Feature Selection Modeling for Predicting House Price in Nashville

Springboard Capstone Project 1

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1. Problem and Objective

Real estate in the US has been an interesting topic for not only developers or investors but also to academic researchers or data enthusiast who wants to understand more about how to predict the house price. In this project, we will focus on the real estate in Nashville where the markets trends indicated an increase of $19,000 about 7% in median home sale over the past year. The average price per square foot for this same period rose to $195, up from $180.

The objective of this project was to determine the features that affects house price in Nashville using linear regression with regularization. In order to achieve this, we had to take several procedures like collecting and preparing the data set ready for modeling. Visualization for this project was essential to find the insight from different features against price. We trained the data set for modeling and test it with the tested data set. During this process, we also had to use regularization like Lasso for feature selections.

2. Data Wrangling and Visualization

With regard to the capstone project which is about feature selections of important attributes that determine house price in Nashville, there were some data wrangling techniques used to prepare the data and ready for modeling.

First of all, checking the format of each feature regarding their datatypes and their observation sizes was my first step. This way I would know if there should be any datatype conversions I should take or any missing values I had to tackle. In this dataset, there were 56,000+ observations with 29 variables and 31 columns (List of features shown in Table 1). There were several features that contained missing values such as the exterior wall, tax district …etc. The house price attribute was numeric as well as land value, building value and total value which were essential to this project.

Table 1: List of Features

Features	Type
Sale Price	Numeric
Legal Reference	String
Sold as Vacant	String
Multiple Parcels Involved in Sale	String
Owner Name	String
Address	String
City	String
State	String

Acreage	Numeric
Tax District	String
Neighborhood	Numeric
image	String
Land Value	Numeric
Building Value	Numeric
Total Value	Numeric
Finished Area	Numeric
Foundation Type	String
Year Built	Numeric
Exterior Wall	String
Grade	String
Bedrooms	Numeric
Full Bath	Numeric
Half Bath	Numeric

Next, I had to check the distribution of price variable whether it was a normal distribution and make correction according to that. The result showed that the price is not normally distributed (Figure 1) and it was hard to interpret, thus I took the log transformation of the price variable so it can be interpretable and became a bell-shaped distribution with a little of skewness to the left. This indicated that some houses were sold higher than the average price which was logical and rational to the current housing market in Nashville. Moreover, total value, land value and building value were also converted to log value so that I could plot them against price in order to check their correlations (Figure 1). Like expected, they all had a positive relationship with price. In addition to this, I also made a heat-map with the correlation matrix to delve more into their relationship with price as shown in Figure 2. Land value, total value, finished value and full bath had moderate correlations with price.

Figure 1: Log Sale Price Distribution and Scatter plot of Log Sale Price and Log Total Value

