DATA ANALYTIC AND PRICE MODELLING USING ENSEMBLE METHODS FOR HIGH RISE RESIDENTIAL IN KUALA LUMPUR

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Contents

Abstract

House, most of the time is the most expensive purchase in a person's lifetime. Yet, amongst of the biggest challenges by individual purchaser or seller is to determine the fair price of the real estate property. If buyer pay above the market price, they will end up with a bigger mortgage that can cost them a high monthly instalment, on the seller side, selling below market value can cost them of lower return of their investment..

The objective of this research project is to conduct data analytic study and build machine learning model that posses profound accuracy in determining the housing price. Around 39000 house's transaction from January 2008 to March 2018 for 953 high rise residential in Kuala Lumpur are extracted. Python programming language was used in this research from data acquisition, data cleaning, data exploration, data visualization and finally data modelling.

Our end goals is to investigates factors that influence the housing price and build several ensemble machine learning models, compare their accuracy and propose the best model that can predict the future housing price based on the model performance.

1. Introduction

1.1 Research Objective

Over the past several decades, machine learning model has been utilized extensively to predict real estate property value all over the world. The recent high growth of machine learning utilization especially in the artificial neural network (ANN) was credited to the increase of high computational power and exponential growth of data. Yet, since from the last decade, there was not many substantial local research that utilize machine learning technique in the context of Malaysia's housing market that can be found online.

For the last 10 years, the change of the market and economic cause the inconsistent price of housing. In 2008 to 2014, the Malaysia House Price Index rise from around 1% to be around 12% in 2014 and drop to 4% in 2015 before hovering around 6% in the recent year (Malaysia House Price Index, n.d.) In 2016, the volume of residential transaction drop from 14% while total transacted value drop to 11% compare to the year before. This cause predicament amongst home buyer and seller on how to accurately assess the price of a house and what type of features that determine the desirability of a certain house compare to others on the market

The diversity of housing characteristics pose challenges to determine accurate price for the a particular property. The price of a property is substantially influenced by it own unique set of structural features(Completion Date, level of storey, total number of block, Tenure, gymnasium, swimming pool, level of security), location features(distance to amenities such as shopping mall and highways) , neighbourhood features (crime rate, population density and income level) and macroeconomic features (Overnight Policy rate, Inflation rate, unemployment rate)

To develop a model that can accurately predict a price of a house is difficult due to numerous of reasons. First, it is not easy to acquire or access the data set of the mentioned attributes above to train the model. Second, the value of house may not be consistent due to specific features across different area or geographic regions. For example, people in the rural tend to prefer a terrace house with a land area compare to people living in the city, which tend to prefer high rise property due to the price and surrounding facilities. Due to these reasons, the machine learning model tend to be developed focusing on a specific regions. Under this project, Location features will be included to account the spatial effect.

Despite of all these obstacles, previous research has shown that it is possible to assess the actual value of a house. The objective of this research is to investigate that features that contribute in determining the value of a house and develop a model that can predict the future value of a house with a profound accuracy

2. Literature Review

2.1 Previous Research Review

Hedonic regression model has been widely used in since 1970's to develop prediction model for housing value. Hedonic pricing model allow the housing price to be assessed internally (structural) and externally(location, neighbourhood and macroeconomic) by breaking down the heterogenous attributes of a house into individual components.

Kain and Quigley (Quigley, 1970) develop hedonic model that include the structural features and location features of the house and study the relationship between the housing price and the house characteristic. While Kenskin (Kenskin, 2008) improve the model by including socio-economic characteristics such as neighbourhood quality satisfaction, distance to amenities and facilities.

Malpezzi (Malpezzi, 2003) stated that hedonic method is one of the way that a house price can be evaluated. In which, by decomposing the heterogenous features of a house into measurable prices and quantities. Therefore using, hedonic method and regression analysis can help to investigate how each attribute help to determine the final overall price. Maelpezzi suggested hedonic approach also consider the age of the properties in which time series attribute also being taken into the consideration.

Typically, hedonic model does account for spatial factors as well, Basu and Thibodeau (Basu, 1998) explain that spatial dependence exist for a few reason. For example, houses in a same region tend to share similar characteristic such as similar design structure. Another reason, house in the same region have the similar distance to the surrounding amenities and other central business district. All of these spatial factor contribute to correlation between the features stated and the final price of the house.

However, technique mention above applied the multiple regression analysis were criticized in other researches. Mainly due to the potential problem relating to the model estimation and assumption. This is amongst the factors of the rise of ensemble method. The idea of ensemble models is to combine multiple independent model and averaging their result to improve the accuracy. Ensemble models can be categorized as three. Bagging, used to reduce variance of the prediction model. Boosting, is aimed

on transforming a collection of weak learner into a strong predictor. Finally, stacking, aimed to decrease prediction biased in addition to variance (Yakov Frayman, 2007)

Fan, Ong and Koh (Gang-Zhi Fan, 2006) stated that multiple regression framework pose problem such as market disequilibrium, selecting independent features and identifying supply and demand. Fan, Ong and Koh claimed that one of the bagging method, tree based model approach is a better alternative to hedonic multiple regression for predicting housing price. This claim was further supported by Ceh, Kilibarda, Lisec and Bajat (Marjan Ceh ˇ, 2018) which showed that tree based approach model (Random Forest) performed significantly higher compare to hedonic multiple regression model.

For boosting algorithm, XGBoost is the recent boosting ensemble method that raise to fame due it highly scalable end to end tree boosting system and novel sparsity aware calculation (Tianqi Chen, 2016). This features lead to fast execution speed and better performance compare to other model. We will apply XGBoost in our study despite there is not much industrial application that can be found.

For Stacking, Frayman, Rolfe and Webb claimed that stacked ensemble performed better compared to the conventional machine learning model (Yakov Frayman, 2007) Frayman, Rolfe and Webb achieved better performing model by combining linear regression, multilayer perceptron, logistic regression and KNN as the based model and used Multilayer Perceptron as the final generalization model. For the selection of the based model for the stack ensemble, we will used the base model similar to Frayman, Rolfe and Webb's.

3. Methodology

3.1 Area of study

Kuala Lumpur is the national capital of Malaysia. The boundary of the city encompasses of 243km2. It is located between the confluence of Klang and Gombak rivers, and situated in the centre of Selangor state. As 2016, the city cater the population of 1.76 million people in the area of just 94 kilometer. This translate to a very high population density of 17,310 people per square mile of area. By 2017, almost 464,000 thousand units are available in Kuala Lumpur area. This research will solely focus on the high rise residential units available in Kuala Lumpur

3.2 Data Acquisition

Under this research, multiple property websites were used for the data acquisition. Using data acquired from www.brickz.com, around 39200 transaction between January 2008 to March 2018 for 951 high rise residential properties in Kuala Lumpur has been scrapped for this research. The web scrapping process was automated using python programming. The type of high rise residential consist of flat, apartment and service resident/condominium. From brickz.com again, several other features were further extracted such as name of the property, address, street name, tenure, type of resident, Level of storeys, lot size, rooms, transaction date and sale price.

Additional information such as year of completion, developer name, maintenance fee, total number of block, total number of storey and total unit available for a particular high rise property were further scrapped from different websites such as;

- www.propsocial.com
- www.propwall.com
- www.durianproperty.com

For any further missing data that is not available through all the website mentioned above were scrapped from numerous forums and social medias. Although housing information acquired from the forum or social media is deemed lower quality and authenticity, we still implement these lower tier of

information into our final dataset with assumption it is better than nothing. Any further leftover missing value will be fill up using imputation method discussed in the next section.

The spatial coordinate for each property was acquired from Google Map API service. All of the coordinates of the properties solely focus in Kuala Lumpur area.

In term of macroeconomic factor, just a single attributes was selected which is Overnight Policy Rate. (OPR). The reason only single macroeconomic factor was selected due to the reasons of others macroeconomic indicator such as GDP and inflation rate was lagging indicator. Which mean that these indexes were formulated after the event has already occurred.

All the acquired data can be summarized as below

Table 1: Type of Variables

	Variables	**Description**	**Format**	**Type**
1.	Name	Name of the property	Category	Neighbourhood
2.	Type	Type of property- flat, apartment or condominium	Category	Structural
3.	Address	Address of the property	Category	Neighbourhood
4.	Street	Name if the neighbourhood	Category	Neighbourhood
5.	Tenure	Freehold or leasehold	Category	Structural
6.	Size	Size of the property	Integer	Structural
7.	Room	Total number of room	Integer	Structural
8.	Completion	Year of completion	Integer	Structural/Time
9.	Developer	Name of Developer/ Developer reputation	Category	Structural
10.	Maintenance fee	Maintenance charge per square foot area	Float	Structural
11.	Block	Total number of block	Integer	Structural

12.	Total Storey	Total number of Storey of particular building	Integer	Structural
13	Level Number	Level number of storey for a particular transacted property	Integer	Structural
14.	Total Unit	Total unit available for a particular high rise property	Integer	Structural
15.	Sale Date	Transaction sale date	Date	Time
16.	Price	Sale price of the property	Integer	Target
17.	Latitude	Latitude coordinate	Float	Neighbourhood
18.	Longitude	Longitude coordinate	Float	Neighbourhood
19.	OPR	Overnight Policy Rate	Float	Macroeconomic
20	Number of Transaction	Total Number of Transaction for each residential	Integer	Structural/Time

All the dataset was imported and manipulated using pandas and numpy package

3.2 Data Cleaning

Data cleaning is a process of identifying and removing inaccurate or corrupted data from the data frame. The data cleaning process is vital to prevent false conclusion derived from the final model. Several type of data cleaning method will be discussed in the next sub section.

3.2.1 Duplicate Data

There were several duplicate rows (house that share exactly the same features). All of these duplicate rows were found to be originated from the property website. All of the duplicate data are dropped from the final dataset.

