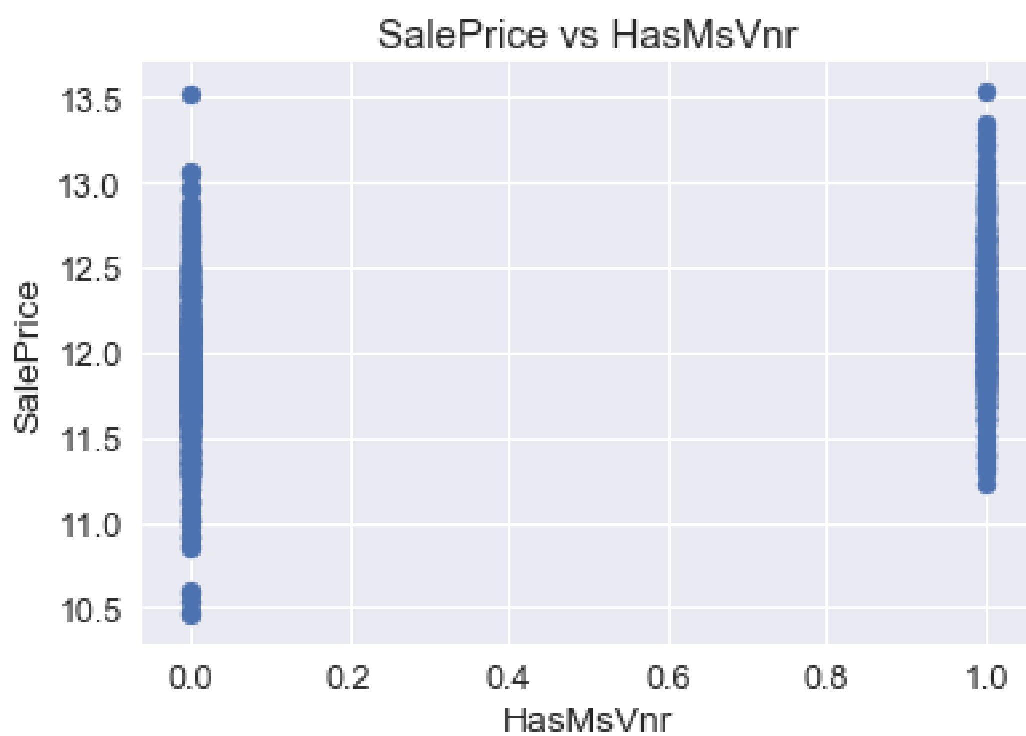

SalePrice vs HasGarage
SalePrice
13.5
13.0
12.5
12.0
11.5
11.0
10.5
0.0
0.2
0.4
0.6
0.8
1.0
HasGarage

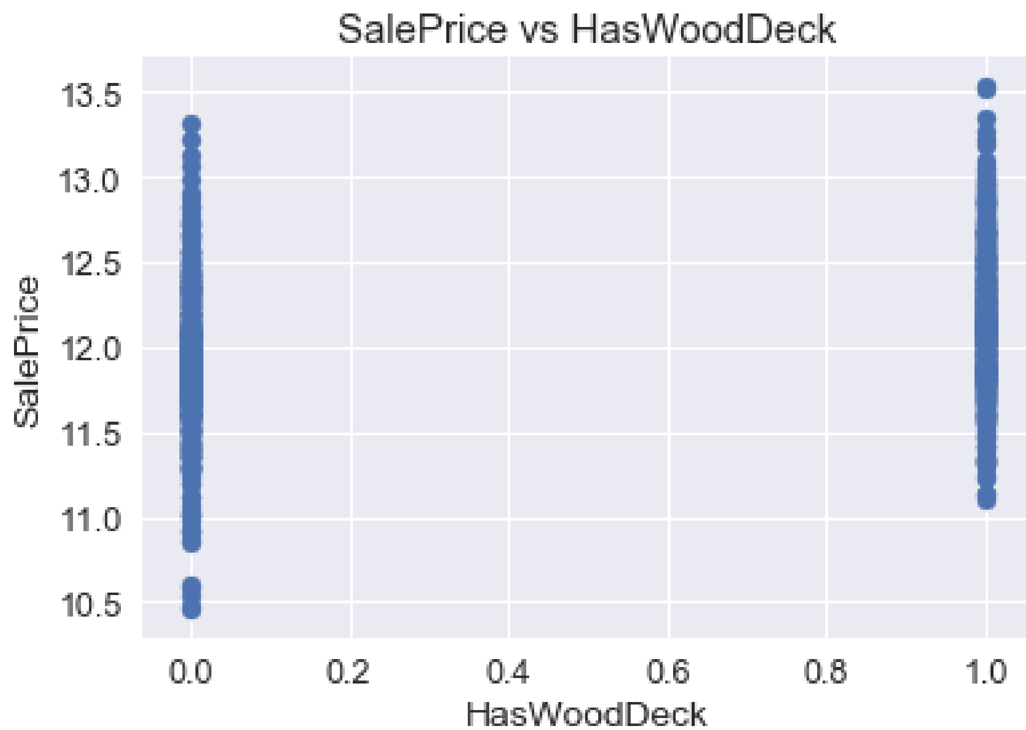

SalePrice vs Has2ndFlr
SalePrice
13.5
13.0
12.5
12.0
11.5
11.0
10.5
0.0
0.2
0.4
0.6
0.8
1.0
Has2ndFlr

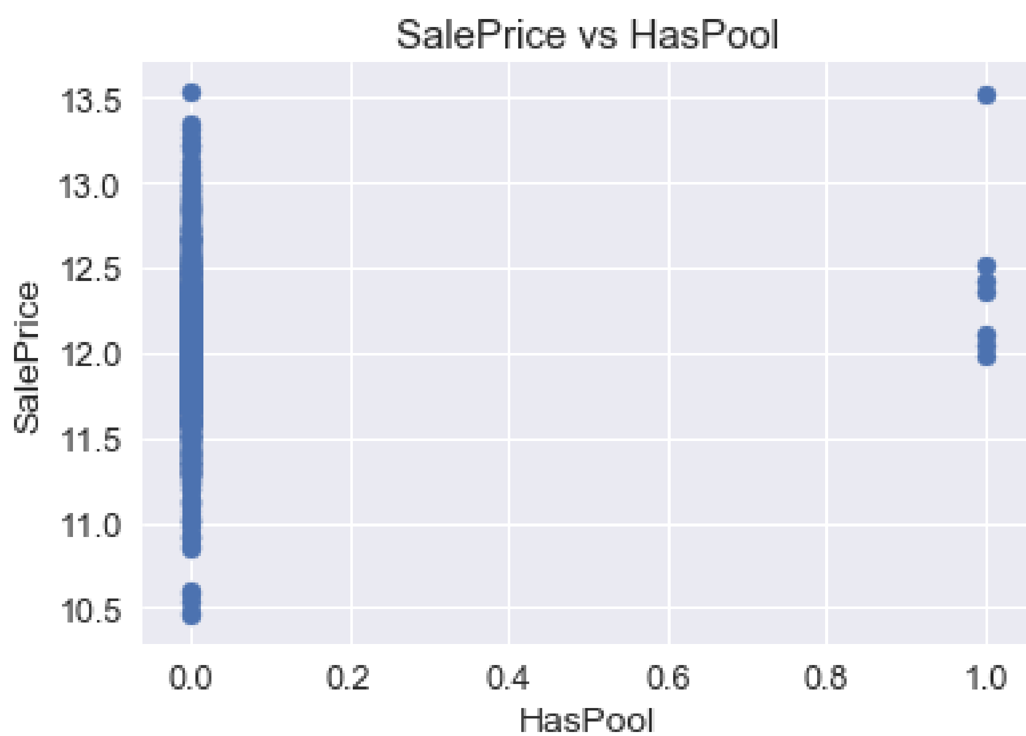

SalePrice vs HasOpenPorch
13.5
13.0
12.5
12.0
11.5
11.0
10.5
SalePrice
0.0
0.2
0.4
0.6
0.8
1.0
HasOpenPorch

