EE 660 Project
Airbnb Dataset Price Prediction

Project Report
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1. Abstract

The Airbnb Housing price validation is important for potential users of the website – both property listers and customers to make informed decisions and can help in establishment of real estate policies. There are a lot of factors which play an important role in determining the price of the listing, such as the neighborhood, Number of rooms in the house, Number of amenities provided etc. This study uses machine learning algorithms as a research methodology to develop a listing price prediction model. This study analyses the price predictability capability of different algorithms like linear regression, tree based regressions etc. along with other attributes like sparsity, algorithmic complexity etc. The performance of each model is evaluated using four different metrics, the R^2 value, mean squared error, mean absolute error and median absolute error.

Keywords : Regression, Decision Tree, Boosting, Ensemble Learning, Random Forest, Airbnb dataset, Listing Price Prediction, Regularization

2. Problem Statement

This study explores the use of different machine learning regression algorithms to predict the nightly price of an Airbnb listing in the city of Los Angeles. It also aims to find the best features of the listing (e.g., Locality, Number of guests it accommodates, Number of beds, Amenities, Ratings, Reviews, etc.) which help in accurately predicting the nightly price. It includes 2 methods of feature selection, data preprocessing, and cross-validation for parameter selection. Another of the goals is to compare various metrics - R^2, Mean Squared Error, Mean Absolute Error and Median Absolute Error - obtained after applying several algorithms like Linear Regression, Random Forest Regression, Gradient Boosting Regression, Lasso Regression, Ridge Regression, XgBoost, and AdaBoost Regression using Decision Tree.
Airbnb's popularity is increasing, it is now bigger than the top five hotel brands put together. Surprisingly enough, it does not own any of the spaces listed on its website! Hosts list their spaces on the website for customer to reserve. The methods in this study can be used as a reference for hosts to set the price on their listings. This creates a sort of a recommender system, which helps hosts and gives them an approximate estimate of the value they can get for their listing.

The complexity of the problem arises due to its high dimensionality, type of features and the difference in the dataset caused by small changes in features. The dataset has a large number of data points which increases the time complexity. Also, it contains many features, 95 to be exact. Of these, 35 are numeric type, including both continuous and discrete. There are 7 categorical features and 53 others too. Preprocessing all these features increases the complexity of the process. Introducing sparsity through lasso regularization helps in reducing the high dimensionality of feature space. Also, the house can be similar, but the price of the listing can change just based on one feature, i.e., the locality or neighborhood. This possible dependencies increase the complexity too. Thus, the main complexities arise from the huge amounts of data points and the number of preprocessing steps required to reduce the high feature dimensionality.

2.1 Literature Review

Most of the information about the different algorithms used are from class notes and the *Scikit* learn library documentation. The documentations consist of detailed descriptions of all the algorithms used along with examples of use cases. Also, *stack exchange* and *Quora* was utilized to get an explanation on gradient tree boosting and it's difference with *XgBoosting*.

2.2 Prior and Related work – None

2.3 Overview of Approach

Our approach to solve the problem is not to reduce the dimensionality without having a significant idea. We know that location is crucial for Airbnb listing prices and we didn't want disregard it. One hot encoding the neighborhood and the other categorical features increased the dimensionality of the problem. To reduce it, we used exploratory data analysis to assess which features are significant and which regression methods to use based on exploratory data set.

We would like to reduce the dimension using ridge and lasso feature selection so that to assess which neighborhoods (and other categorical features) in Los Angeles are actually important feature for its price. The reason why we are using two feature selection technique lies behind the fact that Lasso giving more sparse solutions for the optimization problem, hence more reduced dimensionality whereas Ridge yields higher number of features both depending of the value of the penalty parameter alpha. Hence, we wanted to see which would work better for our case.

After reducing the dimension in both ways, we simply built our hypothesis set based on the exploratory dataset and tuned the parameters using cross-validation. We use the parameters that results in minimum MSE since it's the base error metric. Then, we trained and tested using the original dataset.

3 Project Formulation and Implementation

The Dataset used for this study is sourced from the *Insider Airbnb* website. It is a collection of all the publicly available information from the *Airbnb* website. It contains information on all the listings in Los Angeles on November 4, 2018.

The approach to solve this problem was is shown in Figure 1. It follows standard techniques in solving regression problems, in preprocessing data, reducing complexity and dimensionality, selecting parameters and models and accessing the performance.

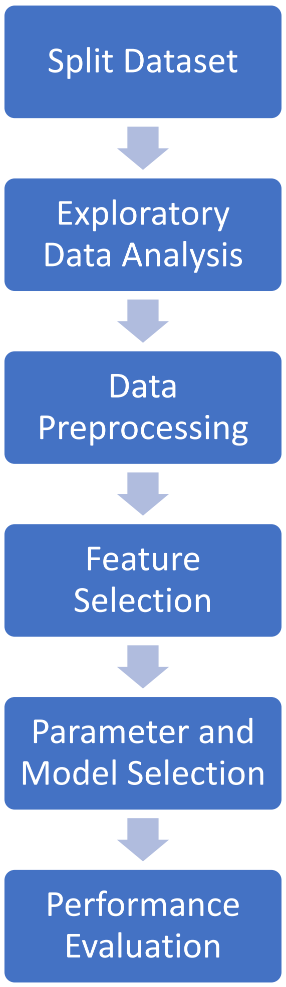
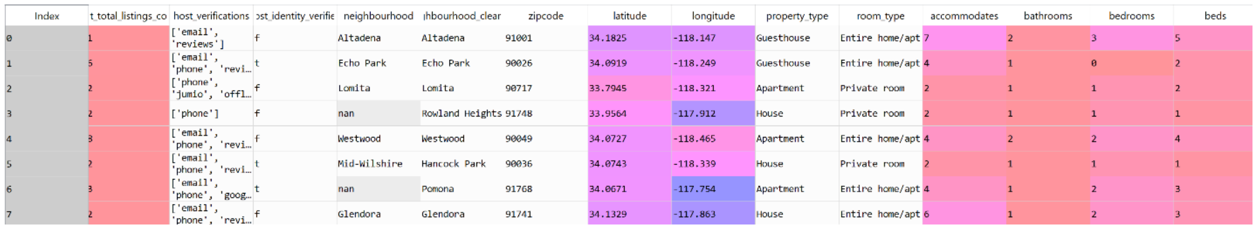


Figure 1

3.1 Dataset and Exploratory Data Analysis

The Dataset contains 43205 data points and consists of 95 features like, latitude, longitude, zip code, neighborhood, accommodates, number of bathrooms, bedrooms, beds, amenities etc. It also includes the price of the listing as put up by the host. A sample of what the dataset looks like is shown in Figure 2. Some of the important features and their data types are listed in the table below.