3.2.2 Incomplete and Missing Data

Any missing numerical value (‘Maintenance’, ’Block’, ’Total Unit’, ’Level Number’, ‘Complete’) will be filled up using median value imputation method of the intended missing feature. The imputation

method use statiscal inference that substitute missing value based on other similar available information. The first tier imputation will group the property based on “Street” feature, follow by “Type” feature. The price will be filled using median “Price” transformation. Any further missing value will be filled up under the second tier imputation by grouping the property based on “Type” followed by filling up using median value imputation of the intended feature. The reason behind such selection is that same type of house in similar neighbourhood tend to share similar characteristic.

3.2.3 Outliers and inconsistence data

Outliers is the data that possessed extreme value or highly deviated from normal distribution. From explanatory data analysis. Outliers made up below 1% of the total data, which allow us to simply omitted the data from our final data set

3.3 Data Filtering, Selection and Transformation

This section explained how the data filtering, selection and transformation is being made

- Remove string based value from any numerical features and convert them into numerical type (int or float)
- Substitute any ordinal category (category with ranking) data into integer. For ‘Type’ feature, Flat = 1 Apartment = 2, Condominium/ Service Residence = 3. For ‘Tenure’, Leasehold = 0 and Freehold =1. The increasing order represent higher quality of house type.
- Substitute any nominal value (category without ranking) into integer. The ‘Street’ feature which in total of 41 unique value are converted into integer using label encoder. The conversion of to numerical value is done for visualization interest and the ‘Street’ feature will be drop before the final modelling.
- Under ‘Maintenance’ variable. Small portion of the value consist of object type “/month”. Any strings text was stripped off and convert into numerical. The ‘/month” value was converted into per fee per square foot area by diving the value by the size of the property

- The ‘Developer’ features were ranked based on The Edge Malaysia Property Excellence Award Top 30 Property Developer. Due to difficulty to rank the developer, all the developer that made through the Edge list will be given rank 1, while other developer that that did not make the list will be given value of 0
- The dataset will be sorted through the ascending date order
- For the time series, a new features ‘SPAMonth’ and ‘SPAYear’ will be generated from the ‘Date’ variable as most machine learning model is not able to handle date type data directly. The ‘SPAMonth’ will be used to observe any seasonality effect while the ‘SPAYear’ will be used to assess the trend effect. Date column will be dropped before the final modelling process.
- From ‘Maintenance’ feature, a new feature features ‘MaintenanceRng’ will be generated which represent the maintenance fee range value. The range value will consist of range 0-0.1,0-0.15,0.15-0.20,0.20-0.25,0.25-0.30, 0.30-0.35, 0.35-0.40, 0.40-0.45, 0.45-0.50, 0.50-2.0. The range value was derived for visualization and data explanatory purpose and will be omitted before the final modelling.
- ‘Median Price Psf’ will be omitted because it is highly correlated with target variable, ‘Price’. ‘Median Price Psf’ will be used only for visualization and EDA purpose.
- ‘Street’, ‘Address’, ‘Longitude’ and ‘Latitude’ represent the spatial coordinate effect and highly correlated to each other. For the final model, ‘Street’ and ‘Address’ will be omitted. Another new features called ‘Zone’ will be generated from ‘Longitude’ and ‘Latitude’ by clustering ‘Longitude’ and ‘Latitude’ based on kmean Euclidean distance. Total 10 clusters will be chosen as the parameter under the kmean clustering. Both of ‘Zone’ and ‘Longitude’ & ‘Latitude’ will be run separately in the final model to see the differences in the model performance.
- Several features are found out to be inconsistence. For example, the “No of Transaction” which represent total number of transactions volume made for a particular property from 2008 to 2018 acquired from Brickz.com is not consistence with total transaction volume with another similar property transaction portal (www.propertyadvisor.com). This variable will be also excluded from the final modelling.

3.4 Exploratory Data Analysis

The purpose of exploratory data analysis (EDA) is to find meaningful pattern or insights, often with the assistance of visualization methods. EDA is also used to investigate the correlation between dependent and independent variables, or amongst independent variables themselves.

Our main interest is this study is to find factors that influence our dependent variable (Price) by investigating the relationship between the independent variables (Complete, Type, Developer, Maintenance, Block, Total Storeys, Level of Stroey, Total Unit, Tenure, Latitude, Longitude, Zone, Rooms, SPAYear,SPAMonth and OPR)

Our dataset consist of 3 type of high rise residential: flat-199 units, apartment-159 units and condominium-581 units. Figure 3.4a will showed total count of each type of property along with the total transaction for each type of high rise residential throughout the study period

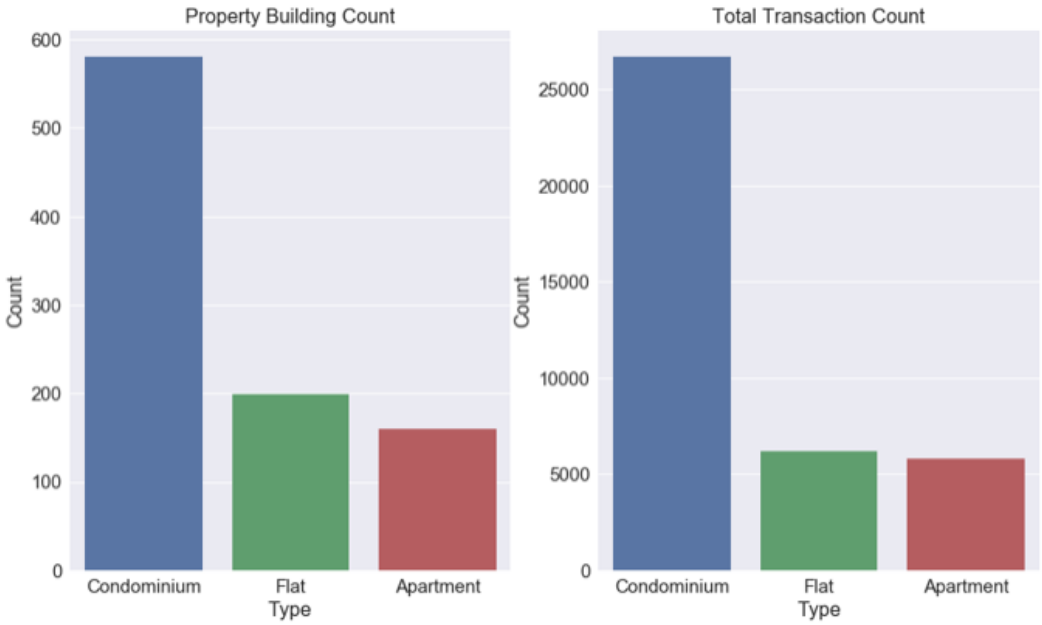

Figure 1: Total Building Count & Total Transaction Count

3.4.1 Descriptive Statistic

Table 2: Descriptive Statistic Table

	Mean	Median	S.D	Min	Max
Price (RM)	800,060	590,000	709,820	10,000	12,000,000
Lot Size (ft2)	1330	1195	679	205	10409
Year Build	2006	2008	7.26	1978	2017
Maintenance Fee (RM)	0.26	0.23	0.12	0.07	2.0
Number of Blocks	3.08	2	3.34	1	31
Total Storey	23.10	22	9.93	2	60
Level of Storey	12.94	12	8.37	0	51
No of Transaction	93.24	75	75.64	1	435
Number of Room	2.75	3	1.31	0	3
Year of Transaction	2014.56	2015	1.89	2008	2018
Month of Transaction	6.94	7	3.43	1	12
OPR rate	3.08	3.0	0.20	2.0	3.5

Data describe function in pandas library allowed us to assess the mean, median, standard deviation, min and maximum value for each of our variable. The main purpose of this assessment is to determine the distribution of the value for each variable and to find any extreme value which may affect the final model.

3.4.2 Price Trend Analysis

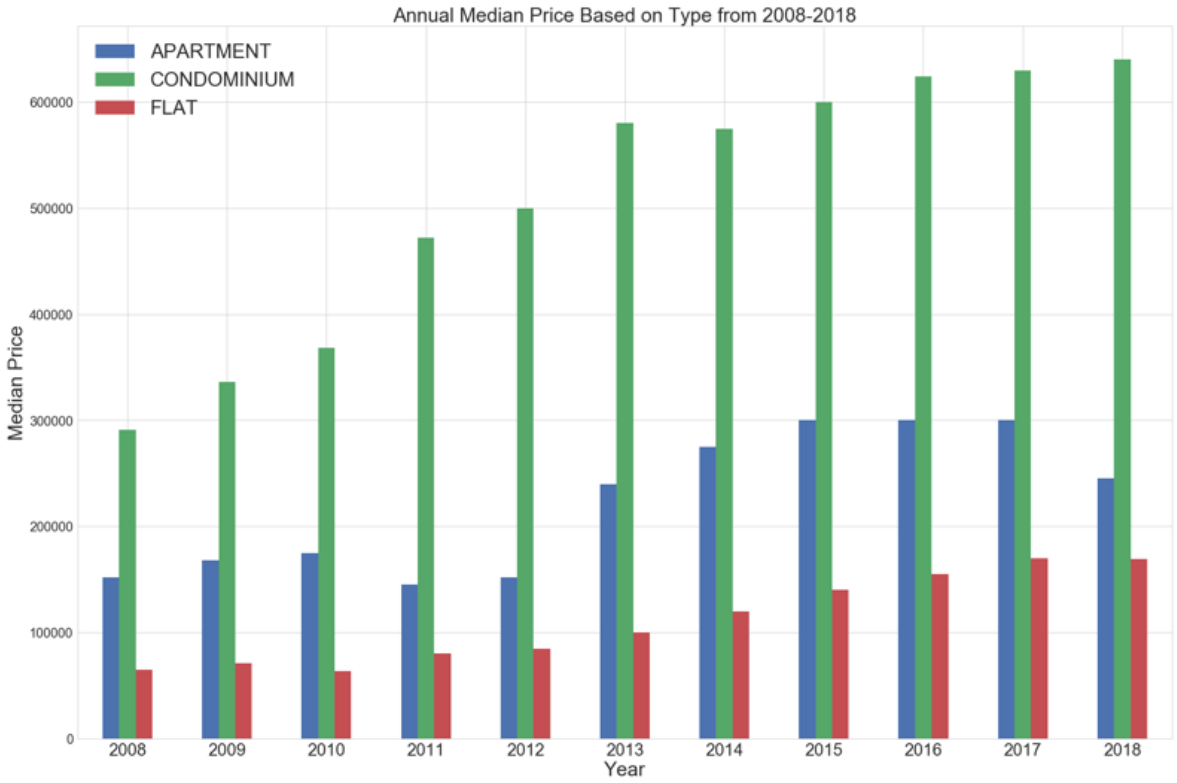

Figure 2: Annual Price Trend

The price for condominium showed tremendous growth of almost 100% from 2008 to 2013 and then start to become stagnant from 2016 to 2018. Price for flat and apartment start to pick up traction after year 2012. Despite the late explosion of price growth for flat, it can be observed that flat still show consistent annual growth up to recent year compare to other two type of property. Apartment showed significant decline of median price on 2018 but it to early to conclude that the price of apartment is declining since the period of this study for 2018 only cover the first quarter of 2018.