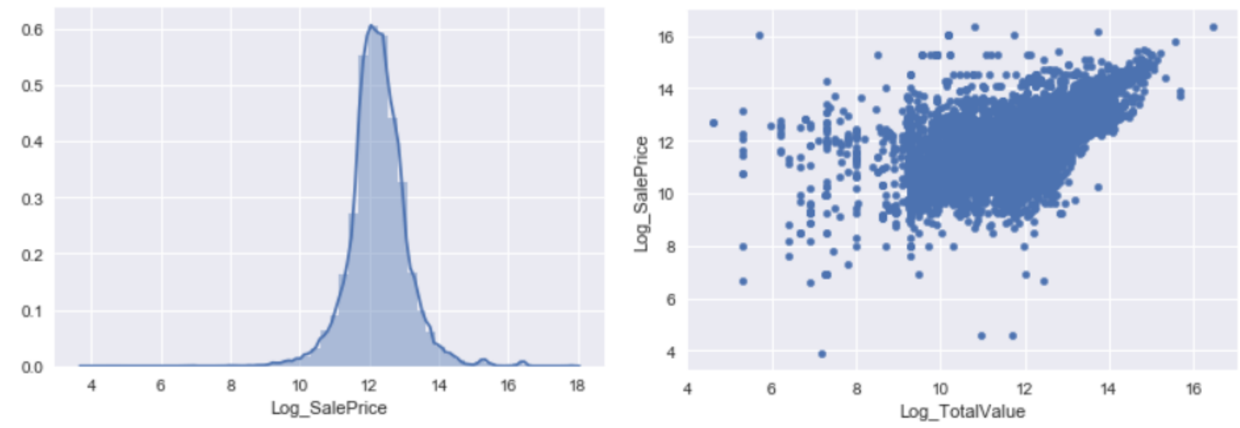
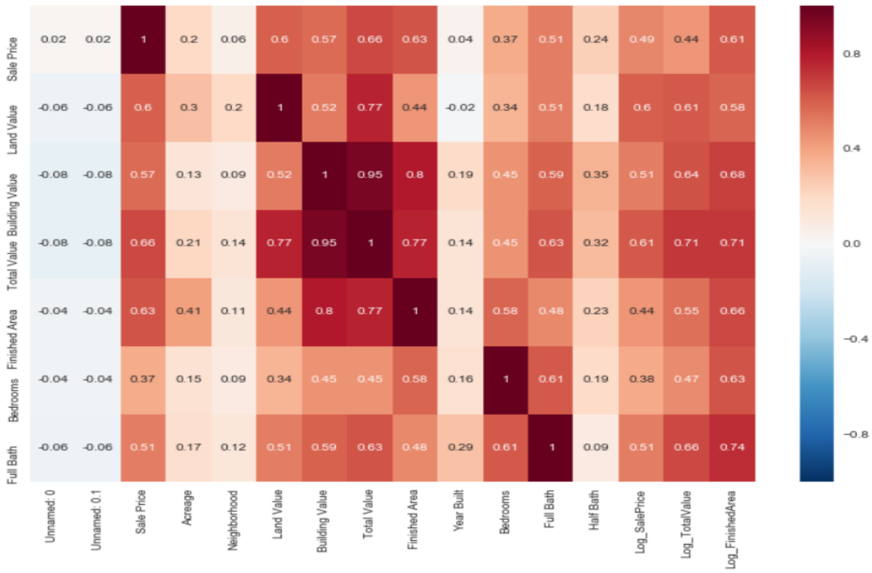


Figure 2: Heatmap with Correlation



After that, we had to deal with missing value. Firstly, to deal with missing value in categorical values like exterior wall and tax district, I had to find the most common value for these features in order to the replace the value against the missing value since forward filling or backward filling would not work in this case. For other numeric variables, I will use their means to replace the missing value. These methods could be done using function fillna() in pandas library. There were not any outliers presented in the data.

Lastly, due to the model I used required the categorical value to be dummy variables, I had to convert the variables to binary value such 0 and 1 to different columns. I used pandas to_dummie() function to tackle this task.

3. Modeling and Result

Since our target value or dependent variable was continuous, we have to use machine learning that support this format and one that simple but powerful model was linear regression. Before we going any further, we had to discuss the concept of BLUE (Best Linear Unbiased Estimators) which was very important for the assumption we were going to make for this model to work. These are the important assumptions for this model:

- The residual term must be normally distributed which mean it has mean of zero and standard deviation of 1
- The residual term must be homoscedasticity and independent
- There should be no perfect collinearity
- The sample data set must be random

In the modeling phase, we had to split the data into training and test set so that we can avoid over-fitting. We used Skit-learn library to split the data using 70/30 splits and results showed: Training and testing set sizes (21131, 32) (9056, 32). With this training set, we had to train the data with linear regression by fitting the target variable with independent variables. Next, we used this fitting value to compare with the test data set to generate the accuracy score or a matric of MSE. The accuracy scores were as following:

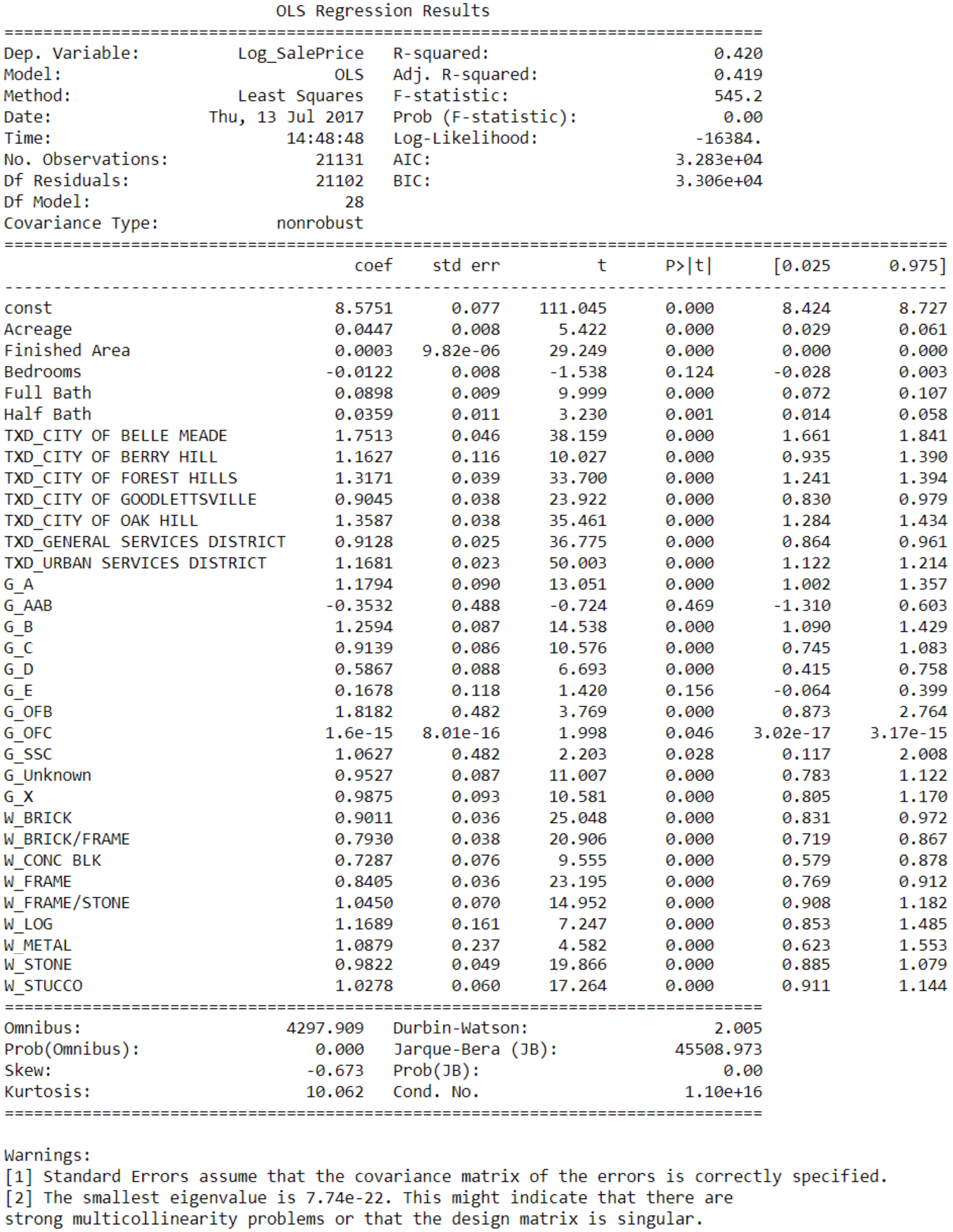
```
Testing Score: 0.411476963149
Training MSE: 0.276040455527
Testing MSE: 0.269870736571
```

The score of 0.41 was not necessarily good but also not so bad either and that is why we believe using regularization might be able to improve the results of this score. The MSE of training and test were very similar which indicated there should be no over-fitting presented in the model. In addition to this result, we also had not forget the statistical result summarized below. The table described each coefficient with its parameter values and standard error as well as p-value. There were two main coefficients that are not statistically significant: the bedroom and G_E. They were not significant because their p-value were higher than 5% of significance level we assumed for this model. The R^2 known as the coefficient of determination for the model is 0.42 which was not bad either and it reflected how much information that the independent variables helped describe the data. The adjusted R^2 was 0.419 which was slightly lower than R^2.