The dataset was split into 2 parts, the first containing 5000 data points, randomly selected from the dataset to be used for Exploratory Data Analysis. The remainder of the dataset, about 38000 data points were used to train models and evaluate their performance. Exploratory Data Analysis was helpful in selecting the best set of features and in turn reduce the dimensionality of the models. The Lasso and Ridge models were used as feature selection techniques for the problem. The Lasso model was used to increase the sparsity of the weights and the Ridge model was used to penalize the weights in turn reducing the weight values.
It was also useful in making meaningful visualizations, like developing a heatmap of the properties with respect to their costs. It gave an estimate of the variation of nightly price with respect to features like number of beds, number of people it accommodates, bed type, property type, room type, review and locality.



Index	t_total_listings_co	host_verifications	ɔst_identity_verifie	neighbourhood	ɪhbourhood_clear	zipcode	latitude	longitude	property_type	room_type	accommodates	bathrooms	bedrooms	beds
0	1	['email', 'reviews']	f	Altadena	Altadena	91001	34.1825	-118.147	Guesthouse	Entire home/apt	7	2	3	5
1	5	['email', 'phone', 'revi…	t	Echo Park	Echo Park	90026	34.0919	-118.249	Guesthouse	Entire home/apt	4	1	0	2
2	2	['phone', 'jumio', 'offl…	f	Lomita	Lomita	90717	33.7945	-118.321	Apartment	Private room	2	1	1	2
3	2	['phone']	f	nan	Rowland Heights	91748	33.9564	-117.912	House	Private room	2	1	1	1
4	3	['email', 'phone', 'revi…	f	Westwood	Westwood	90049	34.0727	-118.465	Apartment	Entire home/apt	4	2	2	4
5	2	['email', 'phone', 'revi…	t	Mid-Wilshire	Hancock Park	90036	34.0743	-118.339	House	Private room	2	1	1	1
6	3	['email', 'phone', 'goog…	t	nan	Pomona	91768	34.0671	-117.754	Apartment	Entire home/apt	4	1	2	3
7	2	['email', 'phone', 'revi…	f	Glendora	Glendora	91741	34.1329	-117.863	House	Entire home/apt	6	1	2	3

Figure 2: Sample of the dataset

Feature Name	Interpretation	Type
id	Notation for the listing	Numeric
host_since	The date since host has been a user	Categorical
neighbourhood	Neighbourhood of the house	String
zipcode	ZIP	Numeric
latitude	Latitude of the location	Numeric
longitude	Longitude of the location	Numeric
property_type	The type of the listing	Categorical
room_type	The type of room in the listing	Categorical
bathrooms	Number of bathrooms in the house	Numeric
bedrooms	Number of bedrooms in the house	Numeric
bed_type	Type of bed in the bedroom	Categorical
amenities	Types of amenities provided	String
price	Price of the listing	Numeric

Important features presented in the dataset.

The Figures below, show visualizations made using the exploratory dataset.