3.4.3 Geographic Analysis – Boundary Analysis

We used gmaps package to assess the geographical distribution (Latitude & Longitude) in this research which consist of 951 location. The total area of coverage will be approximately around 243km2. It can be observed that luxury residential such as condominiums tend to populate hot spot area such as Mont Kiara and KLCC. While cheapest high rise residential such as flat tend to populate the area nearing to the boundary of Kuala Lumpur.

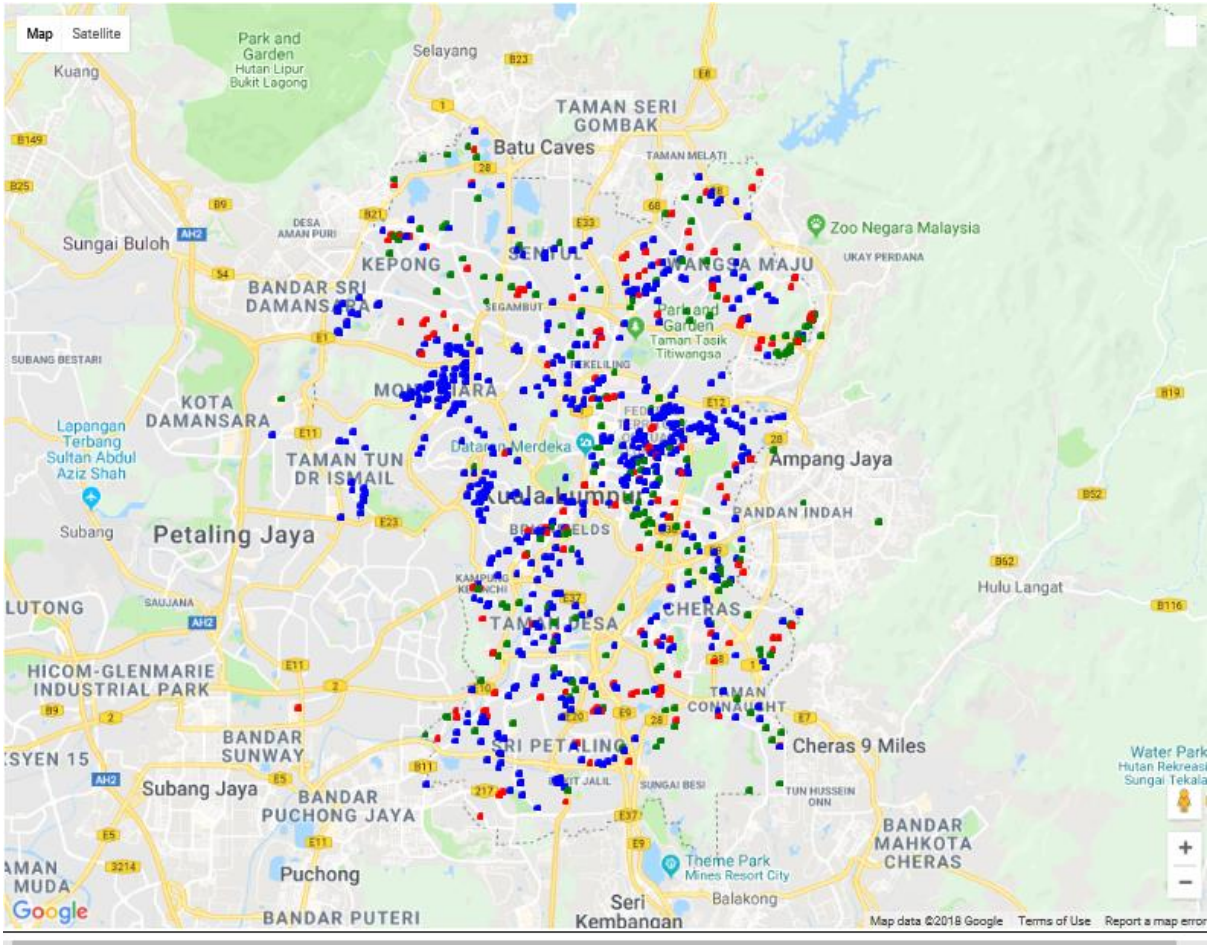

Figure 3: Property Type Distribution with colour coded

3.4.4 Heatmap Analysis

Heatmap is used to assess the intensity of price per square feet using the same google map package

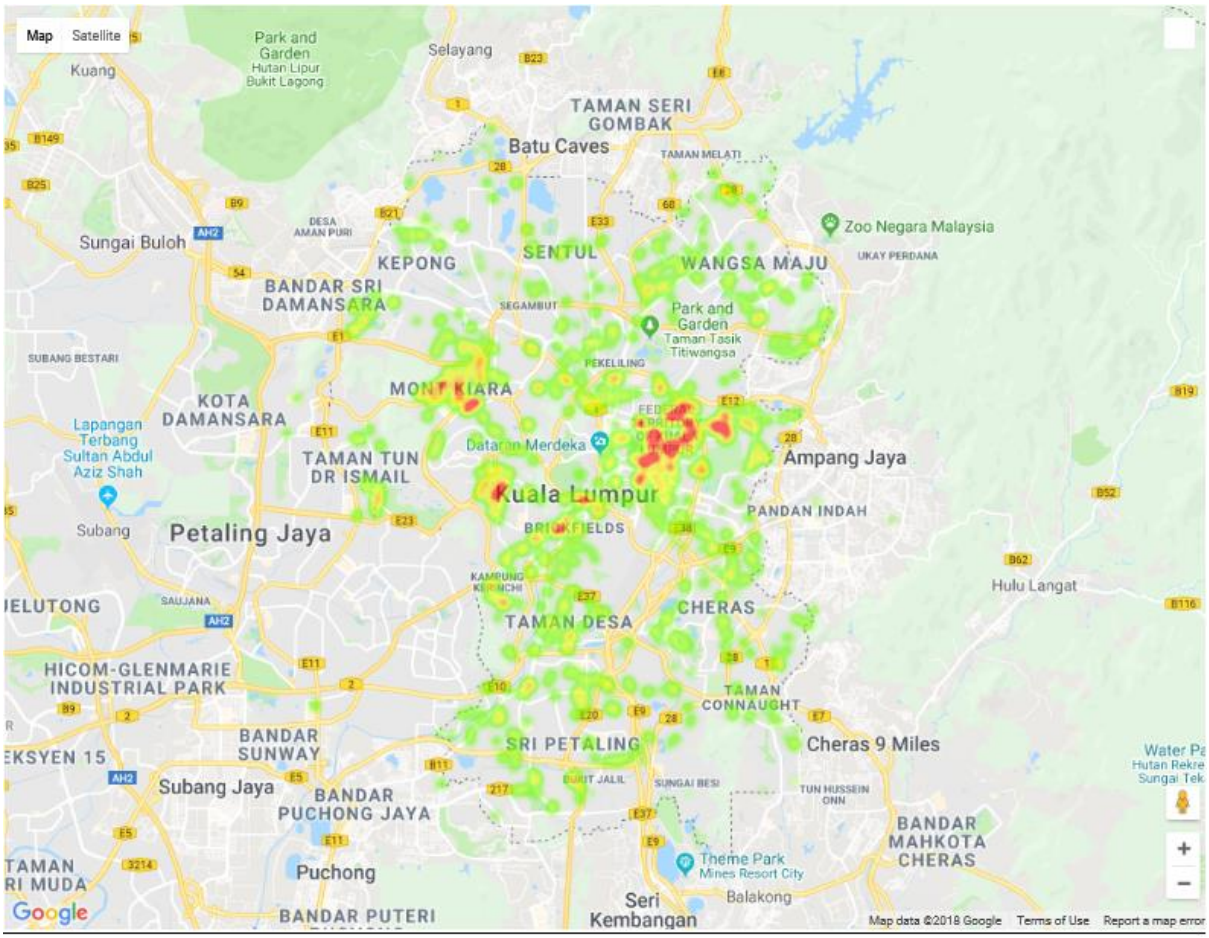

Figure 4: Heatmap for Price Per Square of Area

From the heatmap, it can be observed that highest price per square foot concentrated in KLCC, Mont Kiara and Bangsar area. Boxplot is used to further assess the distribution of the price across the 41 street/neighbourhood in Kuala Lumpur.