In order to improve our result, we would use regularization like L1 or Lasso to intervene. Lasso would perform both variable selection and regularization. After we ran Lasso, we got our result as following:

```
Testing Score: 0.34325587227
Training MSE: 0.306110557796
Testing MSE: 0.301153923281
```

These results were a little worse than the normal linear regression. The score was only 0.34 whereas previous score was 0.41, so the model was worse off than before. The MSE for both train and test were still similar to each other 0.306 and 0.301, respectively. However, even the score of Lasso did not improve, this model was still better in the sense that it reflected what coefficient were important and what not. The result of these terms were presented below:

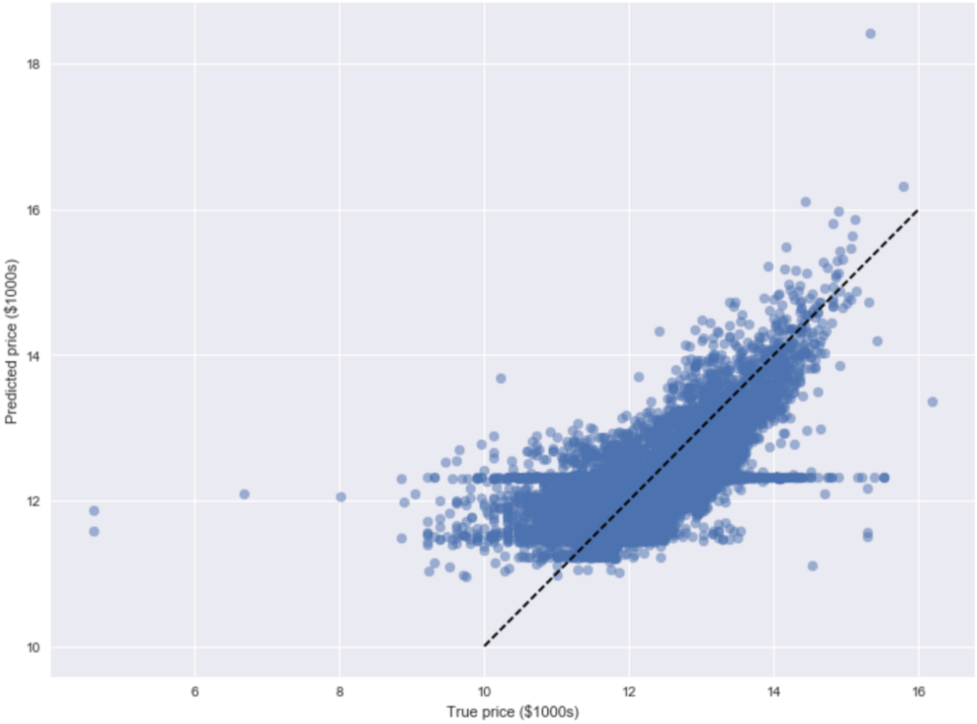


```
                            OLS Regression Results
==============================================================================
Dep. Variable:          Log_SalePrice   R-squared:                       0.420
Model:                            OLS   Adj. R-squared:                  0.419
Method:                 Least Squares   F-statistic:                     545.2
Date:                Thu, 13 Jul 2017   Prob (F-statistic):               0.00
Time:                        14:48:48   Log-Likelihood:                -16384.
No. Observations:               21131   AIC:                         3.283e+04
Df Residuals:                   21102   BIC:                         3.306e+04
Df Model:                          28
Covariance Type:            nonrobust
=================================================================================================
                                    coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------------------------
const                             8.5751      0.077    111.045      0.000       8.424       8.727
Acreage                           0.0447      0.008      5.422      0.000       0.029       0.061
Finished Area                     0.0003   9.82e-06     29.249      0.000       0.000       0.000
Bedrooms                         -0.0122      0.008     -1.538      0.124      -0.028       0.003
Full Bath                         0.0898      0.009      9.999      0.000       0.072       0.107
Half Bath                         0.0359      0.011      3.230      0.001       0.014       0.058
TXD_CITY OF BELLE MEADE           1.7513      0.046     38.159      0.000       1.661       1.841
TXD_CITY OF BERRY HILL            1.1627      0.116     10.027      0.000       0.935       1.390
TXD_CITY OF FOREST HILLS          1.3171      0.039     33.700      0.000       1.241       1.394
TXD_CITY OF GOODLETTSVILLE        0.9045      0.038     23.922      0.000       0.830       0.979
TXD_CITY OF OAK HILL              1.3587      0.038     35.461      0.000       1.284       1.434
TXD_GENERAL SERVICES DISTRICT     0.9128      0.025     36.775      0.000       0.864       0.961
TXD_URBAN SERVICES DISTRICT       1.1681      0.023     50.003      0.000       1.122       1.214
G_A                               1.1794      0.090     13.051      0.000       1.002       1.357
G_AAB                            -0.3532      0.488     -0.724      0.469      -1.310       0.603
G_B                               1.2594      0.087     14.538      0.000       1.090       1.429
G_C                               0.9139      0.086     10.576      0.000       0.745       1.083
G_D                               0.5867      0.088      6.693      0.000       0.415       0.758
G_E                               0.1678      0.118      1.420      0.156      -0.064       0.399