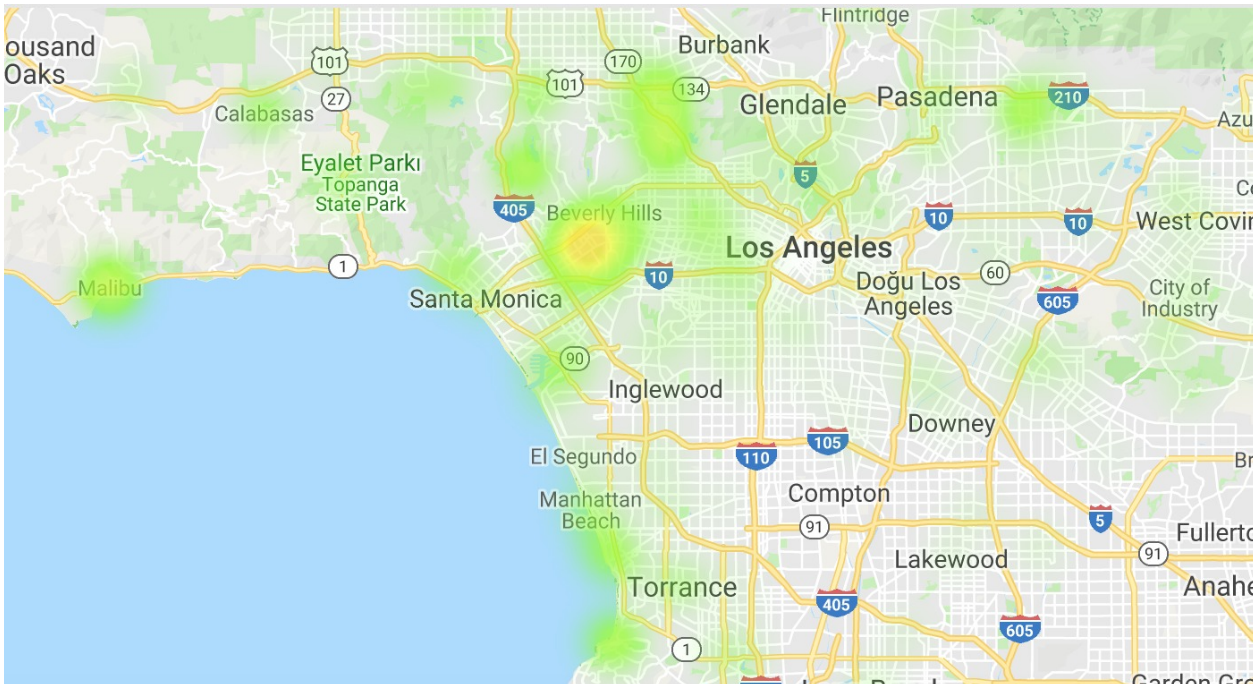


Figure 3: Heat Map of prices in Los Angeles

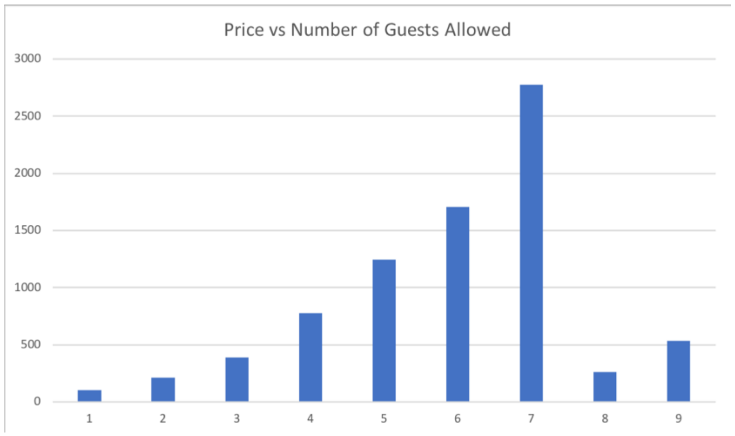


Figure 4

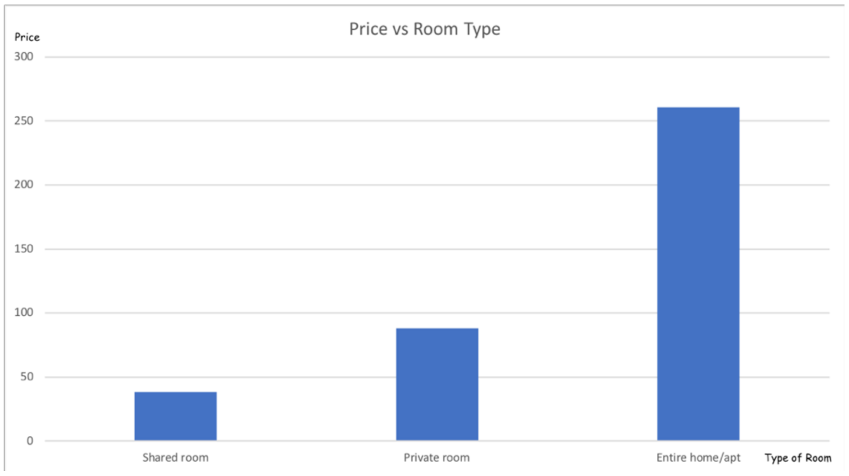


Figure 5

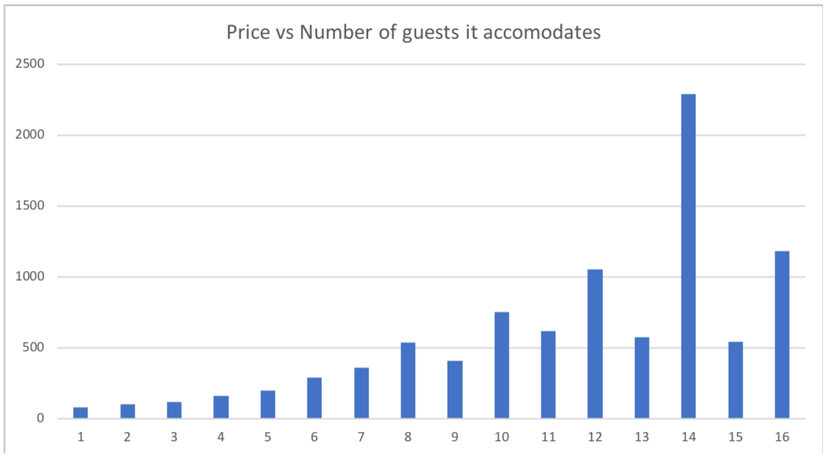


Figure 6

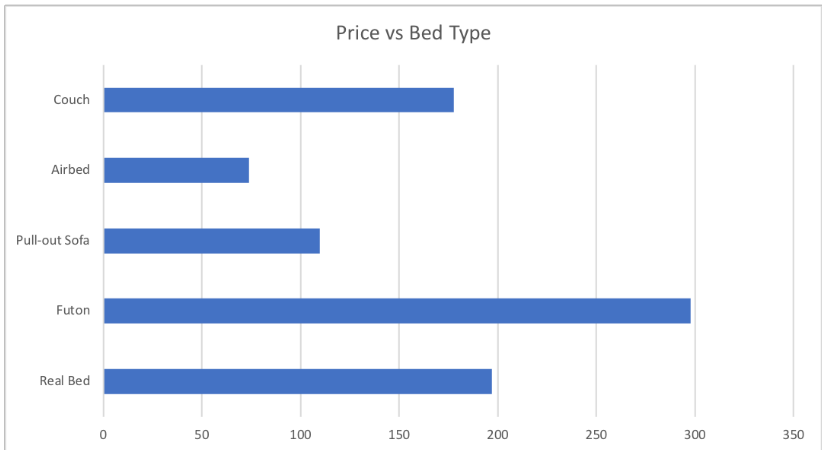


Figure 7

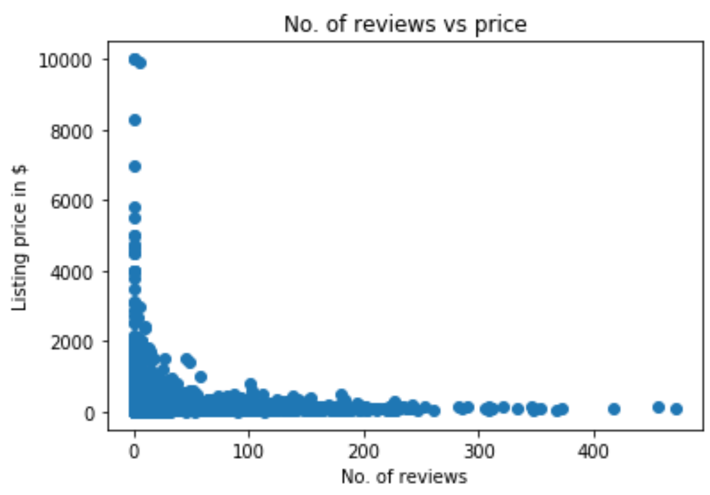


Figure 8

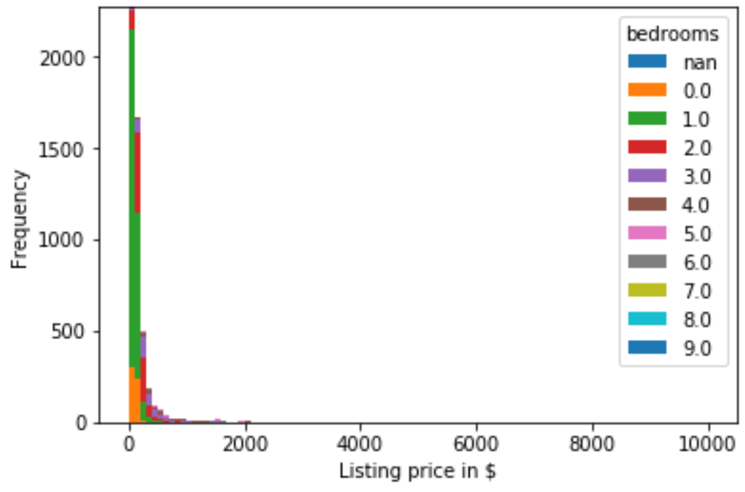


Figure 9

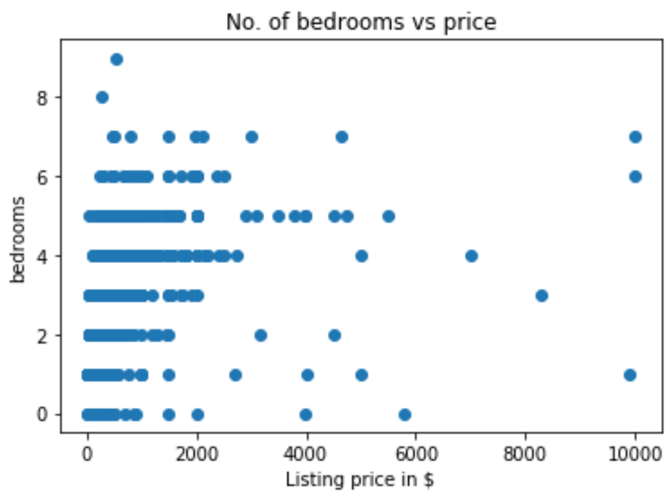


Figure 10

3.2 Data Preprocessing

After analyzing the exploratory dataset, it was observed that there are several features which are redundant. It is fair to assume that features like *host identity, host verification, guest profile picture, url, calendar last scraped* and a few others would not play a role in predicting or determining the price of a listing and hence were subsequently dropped. Further, there were a few features and data points with missing values. In case the data point (listing) had more than 10 missing feature values, the data point was dropped as well. Similarly, if a feature had more than 30% missing data, the feature was dropped. Finally, listing which were 'removed' but which were still a part of the dataset were deleted as well. To maintain uniformity, features the contained *'$'* and *','* were converted to floating point values and the symbols were dropped.

There were several features which were text based. Amenities, was a feature with each point being a list of utilities, (e.g., *{TV, WI-FI, AC, Heater etc.}*). The number of utilities in each list was counted and each data point was replaced with this value. The data also included categorical features like bed type, property type neighborhood etc., these were either one hot encoded, or given numeric value or ranking. Features like property type and bed type were given numeric values from 1 to 5. This helped in giving a higher score to bed types which were *'Real Beds'* and a lower score bed types which were *'Air Beds'*. A similar approach was used for room types as well. The remainder of the categorical features were one hot encoded into a binary format.