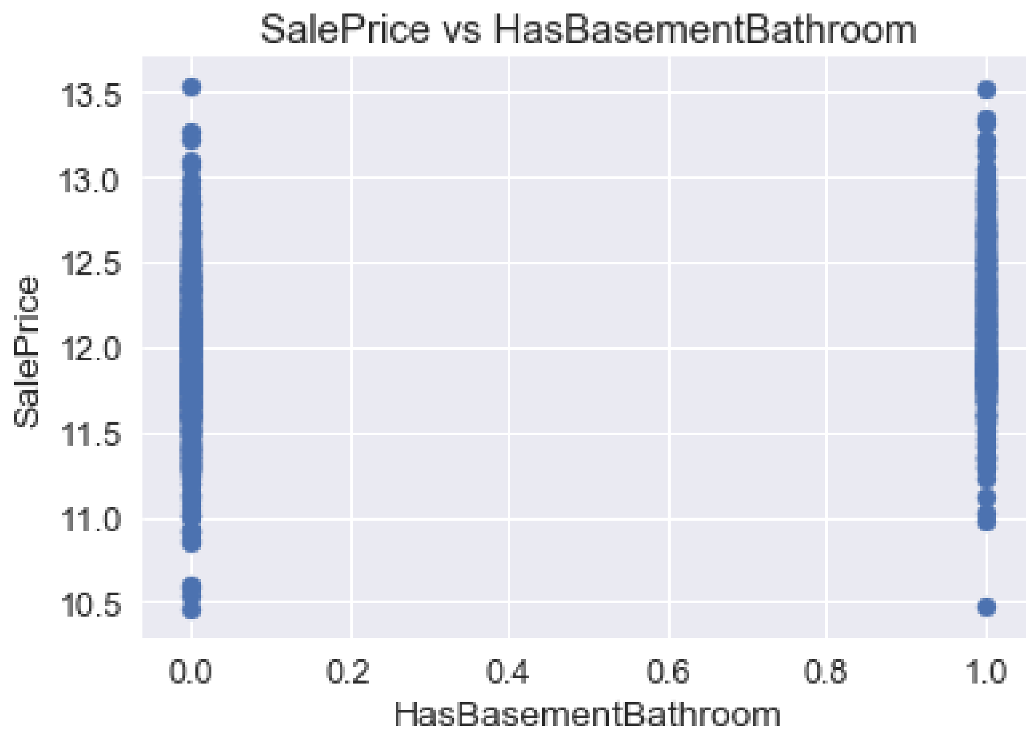

SalePrice vs HasScreenPorch
13.5
13.0
12.5
12.0
11.5
11.0
10.5
SalePrice
0.0
0.2
0.4
0.6
0.8
1.0
HasScreenPorch

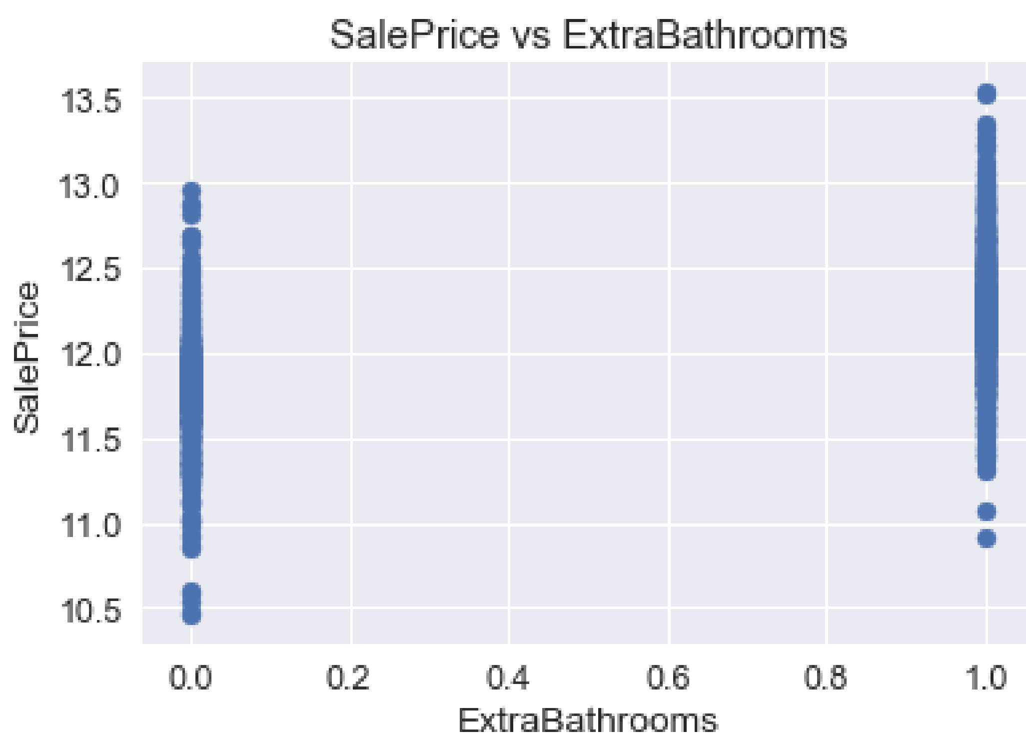

SalePrice vs HasFirePlace
SalePrice
13.5
13.0
12.5
12.0
11.5
11.0
10.5
0.0
0.2
0.4
0.6
0.8
1.0
HasFirePlace

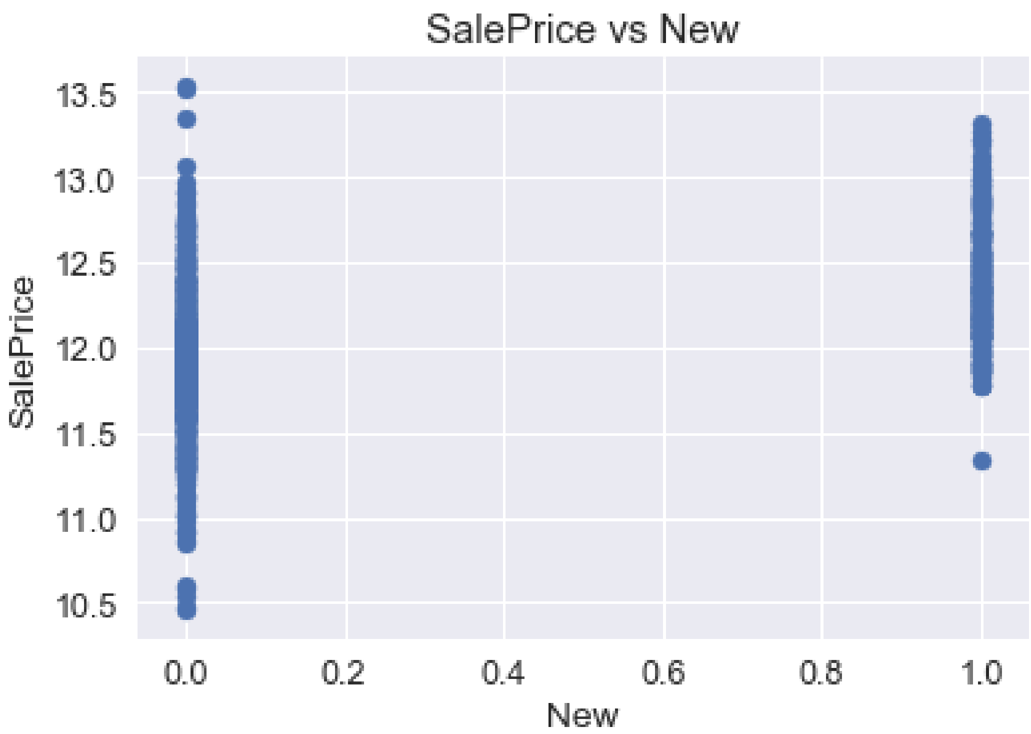

SalePrice vs HasMsVnr
SalePrice
13.5
13.0
12.5
12.0
11.5
11.0
10.5
0.0
0.2
0.4
0.6
0.8
1.0
HasMsVnr