G_OFB                             1.8182      0.482      3.769      0.000       0.873       2.764
G_OFC                            1.6e-15   8.01e-16      1.998      0.046    3.02e-17    3.17e-15
G_SSC                             1.0627      0.482      2.203      0.028       0.117       2.008
G_Unknown                         0.9527      0.087     11.007      0.000       0.783       1.122
G_X                               0.9875      0.093     10.581      0.000       0.805       1.170
W_BRICK                           0.9011      0.036     25.048      0.000       0.831       0.972
W_BRICK/FRAME                     0.7930      0.038     20.906      0.000       0.719       0.867
W_CONC BLK                        0.7287      0.076      9.555      0.000       0.579       0.878
W_FRAME                           0.8405      0.036     23.195      0.000       0.769       0.912
W_FRAME/STONE                     1.0450      0.070     14.952      0.000       0.908       1.182
W_LOG                             1.1689      0.161      7.247      0.000       0.853       1.485
W_METAL                           1.0879      0.237      4.582      0.000       0.623       1.553
W_STONE                           0.9822      0.049     19.866      0.000       0.885       1.079
W_STUCCO                          1.0278      0.060     17.264      0.000       0.911       1.144
==============================================================================
Omnibus:                     4297.909   Durbin-Watson:                   2.005
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            45508.973
Skew:                          -0.673   Prob(JB):                         0.00
Kurtosis:                      10.062   Cond. No.                     1.10e+16
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 7.74e-22. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
```

```
Selected features:
(False, 'Acreage'), (True, 'Finished Area'), (True, 'Bedrooms'), (True, 'F
ull Bath'), (False, 'Half Bath'), (False, 'TXD_CITY OF BELLE MEADE'), (Fal
se, 'TXD_CITY OF BERRY HILL'), (False, 'TXD_CITY OF FOREST HILLS'), (False
, 'TXD_CITY OF GOODLETTSVILLE'), (False, 'TXD_CITY OF OAK HILL'), (False,
'TXD_GENERAL SERVICES DISTRICT'), (False, 'TXD_URBAN SERVICES DISTRICT'),
(False, 'G_A   '), (False, 'G_AAB '), (False, 'G_B   '), (False, 'G_C   ')
, (False, 'G_D   '), (False, 'G_E   '), (False, 'G_OFB '), (False, 'G_OFC
'), (False, 'G_SSC '), (False, 'G_Unknown'), (True, 'G_X   '), (False, 'W_
BRICK'), (False, 'W_BRICK/FRAME'), (False, 'W_CONC BLK'), (False, 'W_FRAME
'), (False, 'W_FRAME/STONE'), (False, 'W_LOG'), (False, 'W_METAL'), (False
, 'W_STONE'), (False, 'W_STUCCO')
```

The terms above showed us that the important features were bedroom, full bath, finished areas and G_X (grade excellent). The scatter plot presented here displayed the relationship between the true price and the predicted price. The plot looked reasonable with the fitted line drew across the data points in the middle.



4. Conclusion

This project gave a new insight to Nashville real estate by offering what features important to the buyers and consequently drove up the price. By improving bedroom, having a full bath and bigger finished areas as well as in an excellent condition, the price of the house would be going up because the buyers willing to pay more. There were certainly ways to improve this model was to use cross validation and hyper parameter tuning on the dataset. This way would polish the results and accuracy score higher due to less over-fitting.

Reference

- https://www.trulia.com/real_estate/Nashville-Tennessee/market-trends
- https://www.kaggle.com/tmthyjames/nashville-housing-date