Imputation was necessary on features with missing data points. Depending on the type of feature, the missing data points were imputed either using the feature mean or the feature median. Features with data type object were imputed using the most frequent value in the column and features with any other data type were imputed using the mean of the feature. The *get_dummies* class in *pandas* was used for *one hot encoding* (converting to binary) categorical features.

Finally, a simple *standardization* technique of converting the data into zero mean and unit variance was implemented by subtracting each data point with the mean and then dividing the resultant by the standard deviation. This was carried out using the *preprocessing* library in *sklearn* and the *Standard Scaler* class.
After the data preprocessing step, the number of features increased to 283. Same preprocessing techniques were applied to the main dataset as well.

3.3 Feature Selection

For datasets with a large number of features or dimensionality, it is important to reduce the complexity. In case of a large number of features, there is a possibility that several features turn out to be redundant, several features have either the same value or a very low variance. The model does not tend to 'learn' much from such features. These kinds of features need to be identified and eliminated. For this reason, feature selection and dimensionality reduction is important. 2 methods of feature selection, Lasso and Ridge, are used and applied to the models mentioned in the abstract. The libraries *linear_models and metrics* from *sklearn* was used.

3.3.1 Feature Selection using Lasso based techniques

In our problem we use one hot encoding for neighborhood information, that leads increase in the dimension of our data. We need to assess which features are important for our final models to consider. In order to do that, we standardize the features so that we can assess their importance using their weight values. According to Tibshirani's book, the Lasso Method for Variable Selection in the Cox Model, he advises to standardize the dummy variables for regularization purposes so that penalization is fair for all features. Thus, for feature selection purposes we standardize the categorical features but for the model selection we do not.