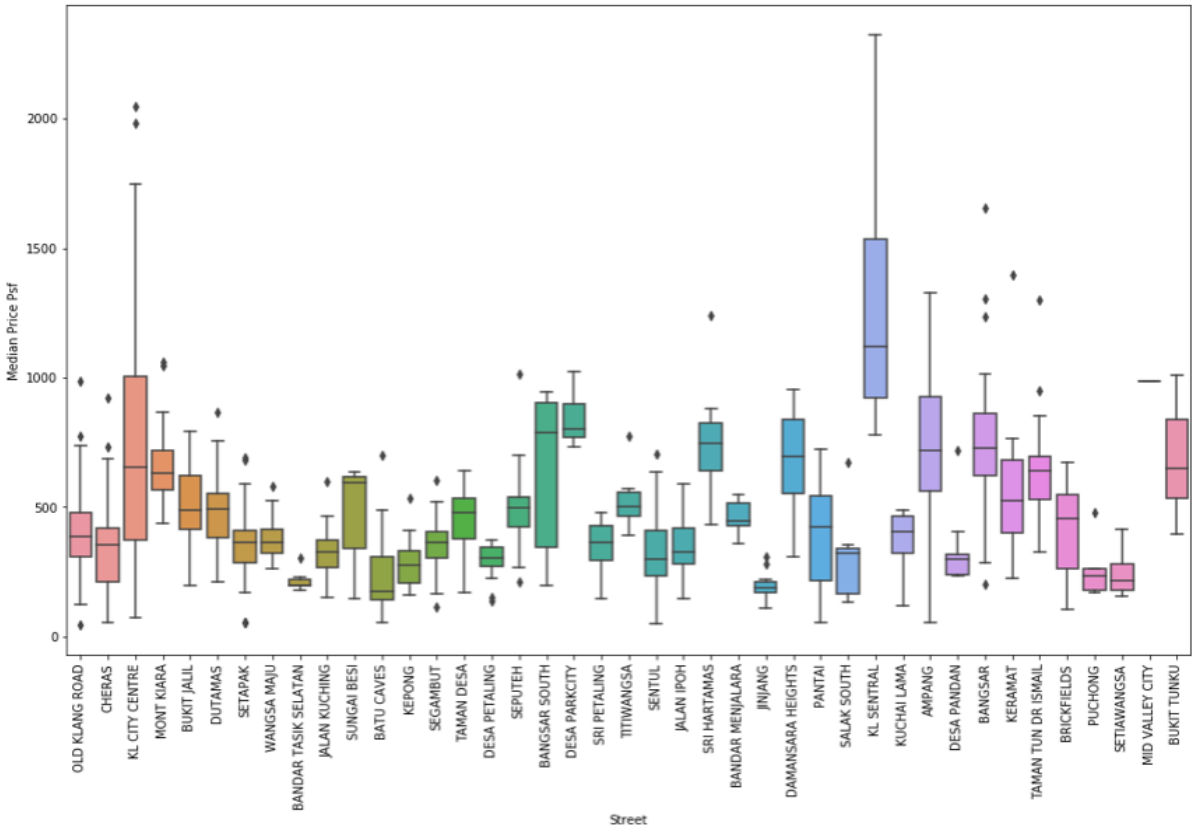

Figure 5: Boxplot of median price based on Neighbourhood

It is confirmed that neighbourhood such as Mont Kiara, KLCC, Bangsar and KL Sentral have higher median price per square area compare to the surrounding neighbourhood. All of these area also located in the centre of Kuala Lumpur, which the economic activity is the highest.

3.4.5 Zone Clustering

Coordinate (Latitude and Longitude) and Street posed complexity to categorize due to the high number. An alternative spatial variable was generated by clustering the coordinate into 10 zones using k-mean clustering. Separate model will also be generated using this zone clustering variable over the spatial coordinate variable (longitude and latitude)

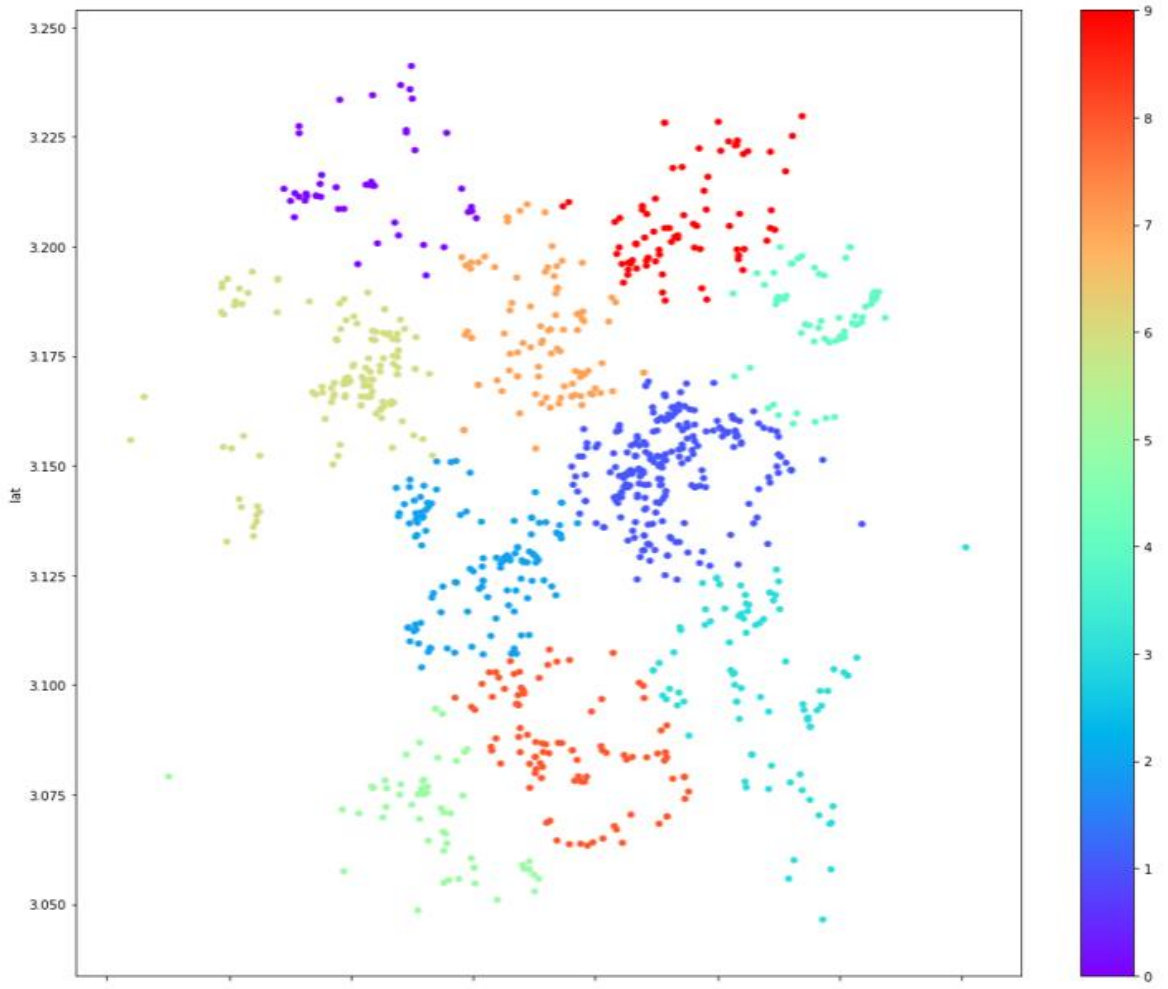

Figure 6: Scatter Plot based on 10 cluster of Kmean

3.4.6 Structural Analysis

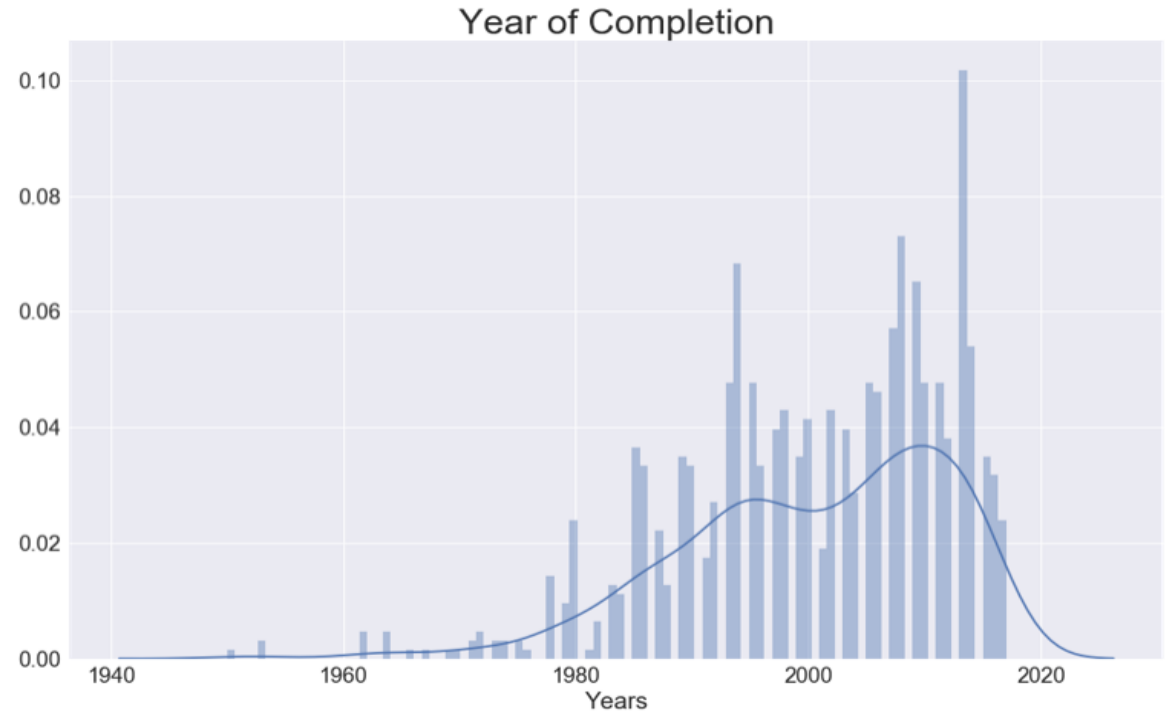

Figure 7: Histogram of Year of Build

Based on our dataset, most of the residentials was built after year 1990, with the most transaction made up from the residentials that are recently built.