SalePrice vs HasWoodDeck
SalePrice
13.5
13.0
12.5
12.0
11.5
11.0
10.5
0.0
0.2
0.4
0.6
0.8
1.0
HasWoodDeck


SalePrice vs HasPool
SalePrice
13.5
13.0
12.5
12.0
11.5
11.0
10.5
0.0
0.2
0.4
0.6
0.8
1.0
HasPool


SalePrice vs HasBasementBathroom
SalePrice
HasBasementBathroom
13.5
13.0
12.5
12.0
11.5
11.0
10.5
0.0
0.2
0.4
0.6
0.8
1.0


SalePrice vs ExtraBathrooms
SalePrice
ExtraBathrooms
13.5
13.0
12.5
12.0
11.5
11.0
10.5
0.0
0.2
0.4
0.6
0.8
1.0



8b. Removing Outliers from GrLivArea

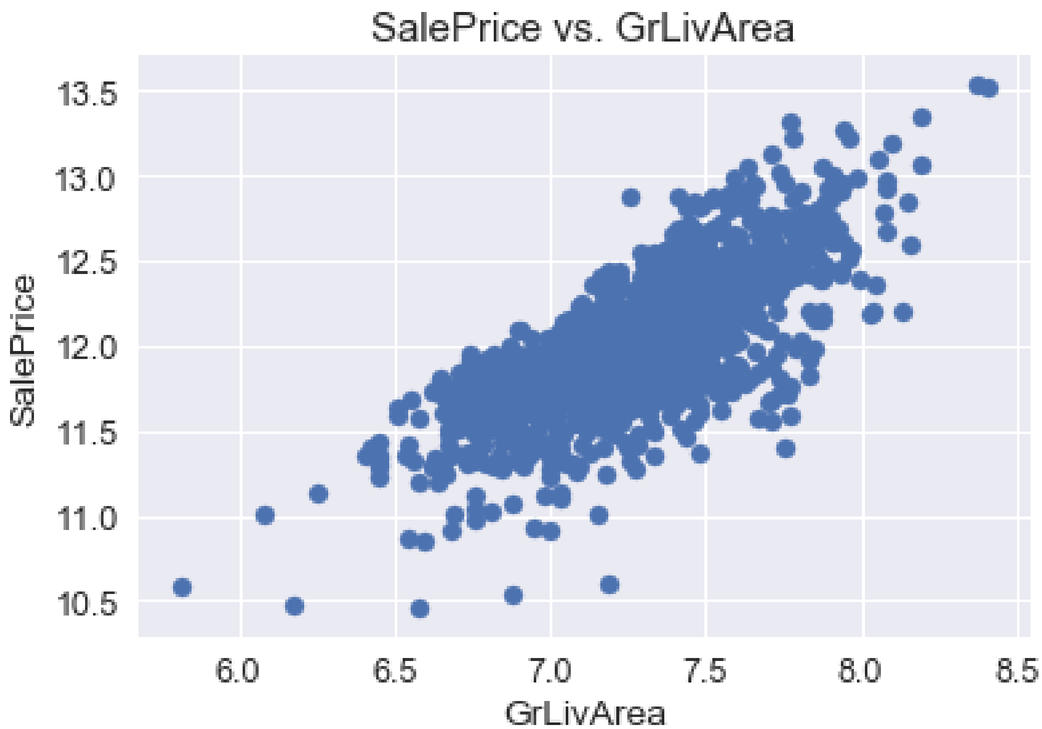
```
In [156]: train_subset = train_subset.drop(train_subset[train_subset['GrLivArea'] > 8.3].index
                                           train_subset[train_subset['SalePrice'] < 12.25].inde
          train_subset.info()

<class 'pandas.core.frame.DataFrame'>
Int64Index: 1458 entries, 0 to 1459
Data columns (total 61 columns):
SalePrice                1458 non-null float64
OverallQual              1458 non-null int64
GrLivArea                1458 non-null float64
GarageCars               1458 non-null float64
GarageArea               1458 non-null float64
1stFlrSF                 1458 non-null float64
FullBath                 1458 non-null int64
YearBuilt                1458 non-null int64
YearRemodAdd             1458 non-null int64
GarageYrBlt              1377 non-null float64
TotRmsAbvGrd             1458 non-null float64
Fireplaces               1458 non-null int64
OpenPorchSF              1458 non-null float64
MasVnrArea               1450 non-null float64
```

```
LotArea                1458 non-null float64
TotalBsmtSF            1458 non-null float64
LotFrontage            1199 non-null float64
WoodDeckSF             1458 non-null float64
HalfBath               1458 non-null int64
BsmtFullBath           1458 non-null float64
BedroomAbvGr           1458 non-null int64
BsmtUnfSF              1458 non-null float64
BsmtFinSF1             1458 non-null float64
2ndFlrSF               1458 non-null float64
ScreenPorch            1458 non-null float64
Neighborhood_E         1458 non-null float64
ExterQual_E            1458 non-null float64
KitchenQual_E          1458 non-null float64
BsmtQual_E             1458 non-null float64
GarageFinish_E         1458 non-null float64
GarageType_E           1458 non-null float64
Foundation_E           1458 non-null float64
FireplaceQu_E          1458 non-null float64
HeatingQC_E            1458 non-null float64
MasVnrType_E           1458 non-null float64
Exterior1st_E          1458 non-null float64
MSZoning_E             1458 non-null float64
Exterior2nd_E          1458 non-null float64
BsmtFinType1_E         1458 non-null float64
GarageCond_E           1458 non-null float64
GarageQual_E           1458 non-null float64
BsmtExposure_E         1458 non-null float64
CentralAir_E           1458 non-null float64
SaleType_E             1458 non-null float64
HouseStyle_E           1458 non-null float64
Electrical_E           1458 non-null float64
PavedDrive_E           1458 non-null float64
BsmtCond_E             1458 non-null float64
LotShape_E             1458 non-null float64
HasBasement            1458 non-null int64
HasGarage              1458 non-null int64
Has2ndFlr              1458 non-null int64
HasOpenPorch           1458 non-null int64
HasScreenPorch         1458 non-null int64
HasFirePlace           1458 non-null int64
HasMsVnr               1458 non-null int64
HasWoodDeck            1458 non-null int64
HasPool                1458 non-null int64
HasBasementBathroom    1458 non-null int64
ExtraBathrooms         1458 non-null int64
New                    1458 non-null int64
dtypes: float64(42), int64(19)
```

memory usage: 706.2 KB

8b-1. SalePrice vs GrLivArea Scatterplot with Outliers Removed

```
In [157]: plt.scatter(train_subset['GrLivArea'], train_subset['SalePrice'])
          plt.title('SalePrice vs. GrLivArea')
          plt.ylabel('SalePrice')
          plt.xlabel('GrLivArea')
          plt.show()
```



1.6.9 9. Getting Predictions

9a. Getting Dummy Variables

```
In [158]: houses_full = pd.get_dummies(houses_full)
          train_subset = pd.get_dummies(train_subset)
```

9b. Filling Missing Values

```
In [159]: houses_full = houses_full.fillna(houses_full.mean())
          train_subset = train_subset.fillna(houses_full.mean())
          test_subset = test_subset.fillna(houses_full.mean())
```

9c. Partitioning Data

```
In [160]: X_train, X_test, y_train, y_test = train_test_split(train_subset.drop('SalePrice', a
                                                               test_size = 0.3, random_state = 
```