Lasso is also a regularization technique based on L_1 norm. It estimates sparse coefficients, i.e., it reduces the number of variables upon which the solution depends. This is done by assuming a Laplacian prior on the weights which yields an objective function which is:

$$J(w) = \min \left(\left\| \underline{Xw} - y \right\|_2^2 + \lambda \|w\|_1 \right)$$

Here, λ is the penalty that allows for the increase in sparsity of the weight vector. A larger value of λ will result in a more sparse solution. λ also penalizes the weights in terms on magnitude, resulting in a more sparse and lower magnitude solution of weights.
In this case, cross-validation is used to select the best λ value (also called α in the code) for the L_1 regularizer. The validation curve was then plotted, and the α value was selected on the basis of best generalization. Which simply means that, select that alpha value where the median absolute error (or R^2 score) for the train set is equal to or almost equal to the median absolute error (or R^2 score) of the validation set. Once the best α has been selected, it is used to select features. The unimportant features were considered those with weight values in the interval of [-0.1, 0.1]. A new data frame was then created, dropping the unimportant features, for training the model.

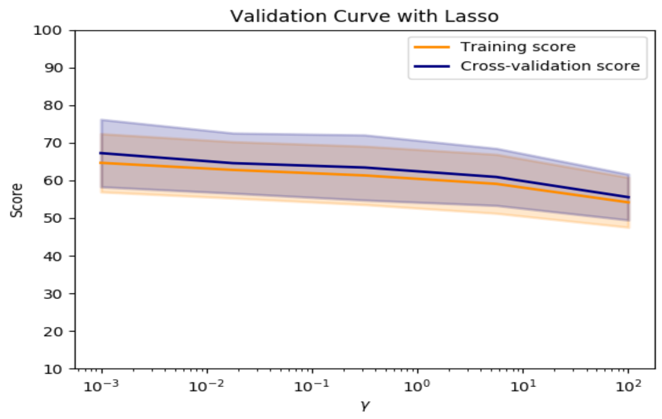


Figure 11: Validation curve for Lasso MSE

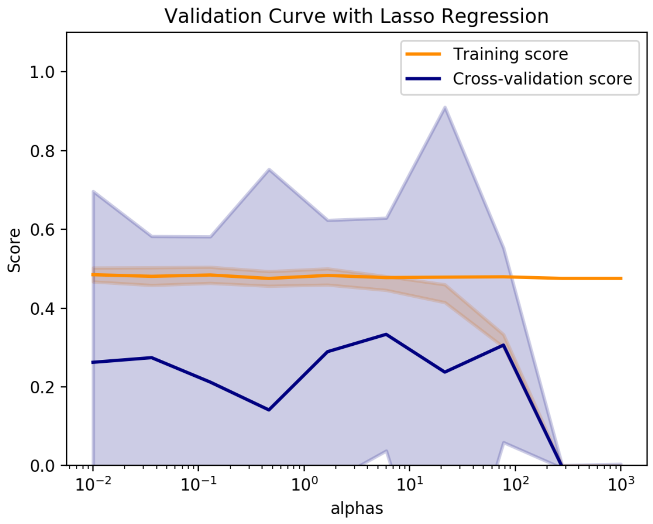


Figure 12: Validation curve for Lasso R square

3.3.2 Feature Selection using Ridge based techniques

This is also termed as L_2 regularizer as it is based on L_2 norm or the Euclidean distance. By imposing a Gaussian prior to the weights, where the variance controls the strength of the prior we obtain an objective function with a term that controls the weights.

$$J(w) = \min\ (\ \left\|\underline{Xw} - y\ \right\|_2^2 + \lambda\|w\|_2^2\ )$$

Here α is the complexity penalty that controls the weight vector. Larger the value of λ, greater is the amount of shrinkage. The algorithmic complexity is the same as the linear regression without regularization.

In this case, cross-validation using train-test split is used to select the best λ value (also called α in the code) for the L_2 regularizer. The validation curve was then plotted, and the α value was selected on the basis of best generalization. Which simply means that, select that alpha value where the median absolute error (or R^2 score) for the train set is equal to or almost equal to the median absolute error (or R^2 score) of the validation set. Once the best α has been selected, it is used to select features. The unimportant features were considered those with weight values in the interval of [-4, 4]. A new data frame was then created, dropping the unimportant features, for training the model.

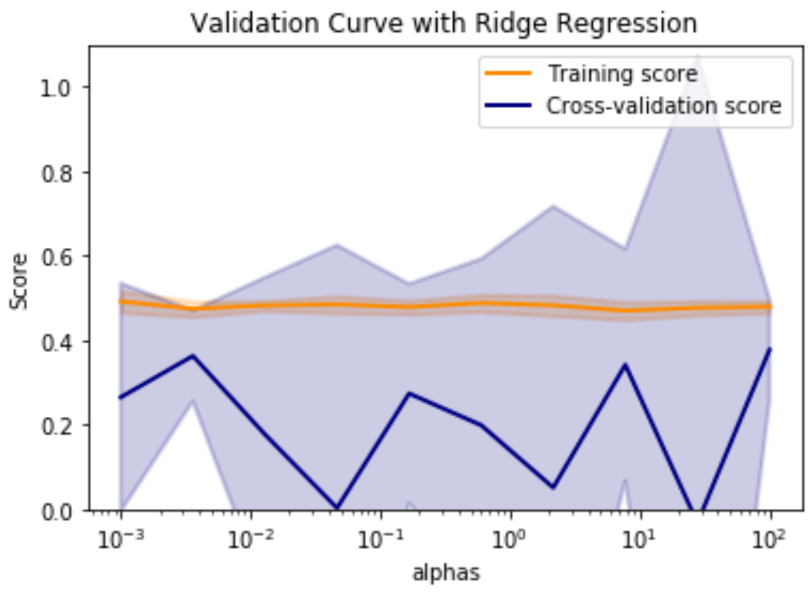


Figure 13: Validation curve with Ridge Regression

Each of these feature selection techniques were used for the various machine learning models mentioned earlier and their performances compared.