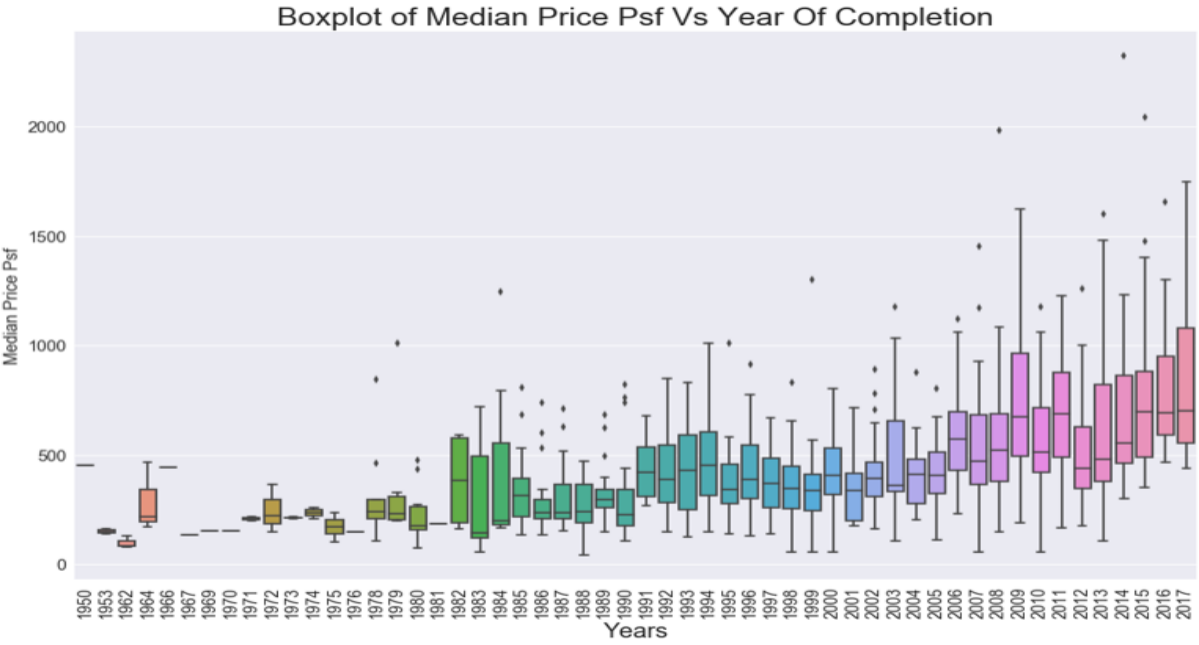

Figure 8: Boxplot of Median Price Psf Vs Year of Completion

Based on the boxplot, the recent completed residential tend to command higher price per square foot. From both of Year of Completion histogram and Boxplot, we hypothesize that the house buyer tend to buy recently completed residential and more tolerance toward the higher price due to more facilities and up to date design offered by newly built residential.

3.4.7 Macroeconomic Analysis (OPR)

Around 2007-2009, subprime mortgage bubble took place in USA. Malaysia was not spared from this recession. Central Bank of Malaysia decided to lower the Overnight Policy Rate to the lowest rate of 2.0% in 2009 as the countermeasure of this economic recession. This step is taken to encourage financial institution to lend money to the end consumer at the cheaper rate which to spur back the economic activities. Using OPR rate for 2008 to 2018, we use line chart to measure if the housing price is correlated with OPR rate. Our initial assumption is that house price should drop if the OPR rate is high and vise versa.

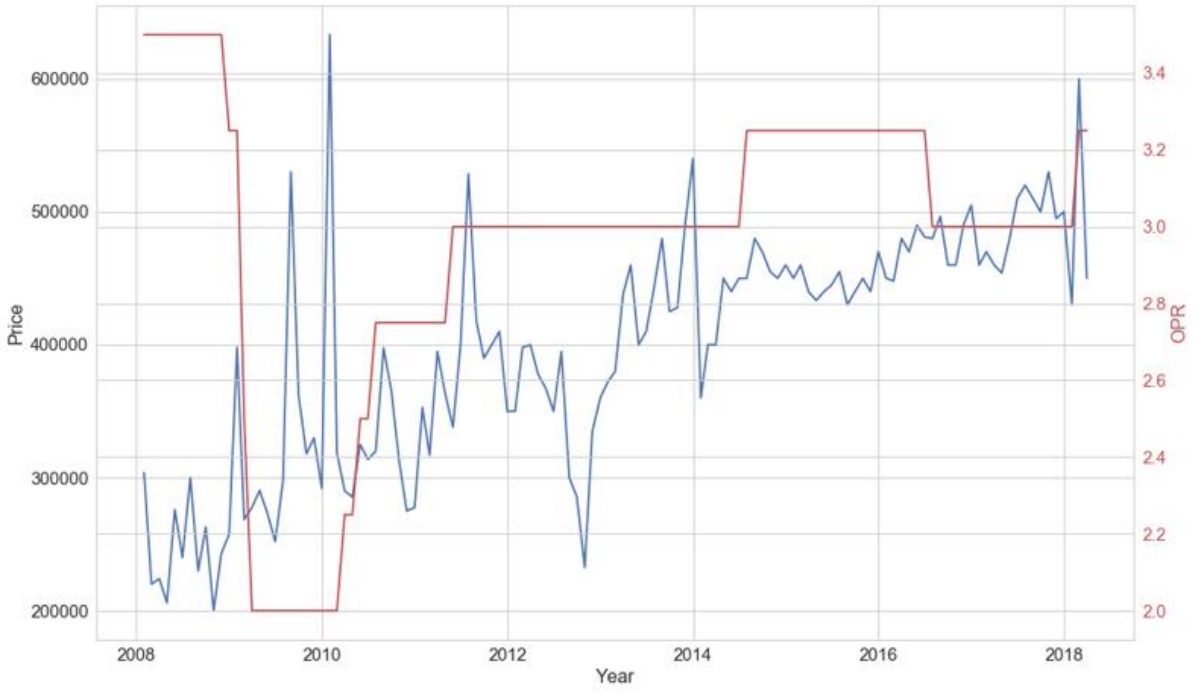

Figure 9:Monthly Median Price Based on OPR

Based on the monthly median price, we could not see any direct correlation between monthly median housing price with OPR rate. Nevertheless, we will further study the feature of importance for OPR on the housing price under the Modelling chapter.

3.4.8 Correlation Analysis

Continuous variables consist of Price, Lot Size, Year Build, Maintenance Fee, Number of Blocks, Total Storey, Level of Storey Transacted, Number of Room, Number of Transaction, Month of Transaction, Year of Transaction and OPR rate. The table below show the aggregated statistic summary for each continuous variable. Scatter plot is used to see the correlation between target variable (Price) and all the independent continuous variables.

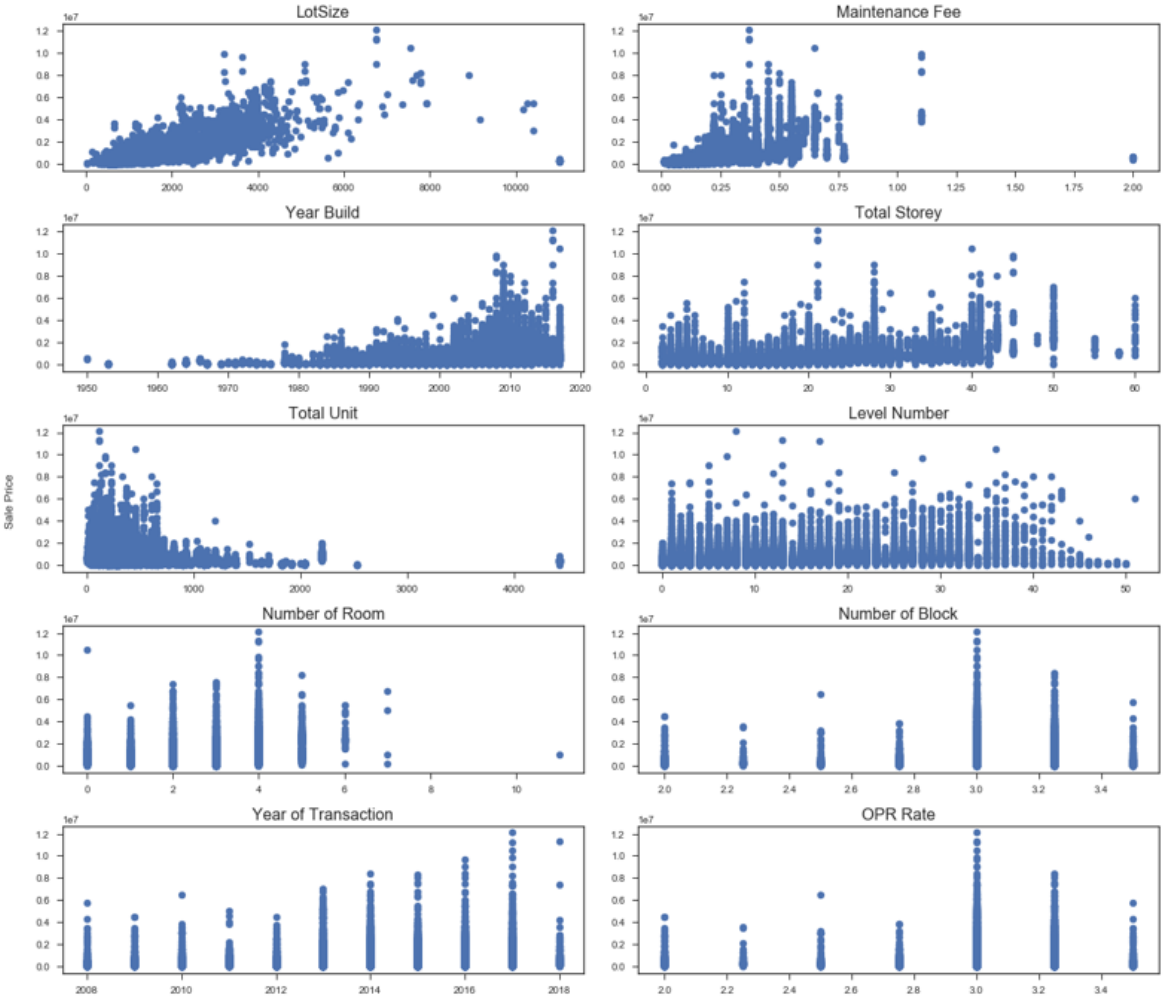

Figure 10: Correlation between Price and other continuous variable

It can be observed that there are several variables were showing positive correlation with Price. These variables that showed strong positive correlation are "Size", "Maintenance Fee", "Year Build" and "Year of Transaction". 'Total Unit' and 'Number of Block' indicated negative correlation which imply that the house price tend to reduce as the total unit of house in a particular residential building increase.