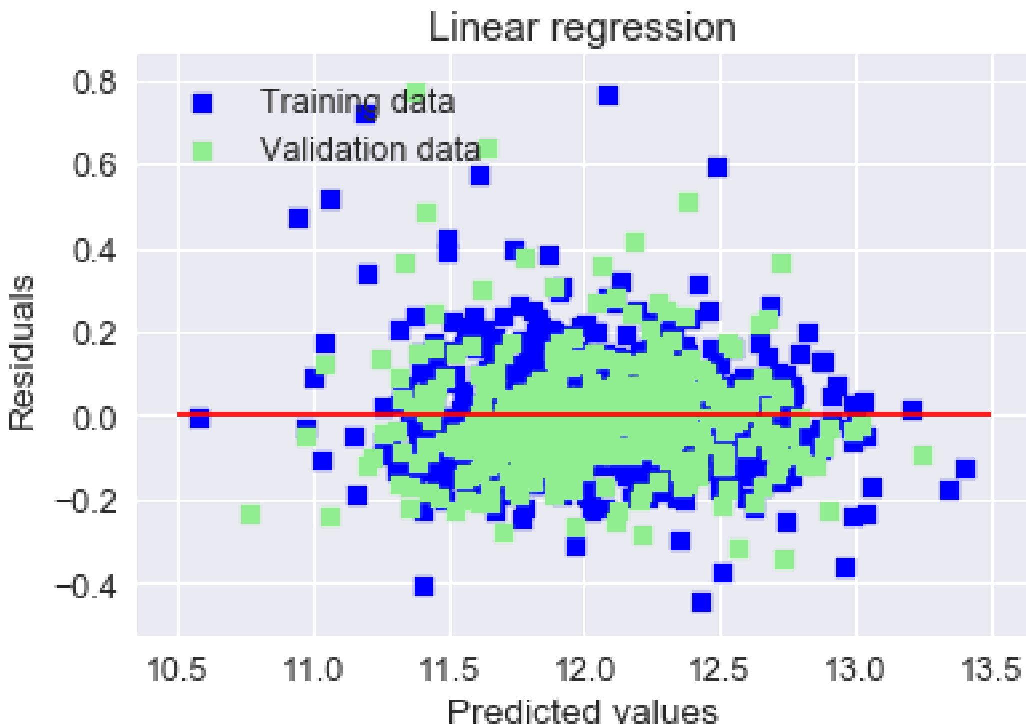
9d. Writing Function to Record RMSE

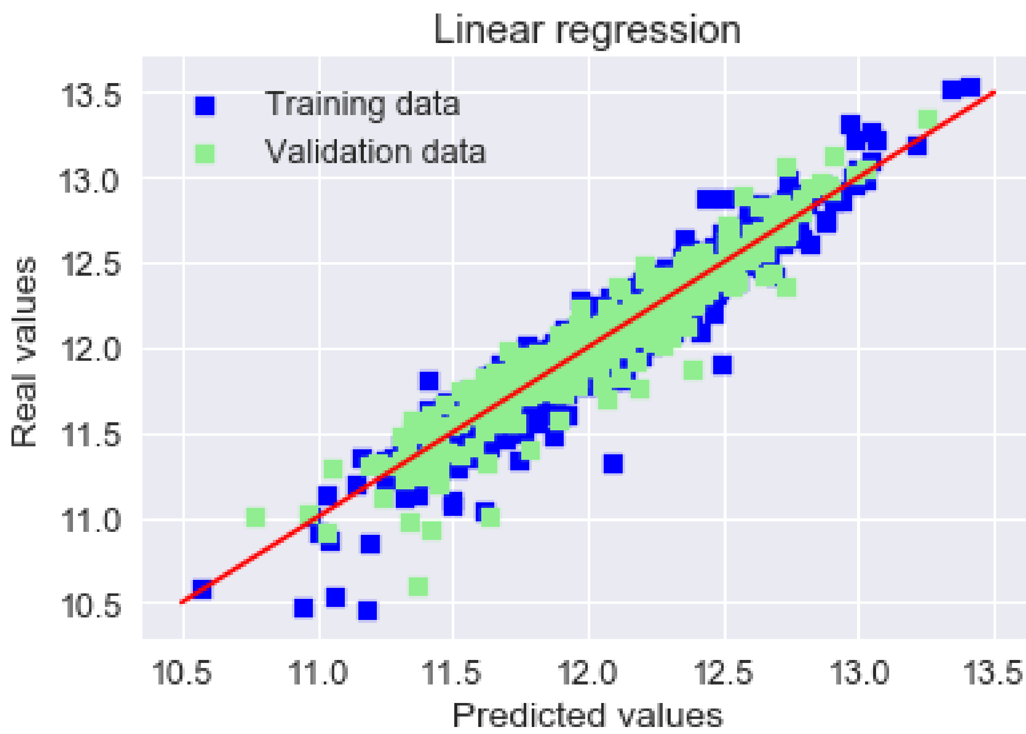
```
In [161]: # Define error measure for official scoring : RMSE
          scorer = make_scorer(mean_squared_error, greater_is_better = False)

          def rmse_cv_train(model):
              rmse= np.sqrt(-cross_val_score(model, X_train, y_train, scoring = scorer, cv = 1
              return(rmse)

          def rmse_cv_test(model):
              rmse= np.sqrt(-cross_val_score(model, X_test, y_test, scoring = scorer, cv = 10)
              return(rmse)
```

9e. Linear Regression Model

```
In [162]: lr = LinearRegression()
          lr.fit(X_train, y_train)

          # Look at predictions on training and validation set
          print("RMSE on Training set :", rmse_cv_train(lr).mean())
          print("RMSE on Test set :", rmse_cv_test(lr).mean())
          y_train_pred = lr.predict(X_train)
          y_test_pred = lr.predict(X_test)

          # Plot residuals
          plt.scatter(y_train_pred, y_train_pred - y_train, c = "blue", marker = "s", label = 
          plt.scatter(y_test_pred, y_test_pred - y_test, c = "lightgreen", marker = "s", label
          plt.title("Linear regression")
          plt.xlabel("Predicted values")
          plt.ylabel("Residuals")
          plt.legend(loc = "upper left")
          plt.hlines(y = 0, xmin = 10.5, xmax = 13.5, color = "red")
          plt.show()

          # Plot predictions
          plt.scatter(y_train_pred, y_train, c = "blue", marker = "s", label = "Training data"
          plt.scatter(y_test_pred, y_test, c = "lightgreen", marker = "s", label = "Validation
          plt.title("Linear regression")
          plt.xlabel("Predicted values")
          plt.ylabel("Real values")
          plt.legend(loc = "upper left")
          plt.plot([10.5, 13.5], [10.5, 13.5], c = "red")
          plt.show()
```

```
RMSE on Training set : 0.124804458115
RMSE on Test set : 0.133658974553
```