As we are applying correlation robust algorithms like random forest and xgBoost, we do not care for correlation, so we don’t use PCA (Principal Component Analysis) for future selection.

3.4 Main Dataset

After successfully selecting the most important features using the feature selection techniques mentioned above, the remainder of the dataset was used to train and test the performance various machine learning models.
The data preprocessing techniques that were used for the main dataset were similar to the ones used for the exploratory dataset. However, for the main dataset, there were approximately 35383 data points that could be used after removing or deleting data points with missing values. This dataset was then divided into training dataset, validation dataset and test dataset.

After preprocessing, the main dataset, the unimportant features as identified earlier were dropped essentially keeping only the important features. Since there were two methods of feature selection, each machine learning model was implemented two times, using each feature selection technique.
Linear Regression, Lasso Regression, Ridge Regression, Gradient Boosting Regressor, Random Forest Regressor, AdaBoost Regressor, and XgBoost Regressors were used to predict the nightly price of each listing in the test dataset along with cross validation to select the best parameters for training.

The Figure below shows the steps involved in predicting the prices of using the main dataset.

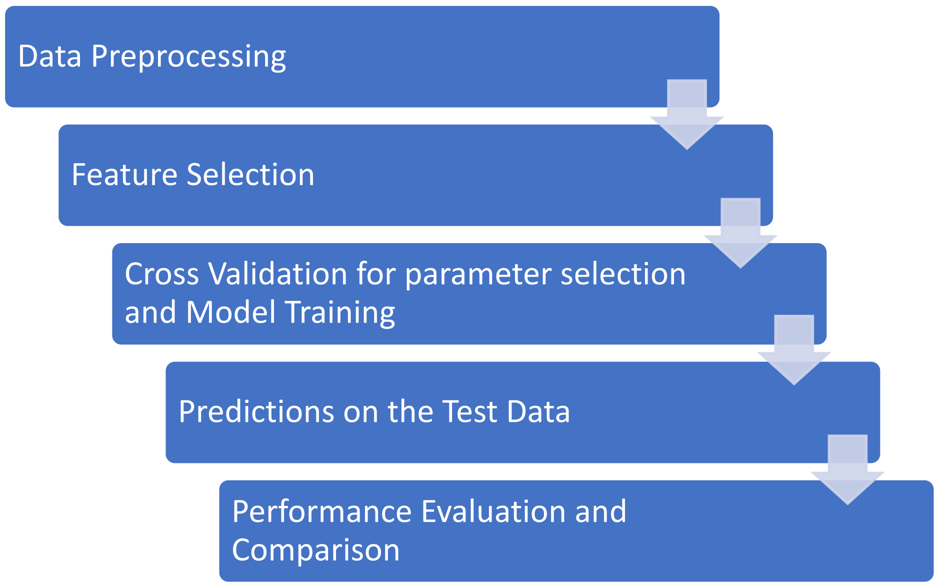

Data Preprocessing
Feature Selection
Cross Validation for parameter selection and Model Training
Predictions on the Test Data
Performance Evaluation and Comparison

Figure 14: Workflow on main dataset

3.5 Model Selection

3.5.1 Regression

Linear Regression fits a linear model with coefficients w = (w_1 , …, w_n) such that it minimizes the sum of square of the error between observed response and the predicted response by the linear approximation.

$$\min \left(\left\| \underline{Xw} - y \right\|_2^2 \right)$$

In terms of algorithmic complexity, even though linear regression has a closed form solution, the implementation on *sklearn* computes the solution using singular value decomposition of X. So, if X is a matrix of size (m, n), then the cost is $O(mn^2)$, where, n >= m.

Section 3.3 describes the regularization techniques (L_1 and L_2 regularizers). These can also be used for training regression models and predicting outputs.

For the exploratory dataset, a 5 fold cross validation is used to estimate the best parameter α for Lasso and Ridge based Regression. No cross validation was performed for simple linear regression. Similar cross validation techniques were used for the main dataset as well.

3.5.2 Discussion on Sparsity

In the above section, we briefly touched on the topics of using different regularization to obtain a sparse or non-sparse solution. The other way of introducing sparsity would be to change the cost function. For example, ridge regression uses the sum of squares of errors as the loss function and when we include L_2 regularization, we get a non-sparse solution. But when L_1 regularization term is added, i.e., lasso regularization, we introduce sparsity through the L_1 lasso term.

3.5.3 Decision Trees

Decision Trees are non-parametric supervised learning method that predicts the value of the target variable by learning simple decision rules inferred from the data features. The algorithmic complexity of using the tree is logarithmic in number of data points used to train the data. As the number of nodes (or depth) of the tree increases, the hypothesis space grows. In the worst case, exponentially many nodes might be needed as each leaf node is used to represent each possible input. Several base estimators can be combined to improve the generalization in a method called ensemble learning. Two types of ensemble learning are:

1. Averaging Methods – In this method, we build several estimators independently and then average the prediction. Example – *random forests*, *bagging* etc.

2. Boosting Methods – In this method, the base estimators are built sequentially tying to reduce the bias of the combined estimator. Example – *Adaboost*, *gradient tree boosting* etc.

3.5.4 Random Forests

The algorithm creates several decision trees by introducing randomness in the construction and average them to obtain the final regressor. While training each of the decision trees, a random set of samples from the training set are drawn with replacement.
A cross validation technique was used to select the best values for *number of estimators*. The criterion used was *'mse'*. It was observed that a good value for *n_estimators* is 200.