Pearson correlation is also used to see the correlation between the structural variables. In the context of housing attributes, several features showed strong correlation between each other. For example, “Total Unit” showed strong positive correlation with “Number of Block”. This is the due to higher number of block able to accommodate higher number of total unit of house for a particular residential. This factor is also true for the correlation between “Level Number” and “Total Storey”. Overall, the independent variable showed little multicollinearity which fulfil our linear regression assumptions.

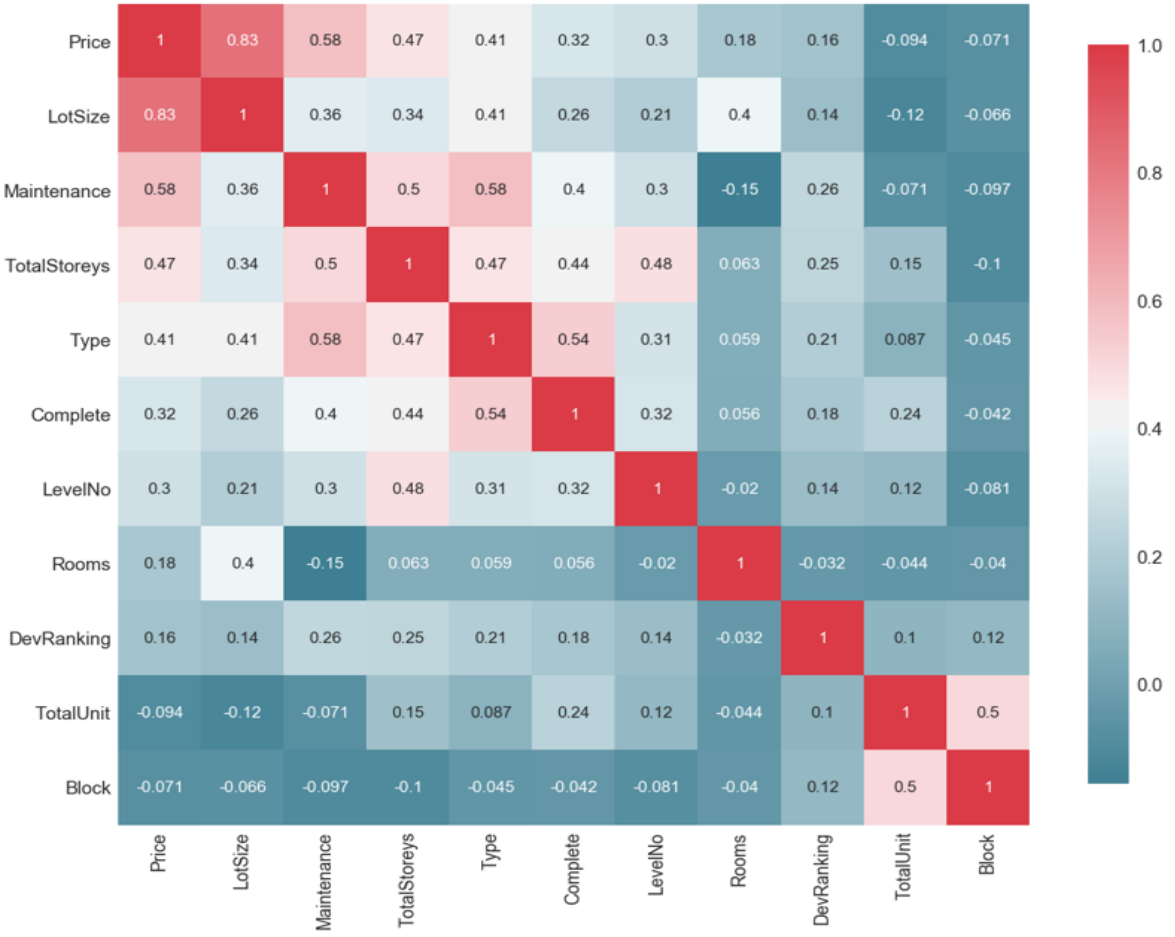

Figure 11: Heatmap of Pearson correlation between structural variables

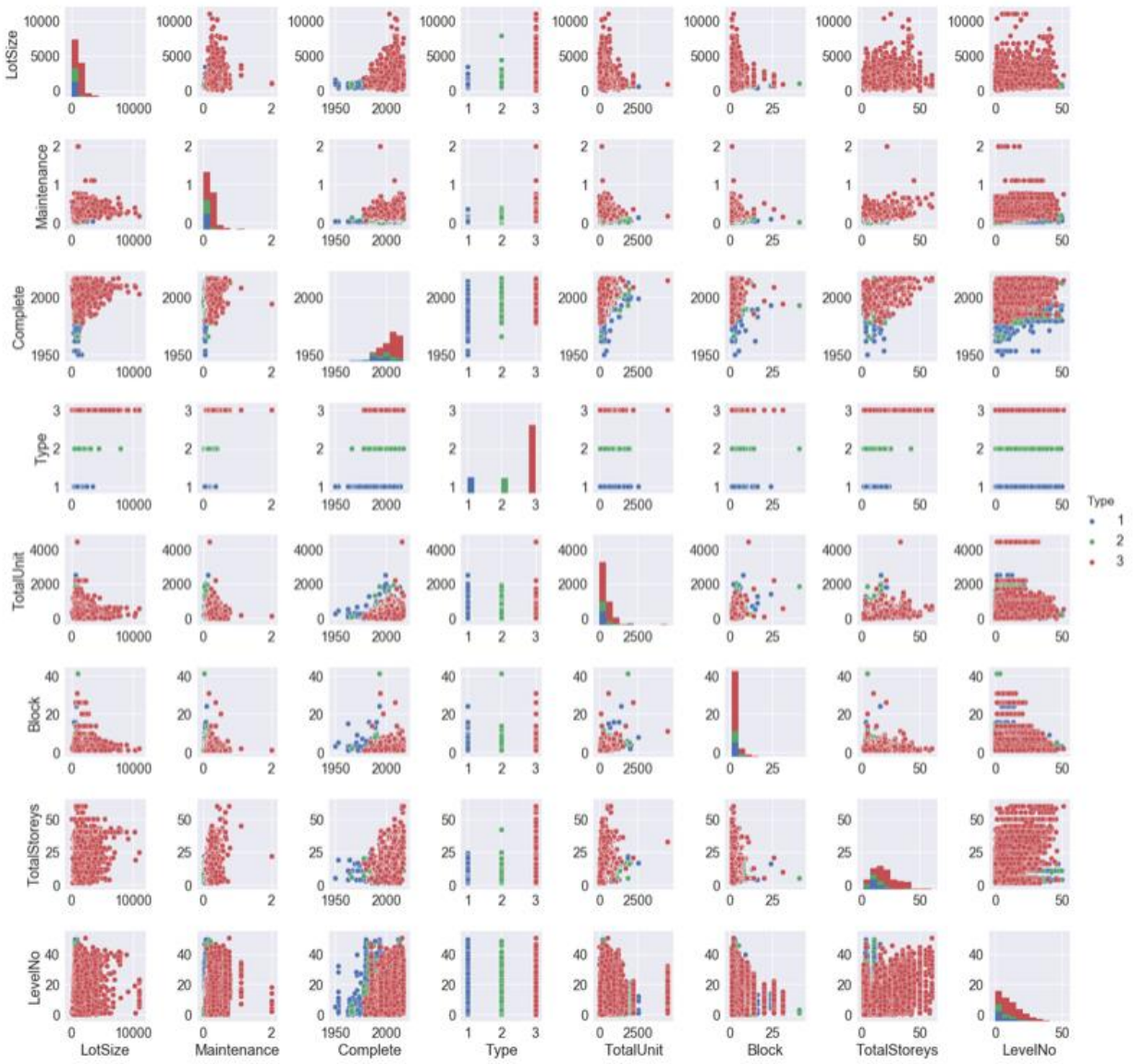

Figure 12:Pair plot of independent structural variables

Pair plot of figure 12 is a used to visualize and further assess the correlation between independent structural variables. Based on our observation on the pair plot, there is no strong correlation displayed between independent variables. We can safely say that there is minimum multicollinearity issue that affect our final models.