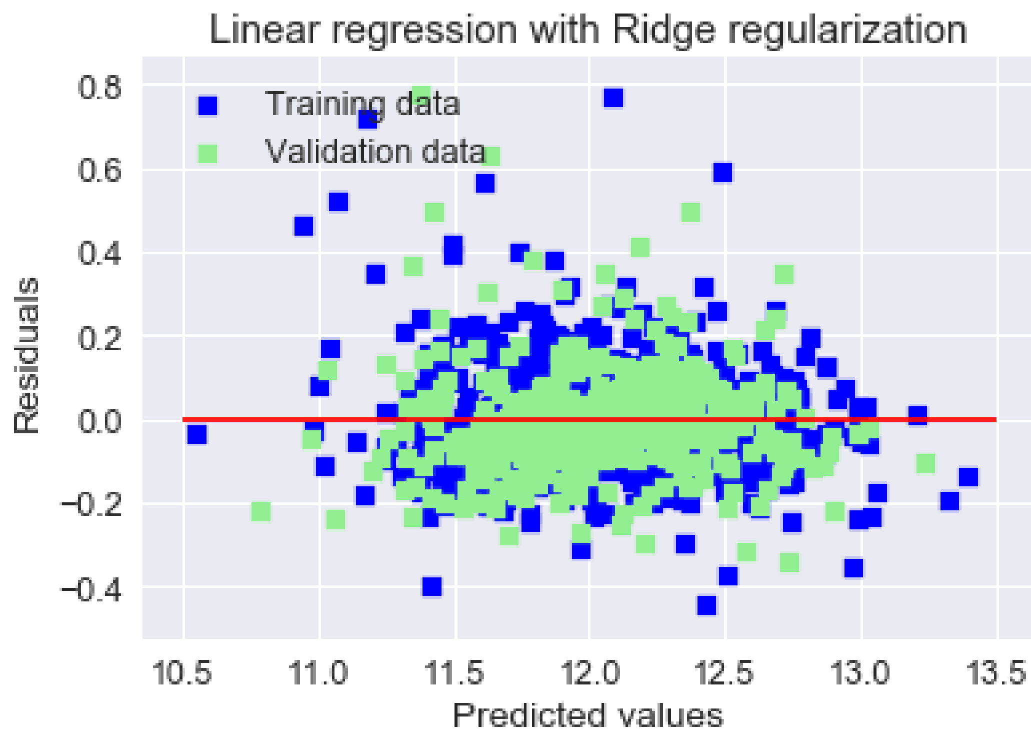


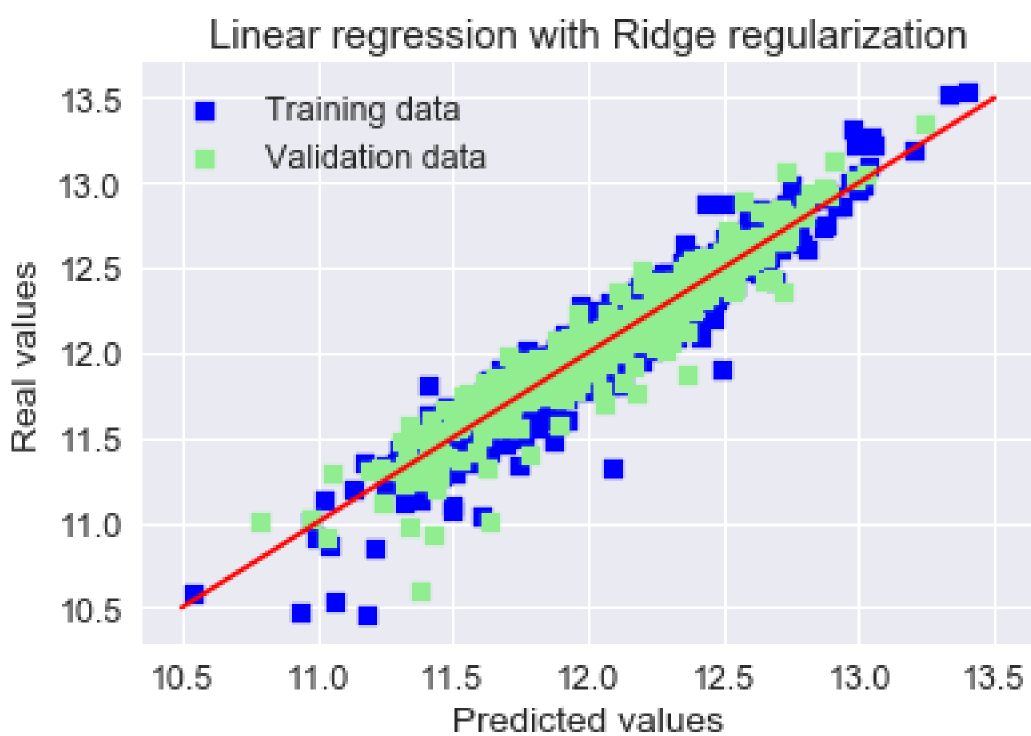
9f. Ridge Model

In [163]:
```
# 2* Ridge
ridge = RidgeCV(alphas = [0.01, 0.03, 0.06, 0.1, 0.3, 0.6, 1, 3, 6, 10, 30, 60])
ridge.fit(X_train, y_train)
alpha = ridge.alpha_
print("Best alpha :", alpha)

print("Try again for more precision with alphas centered around " + str(alpha))
ridge = RidgeCV(alphas = [alpha * .6, alpha * .65, alpha * .7, alpha * .75, alpha *
                          alpha * .9, alpha * .95, alpha, alpha * 1.05, alpha * 1.1,
                          alpha * 1.25, alpha * 1.3, alpha * 1.35, alpha * 1.4],
                cv = 10)
ridge.fit(X_train, y_train)
alpha = ridge.alpha_
print("Best alpha :", alpha)

print("Ridge RMSE on Training set :", rmse_cv_train(ridge).mean())
print("Ridge RMSE on Test set :", rmse_cv_test(ridge).mean())
y_train_rdg = ridge.predict(X_train)
y_test_rdg = ridge.predict(X_test)

# Plot residuals
```

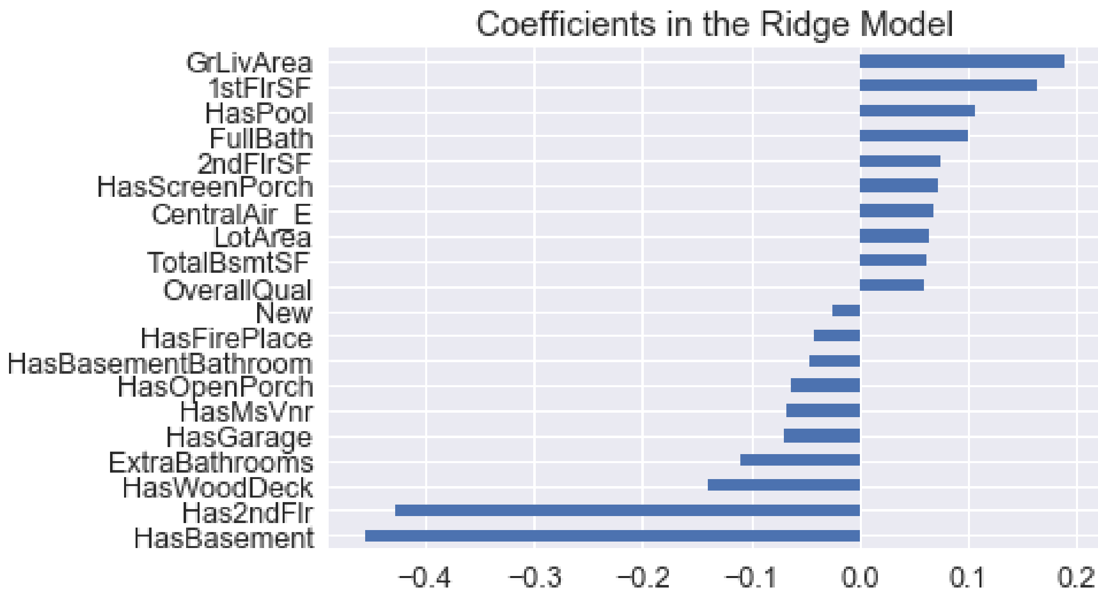
```
    plt.scatter(y_train_rdg, y_train_rdg - y_train, c = "blue", marker = "s", label = "T
    plt.scatter(y_test_rdg, y_test_rdg - y_test, c = "lightgreen", marker = "s", label =
    plt.title("Linear regression with Ridge regularization")
    plt.xlabel("Predicted values")
    plt.ylabel("Residuals")
    plt.legend(loc = "upper left")
    plt.hlines(y = 0, xmin = 10.5, xmax = 13.5, color = "red")
    plt.show()

    # Plot predictions
    plt.scatter(y_train_rdg, y_train, c = "blue", marker = "s", label = "Training data")
    plt.scatter(y_test_rdg, y_test, c = "lightgreen", marker = "s", label = "Validation d
    plt.title("Linear regression with Ridge regularization")
    plt.xlabel("Predicted values")
    plt.ylabel("Real values")
    plt.legend(loc = "upper left")
    plt.plot([10.5, 13.5], [10.5, 13.5], c = "red")
    plt.show()

    # Plot important coefficients
    coefs = pd.Series(ridge.coef_, index = X_train.columns)
    print("Ridge picked " + str(sum(coefs != 0)) + " features and eliminated the other "
          str(sum(coefs == 0)) + " features")
    imp_coefs = pd.concat([coefs.sort_values().head(10),
                         coefs.sort_values().tail(10)])
    imp_coefs.plot(kind = "barh")
    plt.title("Coefficients in the Ridge Model")
    plt.show()
```

```
Best alpha : 0.3
Try again for more precision with alphas centered around 0.3
Best alpha : 0.195
Ridge RMSE on Training set : 0.124772422841
Ridge RMSE on Test set : 0.131839691941
```