3.5.5 Boosting

There are three methods of Boosting which we used:

1. *Adaboost* – In this, a sequence of weak learners is fit on modified versions of data and a weighted majority vote is combined through them to produce the final predictions.
2. *Gradient Tree Boosting* – In this, we start with a differentiable loss function to minimize. We minimize with respect to the predictor function so that the total loss is minimized. This error is minimized by building models sequentially and combining them. New models are added to existing models to correct the errors until no further improvements can be made.
3. *xgBoost* – The principle is similar to Gradient Boosting, the difference being that it uses a more regularized model to control over-fitting and hence gives better performance. It also has improved data structures for better cache utilization which makes the algorithm faster.

While implementing Boosting algorithms, 5-fold cross validation was done in each case, to find the best value of the parameters – depth of the tree and number of estimators. For example, in the case of *Adaboost* algorithm, we got the value of depth of tree as 13 and the number of estimators as 10 in the case of lasso regularization feature selected dataset. Similarly, this was done for all the boosting algorithms. The Boosting methods were implemented for both the exploratory and main datasets.

Some of the important parameters for the boosting algorithms taken under consideration are:

1. *n_estimators* - The number of boosting stages to perform by the algorithm. The default value for it is 100.
2. criterion - The function to measure the quality of a split. Supported criteria are *"mse"* for the mean squared error, which is equal to variance reduction as feature selection criterion and minimizes the L_2 loss using the mean of each terminal node, *"friedman_mse",* which uses mean squared error with Friedman's improvement score

for potential splits, and *"mae"* for the mean absolute error, which minimizes the L1 loss using the median of each terminal node. The default is *mse*.

3. *max_depth* - The maximum depth of the tree. If None, then nodes are expanded until all leaves are pure or until all leaves contain less than *min_samples_split* samples.

3.6 Performance Metrics

The different performance metrics used by us to compute the errors in the predictions and compare our results are as follows:

3.6.1 R^2 or Coefficient of Determination

It is the amount of variation in the data that is explained with the model. It gives information about the goodness of fit of the model. An R^2 value of 1 indicates that the regression line perfectly fits the data.

$$SS_{tot} = \sum_i (y_i - \bar{y})^2$$

This is called the total sum of squares and is proportional to the variance of the data. Also, there is regression sum of squares,

$$SS_{reg} = \sum_i (\hat{y}_i - \bar{y})^2$$

So, the error is expressed as:

$$R^2 = \frac{SS_{reg}}{SS_{tot}}$$

3.6.2 Mean Squared Error

It is the mean value of the squared deviations of the predictions from the true value over the test space. The *MSE* is desired to be as low as possible. A *MSE* of 0 means that the model predicts the observations perfectly.

$$MSE = \frac{1}{n}\sum_{i=1}^{n} (\hat{y}_i - y_i)^2$$

3.6.3 Mean Absolute Error

It is a measure of the difference between two continuous variables. This uses the same scale as the data being measured and hence is a scale-dependent measurement.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |\hat{y}_i - y_i|$$

3.6.4 Median Absolute Error

The median absolute error is useful basically it is essentially insensitive to outliers (as long as there aren't too many of them). This is because it is the median of all the absolute values of the residuals, and the median is unaffected by values at the tails. So, this loss function can be used to perform robust regression. In contrast, the mean squared error can be highly sensitive to outliers, and mean absolute error can be somewhat sensitive to outliers (although less so than the mean squared error).

Note that using the median absolute error only corrects for outliers in the response/target variable, not for outliers in the predictors/feature variables.

All these error metrics were applied to results of the different models on both the exploratory and main dataset and the results are compared based on these metrics.

4. Results

For the exploratory dataset, the results for training data are as followed :

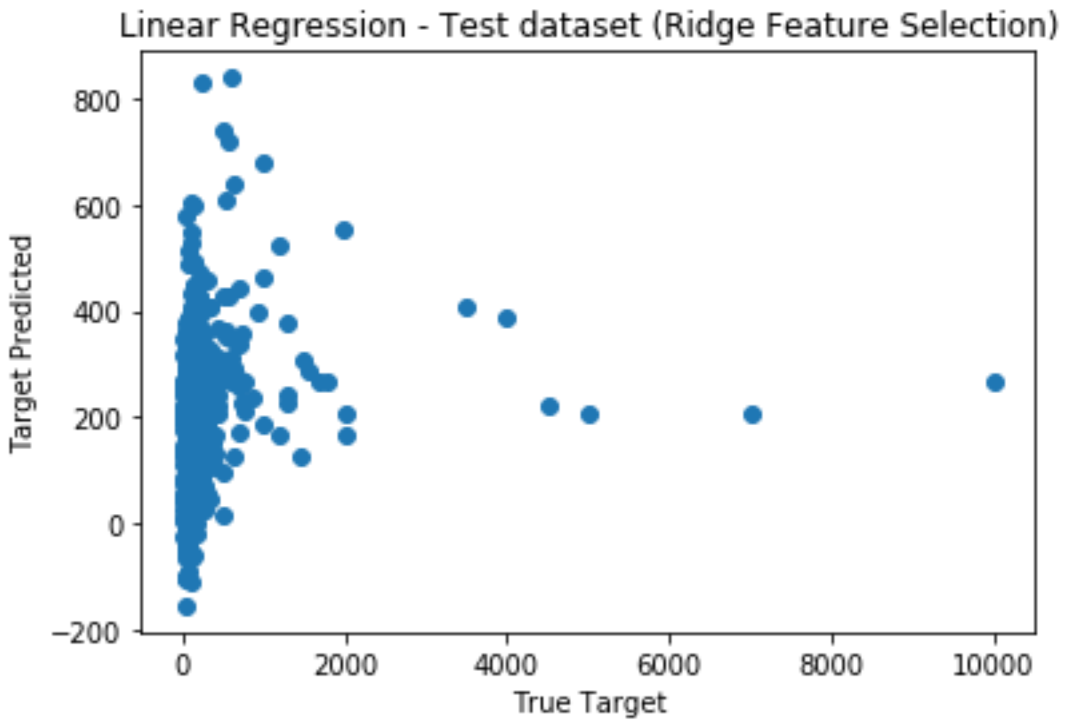
Model	**Lasso Regularization Feature Selection**	**Ridge Regularization Feature Selection**
Linear Regression	Train R^2: 0.460771 Train MSE: 112699.0 Train MAE: 120.368 Train MdAE: 71.8074	Train R^2: 0.470278 Train MSE: 114057.0 Train MAE: 123.621 Train MdAE: 71.9417
Ridge Regression	Train R^2: 0.50464824774 Train MSE: 91635.9200188 Train MAE: 114.647350181 Train MdAE: 67.9775831791	Train R^2: 0.460996584788 Train MSE: 107741.014363 Train MAE: 118.393858424 Train MdAE: 69.7982541206
Lasso Regression	Train R^2: 0.493520552963 Train MSE: 93694.4502327 Train MAE: 109.662524432 Train MdAE: 57.1338404249	Train R^2: 0.473940133237 Train MSE: 112007.443673 Train MAE: 115.25785065 Train MdAE: 63.0713711506
Random Forest	Train R^2: 0.45448 Train MSE: 14364.36917 Train MAE: 31.629587912 Train MdAE: 20.66500	Train R^2: Train MSE: Train MAE: Train MdAE:
XGBoost	Train R^2: 0.928866038768 Train MSE: 12685.1040267 Train MAE: 44.696708187 Train MdAE: 26.2062416077	Train R^2: 0.634045303358 Train MSE: 72638.2715097 Train MAE: 107.721115738 Train MdAE: 57.9860572815