3.4.9 Price Distribution Analysis & Feature Engineering

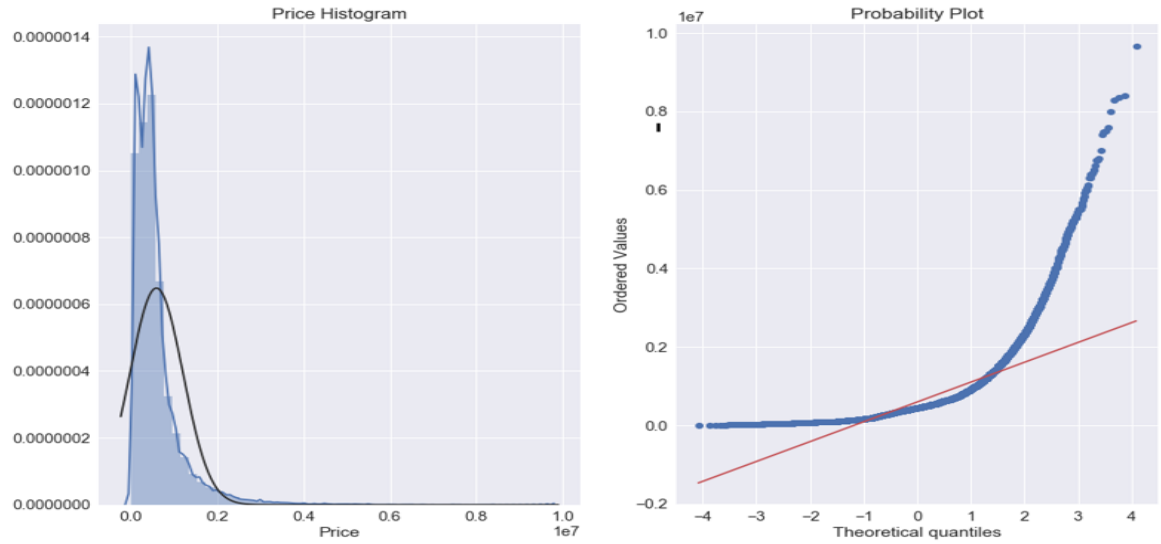

Figure 13: Price Distribution & q-q plot

The Price Histogram is not normally distributed and highly skewed to the right tail. Skewness is undesirable for the final modelling as most of the machine learning algorithms make regards the shape (distribution) of data namely normal distribution. The Q-Q plot further indicate how much is the deviation of our Price distribution from the normal distribution.

We use log transformation to transform the Price into normal distribution. Additionally, using log transformation help to minimize the impact of outliers

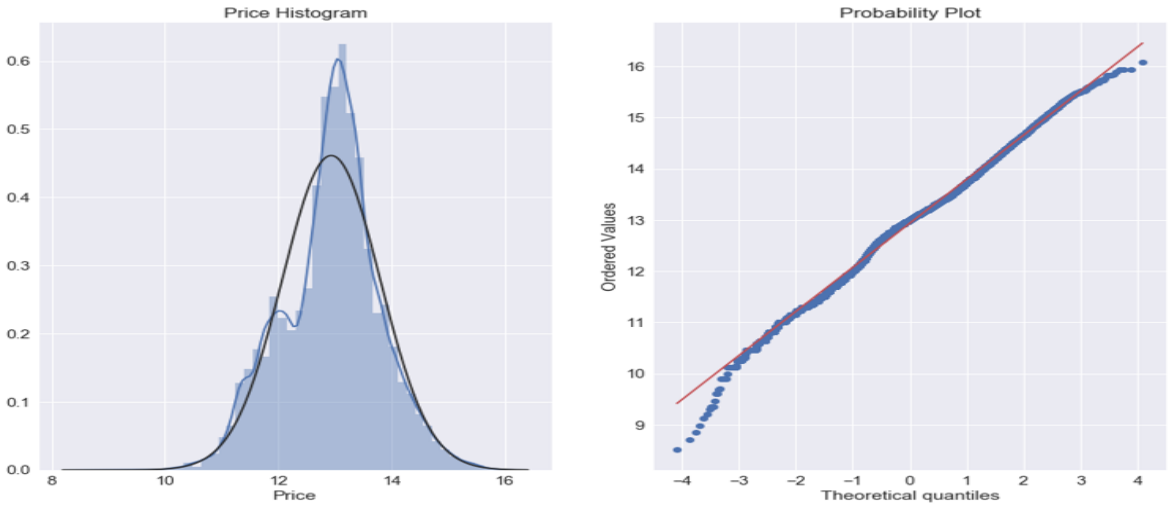

Figure 14: Price Distribution & q-q plot after log transformation

4. Data Modelling

Ensemble learning is a technique that combine multiple learners to increase the prediction power of the model. Under this section, we will apply 3 ensemble method which are bagging (Random Forest), Boosting (Extreme Gradient Boost) and stack generalization (several combination of different algorithm). We use the pre-built ensemble models from sklearn library instead of building one from the scratch.

The final dataset after all the pre-processing activities discussed under the previous chapter will be 30949 rows and 17 columns. We will sort the data set into based on transaction date whereby the oldest transaction will be on the top. 80% of this data will be training set and the remaining 20% of the most recent transaction will become our test set. The target variable, Price for the test set, will be removed. By the end of the modelling activities, we will compare the result derived from the prediction model of the test set with the actual value.

4.1 Bagging (Random Forest)

Bagging which stand for bootstrap aggregation, involves creating samples from the dataset with replacement. Random Forest is one of the machine learning model under Bagging. It give prediction based on majority voting (for classification case) or averaging (for regression case). Each tree (learner) in random forest is build independently from each other. For example, N is the size of the sample for the dataset, and M is the total number of tree. A subset of m<M Is randomly chosen to grow the each tree on a bootstrap sample. Unpruned tree is grown from each of the bootstrap sample. The best split among random sample of m variable is selected based on the information gain formula. After large number of trees are generated, the final prediction are averaged over the different trees.. Random forest require minimum preparation of the dataset and minimize overfitting. Another advantage of using Random forest under sklearn package is the ability to generated separate holdout set than can be used as the validation set. This hold out set which also called Out of Bag (OOB) can be used to test if the model is overfitting.

The hyperparameters for this random forest:

Table 3: Parameter for Random Forest

Parameters	Description	Value
n_estimator	Number of tree estimator	300
min_sample_leaf=5	Minimum number of sample in the leaf node	5
max_features	Number of features to consider when looking for the best split	0.50
oob_true	Out of the bag feature, Random forest only use 67% of the bootstrapped data for training, the remaining 33% which also called OOB can be used for validation set	True

4.2 Boosting (XGBoost)

Boosting algorithm trained based on the data iteratively and update the instances weight according to the different between predicted and actual values. The update of the weight depend of the algorithm that being used. Misclassified learner get weight increase while correct classification get weight reduction. This lead to the classifier give more attention to the misclassified one.

We use XGBoost algorithm due to the reputation that it received. In the recent year, XGBoost has been used extensively especially in Kaggle competition. This due to the several advantages that this algorithm possessed. First, it is extremely fast and second, it performance is top notch especially when it comes to tubular dataset.

Table 4: Parameter for XGBoost

Parameters	Description	Value
colsample_bytree	Subsample of columns when constructing each tree	0.04
gamma	Minimum loss reduction required to make further partition on leaf node of tree	0.045
Learning_rate	Step size shrinkage used in update to prevent overfitting	0.07
max_depth	Maximum depth of tree	20
min_child_weight	Minimum sum of instance weight needed in a child	1.5
n_estimators	Number of learner	300
reg_alpha	L1 regularization on weight	0.65
reg_lambda	L2 regularization on weight	0.45
subsample	Subsample ratio in the traini9ng instance	0.95

4.3 Stacking

Unlike previous 2 methods which use multiple models of the same kind to improve accuracy, Stacking Generalization Ensemble is an ensemble method that use different kind of models. What is unique about stack ensemble is it's ability to train new model by combining previously trained model on the same dataset. The initial level of classifiers were trained separately and their results are combined using another classifier. The result of the stack ensemble can be simply achieved by averaging the initial classifiers prediction or by using weighted sum.

Compare to the previous two ensemble models. The hyperparameter for each classifier inside the stack ensemble need to be tuned separately. We use linear regression, ridge regularization, random forest, gradient boosting light and neural network(MLP) as the 0 level model (initial model) and linear regression as the second level model. The reasons behind selecting such model is because they are

different pattern of generalization model and have different biases thus can lead to efficient ensemble. As for the level 1 learner, linear regression is selected due to the simplicity of this model

Table 5: Models and Parameter for Stack Ensemble

Model	Description	Value
Linear Regression	Use Basic Linear Regression method	n_job = 1
Ridge	Linear least square with l2 regularization	alpha = 4.84
Random Forest Regressor	Random forest regressor model	n_estimators = 40, max_depth = 3,
Gradient Boost Regressor	Additive model in a forward stage wise fashion	n_estimator =40, max_depth=2
Multi Layer Perceptron	Multilayer Perceptron Regressor that optimize stochastic gradient descent	Hidden_layer_size=(90,90), alpha=2
1 Level Model Linear regression	Use Basic Linear Regression method	N_job = 1

5. Results

The aim of this chapter is to assess the performance for each model. Next, we will investigate the variables which have the strong feature of importance using the result derived from the models.

5.1 Accuracy

We use the coefficient of determination, R^2 and Root Mean Square Error (RMSE) to determine the accuracy of prediction for all our ensemble model. R^2 is the proportion of the variance in the dependent variable that is predictable from the independent variables. It measure of how closed the data to the fitted regression line. The highest core for R^2 will be 1 and the worst is 0. While RMSE is used to measure the differences between value (sample or population values) predicted by a model and the actual value.

The dataset for the accuracy assessment will be divided into train and test set. The accuracy comparison between train set and test set is used to determine if the model is overfitting (higher score of train set over test set indicate overfitting)

Table 6: Accuracy Score

Model	RMSE train	RMSE test data	R^2 Train	R^2 Test	OOB
Random Forest	0.174	0.235	0.96	0.92	0.93
XGBoost	0.159	0.23	0.98	0.92	NA
Stack Ensemble	0.313	0.319	0.87	0.86	NA

Stack Ensemble performed the worst compare to the Random Forest and XGBoost with around 0.86 R^2 score. Both Random Forest and XGBoost showed similar R^2 score at 0.92, yet XGBoost showed less RMSE of both train set and test set compare to Random Forest.. Despite the higher score of RMSE train set to RMSE test set, we concluded that our model is not overfitted due the high OOB score of the random forest.

5.2 Feature of Importance

Since the stacking ensemble is a combination between different algorithm, it is nearly impossible for us to assess the features of importance. So we ignore the feature of importance for stacking ensemble and focus on the other two, Random Forest and XGBoost. After all, this two ensemble accuracy performance is much higher compare to the stack ensemble.