Linear regression with Ridge regularization
Training data
Validation data
Residuals
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
10.5
11.0
11.5
12.0
12.5
13.0
13.5
Predicted values


Linear regression with Ridge regularization
Training data
Validation data
Real values
13.5
13.0
12.5
12.0
11.5
11.0
10.5
10.5
11.0
11.5
12.0
12.5
13.0
13.5
Predicted values

```
Ridge picked 60 features and eliminated the other 0 features
```

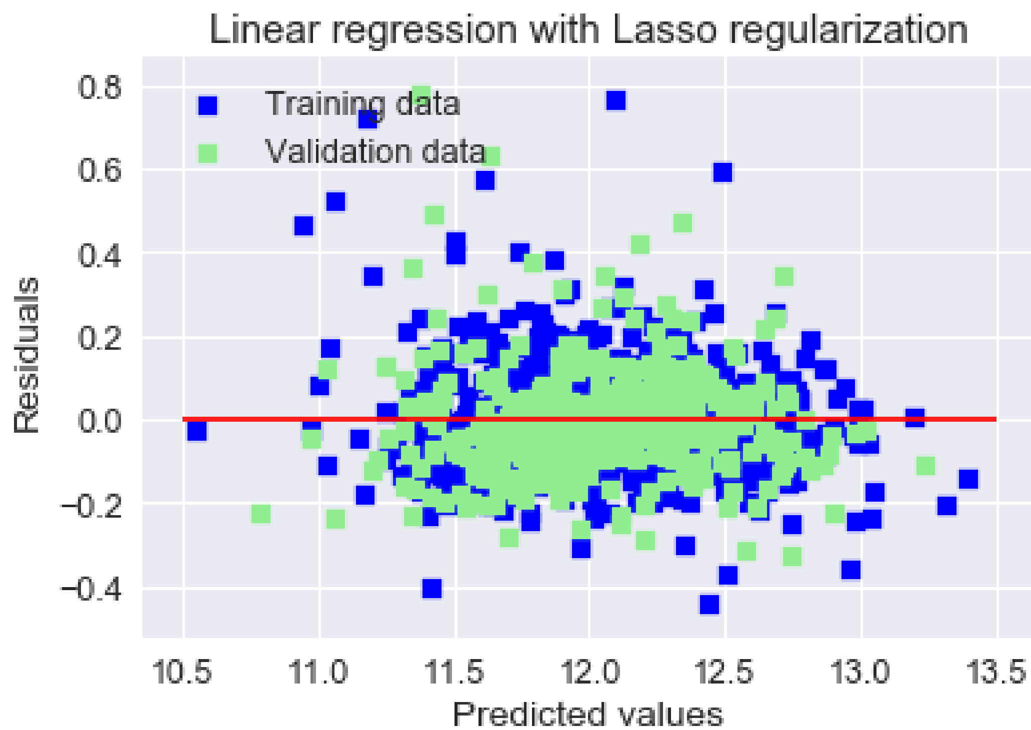


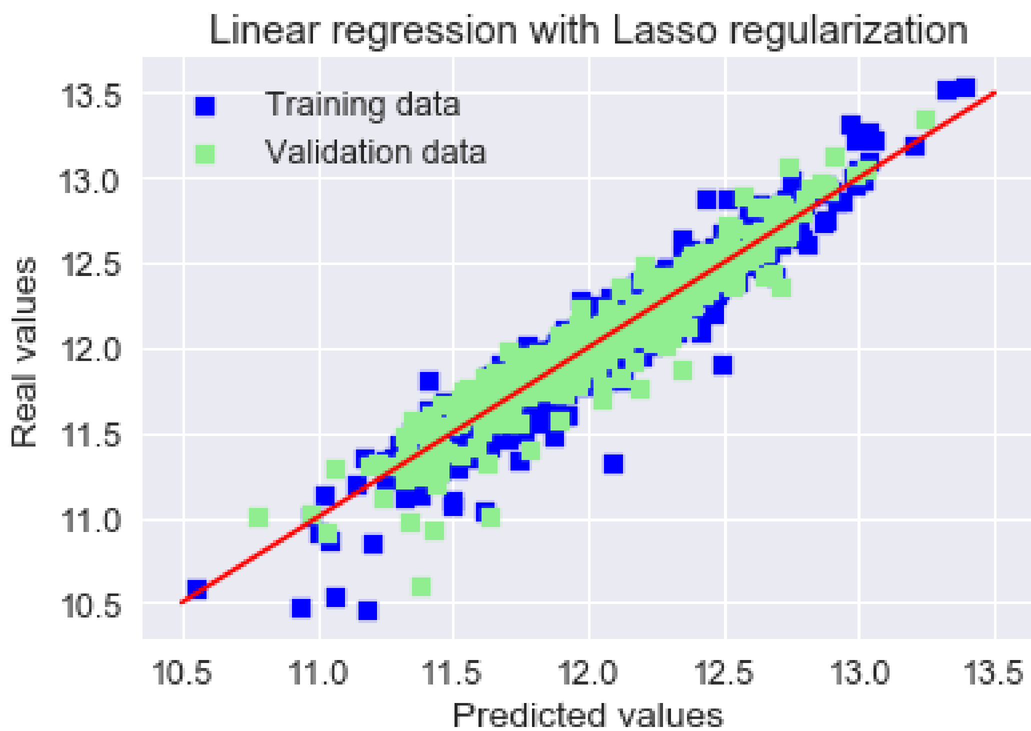
9g. Lasso Model

In [164]:
```
# 3* Lasso
lasso = LassoCV(alphas = [0.0001, 0.0003, 0.0006, 0.001, 0.003, 0.006, 0.01, 0.03, 0
                          0.3, 0.6, 1],
                max_iter = 50000, cv = 10)
lasso.fit(X_train, y_train)
alpha = lasso.alpha_
print("Best alpha :", alpha)

print("Try again for more precision with alphas centered around " + str(alpha))
lasso = LassoCV(alphas = [alpha * .6, alpha * .65, alpha * .7, alpha * .75, alpha *
                          alpha * .85, alpha * .9, alpha * .95, alpha, alpha * 1.05,
                          alpha * 1.1, alpha * 1.15, alpha * 1.25, alpha * 1.3, alpha
                          alpha * 1.4],
                max_iter = 50000, cv = 10)
lasso.fit(X_train, y_train)
alpha = lasso.alpha_
print("Best alpha :", alpha)

print("Lasso RMSE on Training set :", rmse_cv_train(lasso).mean())
print("Lasso RMSE on Test set :", rmse_cv_test(lasso).mean())
y_train_las = lasso.predict(X_train)
y_test_las = lasso.predict(X_test)
```

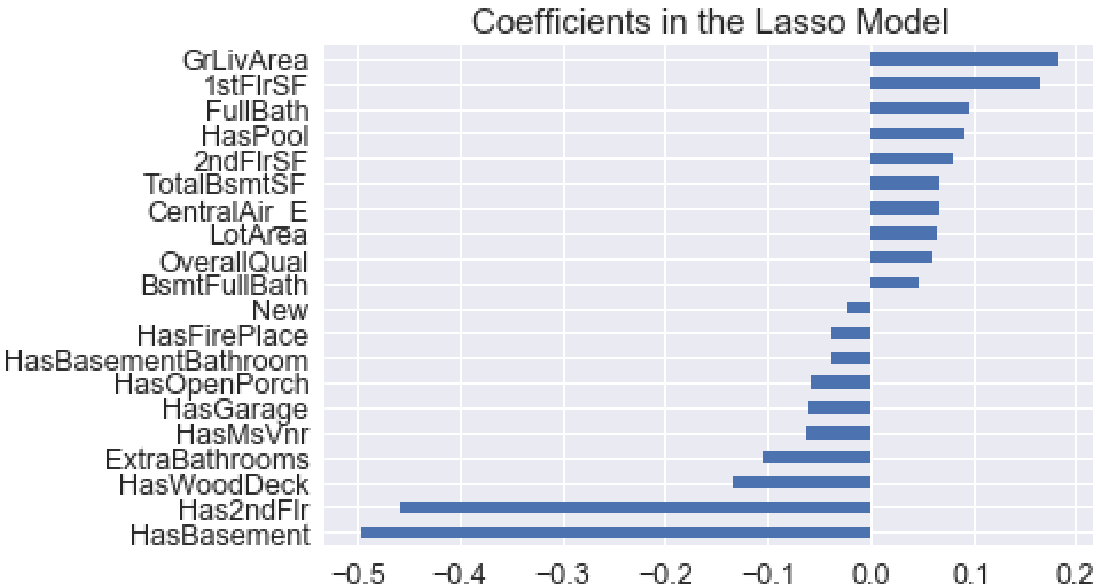
```python
        # Plot residuals
        plt.scatter(y_train_las, y_train_las - y_train, c = "blue", marker = "s", label = "T
        plt.scatter(y_test_las, y_test_las - y_test, c = "lightgreen", marker = "s", label =
        plt.title("Linear regression with Lasso regularization")
        plt.xlabel("Predicted values")
        plt.ylabel("Residuals")
        plt.legend(loc = "upper left")
        plt.hlines(y = 0, xmin = 10.5, xmax = 13.5, color = "red")
        plt.show()

        # Plot predictions
        plt.scatter(y_train_las, y_train, c = "blue", marker = "s", label = "Training data")
        plt.scatter(y_test_las, y_test, c = "lightgreen", marker = "s", label = "Validation d
        plt.title("Linear regression with Lasso regularization")
        plt.xlabel("Predicted values")
        plt.ylabel("Real values")
        plt.legend(loc = "upper left")
        plt.plot([10.5, 13.5], [10.5, 13.5], c = "red")
        plt.show()

        # Plot important coefficients
        coefs = pd.Series(lasso.coef_, index = X_train.columns)
        print("Lasso picked " + str(sum(coefs != 0)) + " features and eliminated the other " 
              str(sum(coefs == 0)) + " features")
        imp_coefs = pd.concat([coefs.sort_values().head(10),
                              coefs.sort_values().tail(10)])
        imp_coefs.plot(kind = "barh")
        plt.title("Coefficients in the Lasso Model")
        plt.show()
```

```
Best alpha : 0.0001
Try again for more precision with alphas centered around 0.0001
Best alpha : 6e-05
Lasso RMSE on Training set : 0.124920699681
Lasso RMSE on Test set : 0.132494703915
```


Linear regression with Lasso regularization
Training data
Validation data
Residuals
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
10.5
11.0
11.5
12.0
12.5
13.0
13.5
Predicted values


Linear regression with Lasso regularization
Training data
Validation data
Real values
13.5
13.0
12.5
12.0
11.5
11.0
10.5
10.5
11.0
11.5
12.0
12.5
13.0
13.5
Predicted values

```
Lasso picked 59 features and eliminated the other 1 features
```