Table 7: Comparison of features of important between ensemble model

Variables	Random Forest	XGBoost	Stacking
Type	0.308	0.013	NA
Size	0.280	0.154	NA
Maintenance Fee	0.220	0.073	NA
Total Storey	0.052	0.076	NA
Year Build	0.025	0.073	NA
Latitude	0.020	0.146	NA
Longitude	0.016	0.111	NA
Total Unit	0.011	0.071	NA
Tenure	0.011	0.011	NA
Rooms	0.010	0.023	NA
Level Number	0.006	0.126	NA
Number of Block	0.005	0.036	NA
OPR	0.005	0.026	NA
Developer Reputation	0.001	0.006	NA

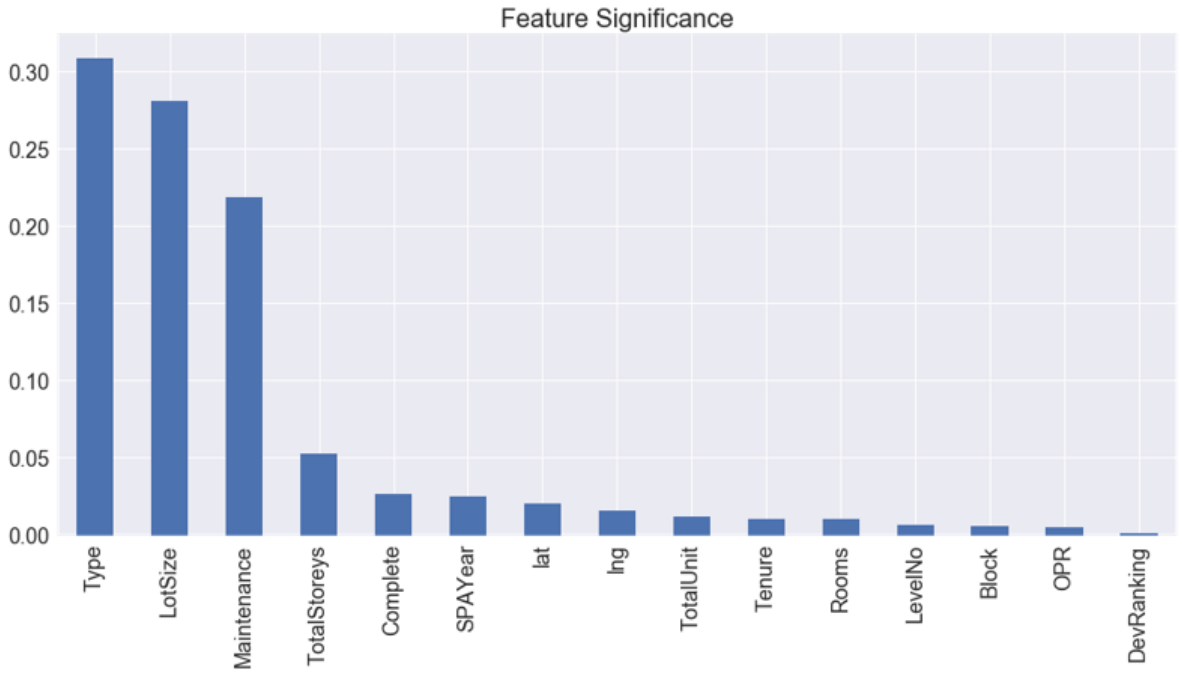

Figure 15: Features Importance for Random Forest

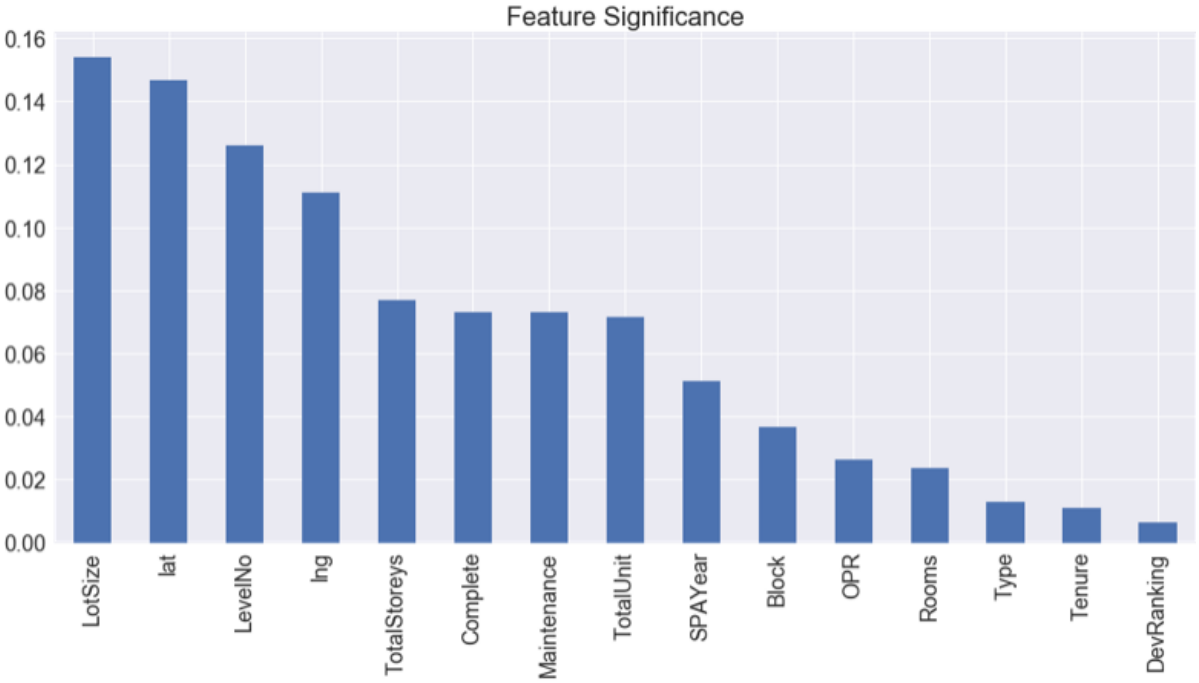

Figure 16: Feature Importance for XGBoost

Surprisingly, Both Random Forest and XGBoost showed different features of importance. Random forest select Type, Size and Maintenance Fee is the top 3 most important feature while XGBoost choose Size, latitude and Level Number as the most importance feature. Yet, both model agree that Size is the most important feature in determining the price of the house. For the final prediction model, we will chose XGBoost because not just it possess higher accuracy score, but the feature of importance shown by XGboost tend be more uniformly distributed amongst its variable.

We used test set to predict the price and compare the predicted price with the actual price. The figure 20 showed the sample of predicted house price value with the actual price value.

	Name	Address	LotSize	Date	ActualPrice	PredictedPrice
1	11 MONT KIARA	D-30-2, JALAN KIARA 1	3315	20/10/2016	2,500,000	2,807,221
2	WANGSA MAJU SEKSYEN 1	102, OFF JALAN 3/27A, OFF JALAN 1/27A	531	20/10/2016	238,000	167,483
3	DESA PANDAN FLAT BLOCK B	B13-4-6, DESA PANDAN	721	20/10/2016	130,000	171,576
4	SERI MAS	5-9-1, JALAN 4/89A	958	20/10/2016	365,000	327,317
5	BUKIT ANGGERIK	35-3, JALAN 2/154	603	20/10/2016	56,000	88,729
6	PRIMA DAMANSARA	8D-1-1 (D31), JALAN CHEMPENAI	1356	20/10/2016	1,300,000	1,241,326
7	VISTA MUTIARA	B-18-19, BATU 61/2, JALAN KEPONG	1001	20/10/2016	485,000	405,991
8	SUTERA BUKIT TUNKU	B-3-2, JALAN TUN ISMAIL	5522	20/10/2016	3,700,000	2,854,916
9	LAMAN SURIA	00-05, OFF JALAN BUKIT KIARA BAYU	506	20/10/2016	67,100	388,375
10	PUTRA SURIA RESIDENSI	B-15-6, JALAN JELAWAT 2	748	20/10/2016	380,000	354,116
11	ROYAL DOMAIN SRI PUTRAMAS 2	B2-26-01, JALAN PUTRAMAS	1173	20/10/2016	560,000	550,423
12	ROYAL DOMAIN SRI PUTRAMAS 2	A1-15-07, JALAN PUTRAMAS	1130	20/10/2016	580,000	557,044
13	SUTERA BUKIT TUNKU	B-3-1, JALAN TUN ISMAIL	5522	20/10/2016	3,700,000	2,854,916
14	HAMPSHIRE RESIDENCES	M1B-4-210, PERSIARAN HAMPSHIRE OFF JALAN AMPANG	2852	20/10/2016	2,187,000	2,138,242
15	KETUMBAR HEIGHTS	A-10-5, JALAN 6/95B	755	21/10/2016	315,000	306,683
16	BAYU TASIK 2	A-4-9, JALAN PERMAISURI 5	926	21/10/2016	420,000	389,686
17	WINNER COURT B	16-4-10, JALAN 1/125A	829	21/10/2016	320,000	284,758
18	THE OVAL	36-1, LORONG KUDA	7793	21/10/2016	7,500,000	7,773,202
19	MANDA'RINA COURT	B-3A-1, JALAN 10/142	775	21/10/2016	360,000	311,992
20	SERI MALAYSIA	09-27, JALAN 3/141	657	21/10/2016	150,000	111,764
21	SEGAR APARTMENT	D-04-173, JALAN 1A	667	21/10/2016	160,000	181,202
22	MERCU SUMMER SUITES	B-23-05, 8 JALAN CENDANA	493	21/10/2016	480,000	488,550
23	BUSTAN SHAMELIN	13-2-9, JALAN 2/91A	1023	21/10/2016	330,000	274,463
24	PKNS KAMPUNG BARU	20R, RAJA MUDA MUSA	843	21/10/2016	225,000	190,488

Figure 17: Housing Price Prediction Sample using XGBoost

6. Conclusion

We have successfully doing data analytic in finding the importance feature that affect the housing price. We also managed to develop prediction model that capable of predicting the housing price with profound accuracy. We concluded that we met our objective

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