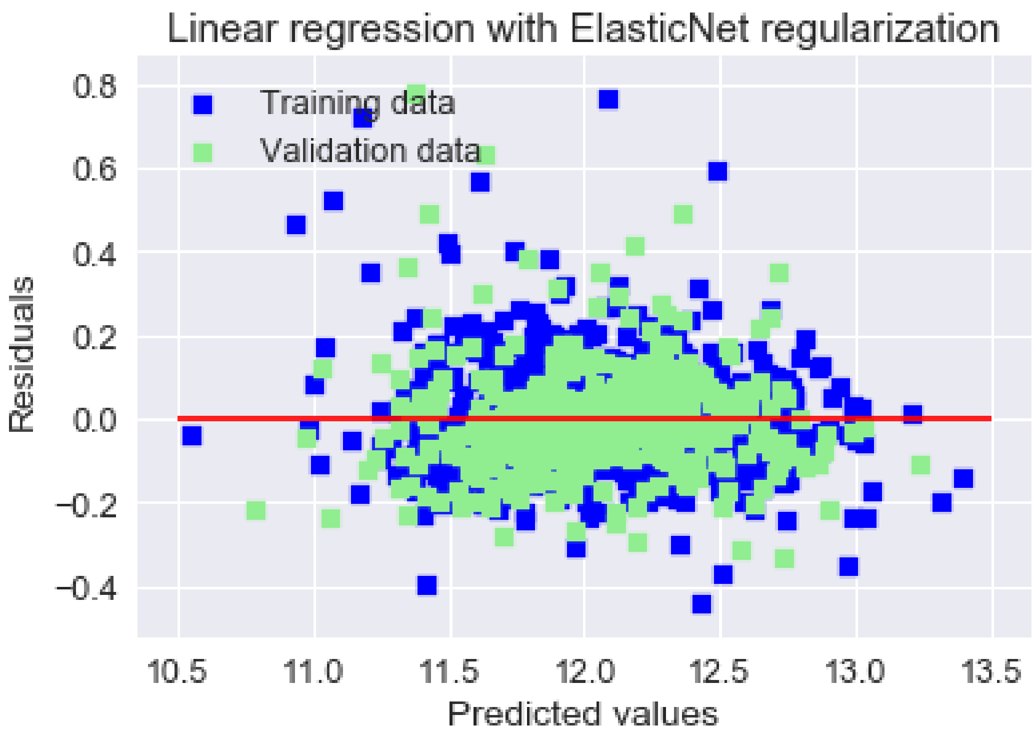


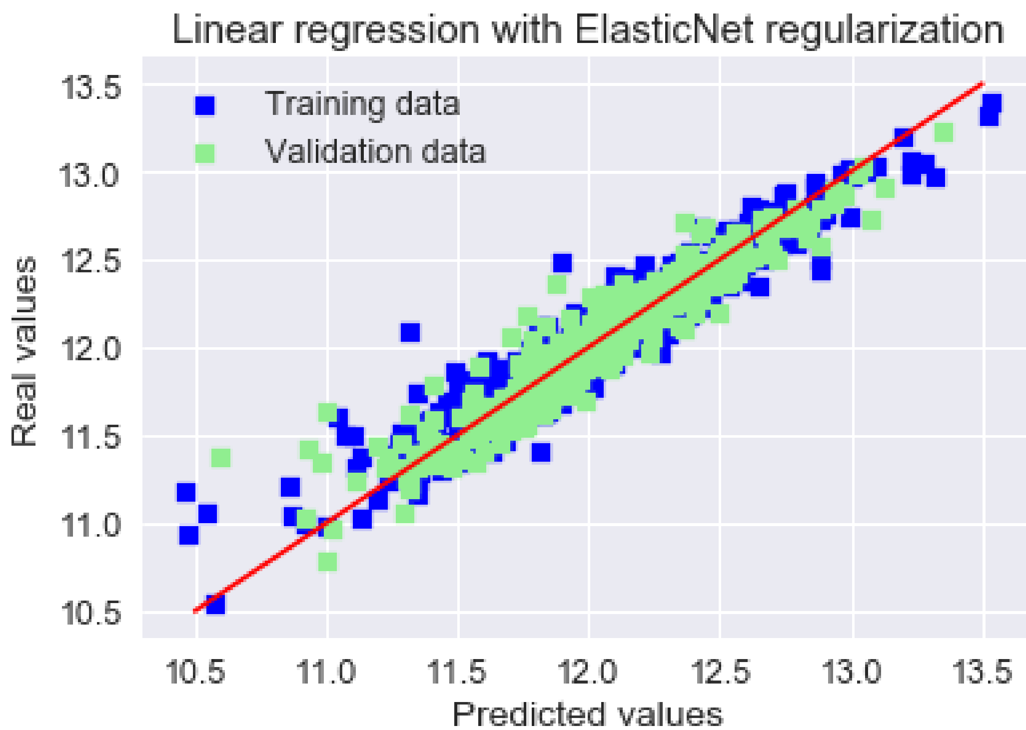
9h. ElasticNet Model

```
In [165]: elasticNet = ElasticNetCV(l1_ratio = [0.1, 0.3, 0.5, 0.6, 0.7, 0.8, 0.85, 0.9, 0.95,
                                    alphas = [0.0001, 0.0003, 0.0006, 0.001, 0.003, 0.006,
                                              0.01, 0.03, 0.06, 0.1, 0.3, 0.6, 1, 3, 6],
                                    max_iter = 50000, cv = 10)
          elasticNet.fit(X_train, y_train)
          alpha = elasticNet.alpha_
          ratio = elasticNet.l1_ratio_
          print("Best l1_ratio :", ratio)
          print("Best alpha :", alpha )

          print("Try again for more precision with l1_ratio centered around " + str(ratio))
          elasticNet = ElasticNetCV(l1_ratio = [ratio * .85, ratio * .9, ratio * .95, ratio, ra
                                    alphas = [0.0001, 0.0003, 0.0006, 0.001, 0.003, 0.006, 0.0
                                    max_iter = 50000, cv = 10)
          elasticNet.fit(X_train, y_train)
          if (elasticNet.l1_ratio_ > 1):
              elasticNet.l1_ratio_ = 1
          alpha = elasticNet.alpha_
          ratio = elasticNet.l1_ratio_
          print("Best l1_ratio :", ratio)
          print("Best alpha :", alpha )
```

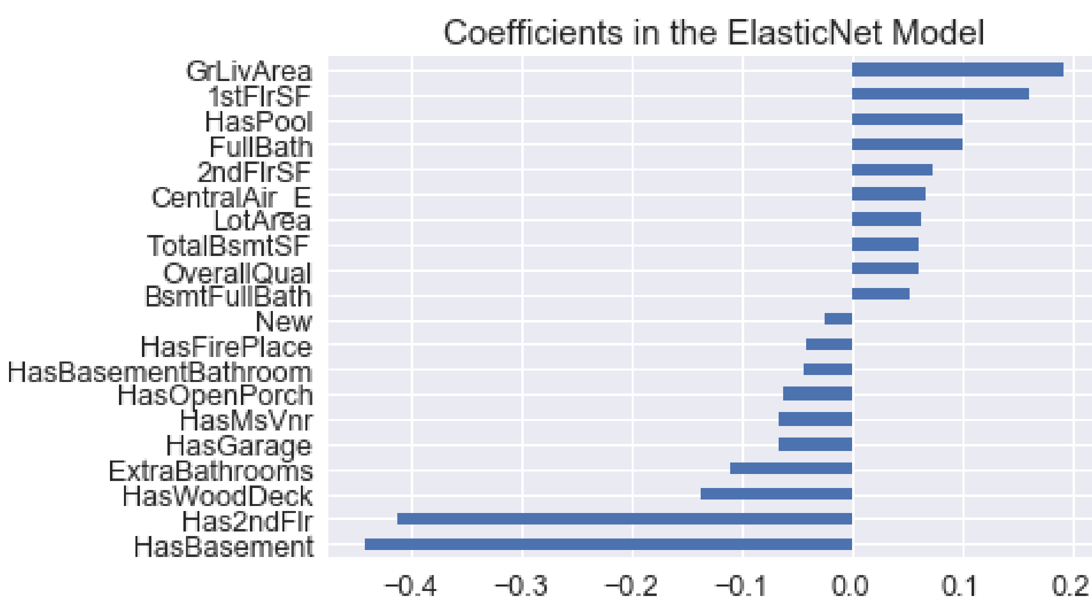
```
print("Now try again for more precision on alpha, with l1_ratio fixed at " + str(rati
      " and alpha centered around " + str(alpha))
elasticNet = ElasticNetCV(l1_ratio = ratio,
                          alphas = [alpha * .6, alpha * .65, alpha * .7, alpha * .75
                                    alpha * .95, alpha, alpha * 1.05, alpha * 1.1, al
                                    alpha * 1.35, alpha * 1.4],
                          max_iter = 50000, cv = 10)
elasticNet.fit(X_train, y_train)
if (elasticNet.l1_ratio_ > 1):
    elasticNet.l1_ratio_ = 1
alpha = elasticNet.alpha_
ratio = elasticNet.l1_ratio_
print("Best l1_ratio :", ratio)
print("Best alpha :", alpha )

print("ElasticNet RMSE on Training set :", rmse_cv_train(elasticNet).mean())
print("ElasticNet RMSE on Test set :", rmse_cv_test(elasticNet).mean())
y_train_ela = elasticNet.predict(X_train)
y_test_ela = elasticNet.predict(X_test)

# Plot residuals
plt.scatter(y_train_ela, y_train_ela - y_train, c = "blue", marker = "s", label = "Tr
plt.scatter(y_test_ela, y_test_ela - y_test, c = "lightgreen", marker = "s", label =
plt.title("Linear regression with ElasticNet regularization")
plt.xlabel("Predicted values")
plt.ylabel("Residuals")
plt.legend(loc = "upper left")
plt.hlines(y = 0, xmin = 10.5, xmax = 13.5, color = "red")
plt.show()

# Plot predictions
plt.scatter(y_train, y_train_ela, c = "blue", marker = "s", label = "Training data")
plt.scatter(y_test, y_test_ela, c = "lightgreen", marker = "s", label = "Validation d
plt.title("Linear regression with ElasticNet regularization")
plt.xlabel("Predicted values")
plt.ylabel("Real values")
plt.legend(loc = "upper left")
plt.plot([10.5, 13.5], [10.5, 13.5], c = "red")
plt.show()

# Plot important coefficients
coefs = pd.Series(elasticNet.coef_, index = X_train.columns)
print("ElasticNet picked " + str(sum(coefs != 0)) + " features and eliminated the oth
imp_coefs = pd.concat([coefs.sort_values().head(10),
                       coefs.sort_values().tail(10)])
imp_coefs.plot(kind = "barh")
plt.title("Coefficients in the ElasticNet Model")
plt.show()
```

```
Best l1_ratio : 0.1
Best alpha : 0.0001
Try again for more precision with l1_ratio centered around 0.1
Best l1_ratio : 0.085
Best alpha : 0.0003
Now try again for more precision on alpha, with l1_ratio fixed at 0.085 and alpha centered arou
Best l1_ratio : 0.085
Best alpha : 0.000195
ElasticNet RMSE on Training set : 0.124827915458
ElasticNet RMSE on Test set : 0.132185935611
```






```
ElasticNet picked 59 features and eliminated the other 1 features
```



1.6.10 10. Kaggle Predictions

10a. Dropping Target Variable

```
In [166]: test_subset = test_subset.drop(['SalePrice'], axis = 1)
```

10b. Getting Predictions

```
In [167]: predictions = lasso.predict(test_subset)
          predictions = np.expm1(predictions)
```

10c. Creating Submission DataFrame and CSV

```
In [168]: ID = test['Id']
          submission = pd.DataFrame({'Id' : ID, 'SalePrice': predictions})
          submission.to_csv('SalePrice_Predictions.csv', index=False)
          submission.head()
```

Out[168]:

	Id	SalePrice
1460	1461	123014.788596
1461	1462	159440.482579
1462	1463	182106.821506
1463	1464	193958.762850
1464	1465	207943.672650