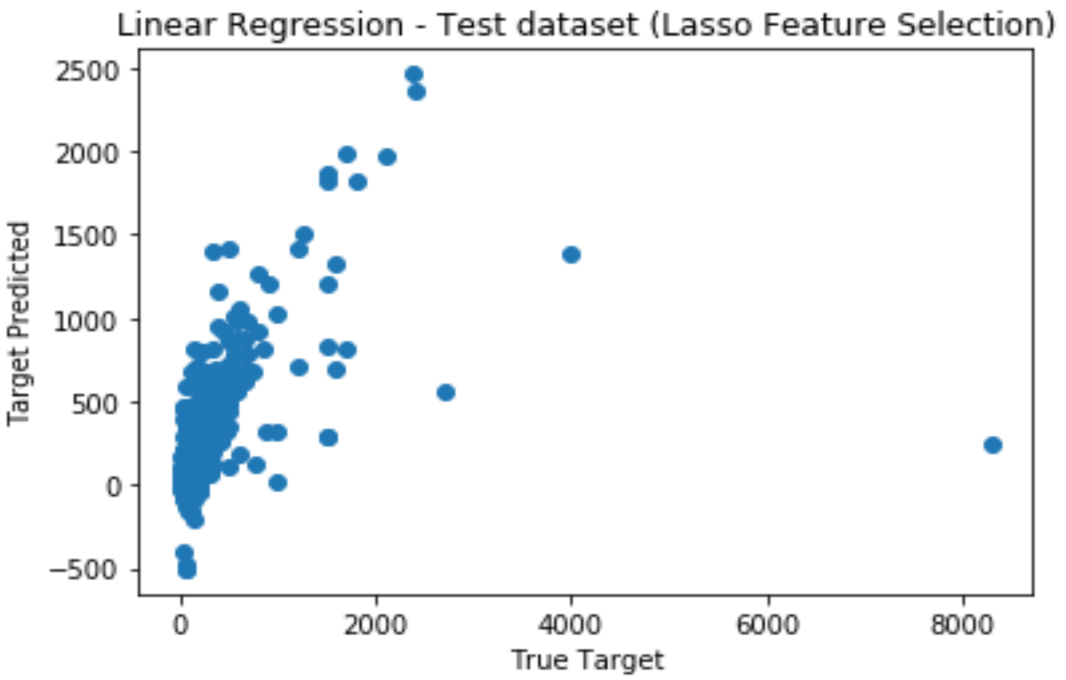
AdaBoost	Train R^2: 0.987718030819 Train MSE: 2658.38462186 Train MAE: 33.3731058558 Train MdAE: 21.9298428844	Train R^2: 0.98882 Train MSE: 2407.29 Train MAE: 30.9086 Train MdAE: 19.8574
Gradient Boost	Train R^2: 0.919835 Train MSE: 16144.65693 Train MAE: 49.8042031 Train MdAE: 29.32140	Train R^2: 0.902682 Train MSE: 18568.47489 Train MAE: 53.209386 Train MdAE: 34.57892

For the exploratory dataset, the results for testing data are as followed :

Model	**Lasso Regularization Feature Selection**	**Ridge Regularization Feature Selection**
Linear Regression	Test R^2: 0.165278 Test MSE: 182458.304729 Test MAE: 127.228907 Test MdAE: 66.218658	Test R^2: 0.041332 Test MSE: 244336.123976 Test MAE: 167.092359 Test MdAE: 95.460335
Ridge Regression	Test R^2: 0.4146522512 Test MSE: 189868.19866871 Test MAE: 122.19659277 Test MdAE: 62.378580583	Test R^2: 0.300629965 Test MSE: 384219.361161 Test MAE: 150.01496 Test MdAE: 77.1115613666

Lasso Regression	Test R^2: 0.5450 Test MSE: 88199.3436321 Test MAE: 119.3002183 Test MdAE: 56.1952260469	Test R^2: 0.48336956 Test MSE: 136719.0218 Test MAE: 114.523376119 Test MdAE: 66.06521297
Random Forest	Test R^2: 0.43365 Test MSE: 126060.4462 Test MAE: 88.934 Test MdAE: 28.993	Test R^2: 0.398257 Test MSE: 144212.8261 Test MAE: 92.4763 Test MdAE:33.4378
XGBoost	Test R^2: 0.3668 Test MSE: 168546.489097 Test MAE: 89.325812 Test MdAE: 26.287411	Test R^2: 0.111479 Test MSE: 230790.129840 Test MAE: 136.355123 Test MdAE: 41.748962
AdaBoost	Test R^2: 0.375405 Test MSE: 73734.373263 Test MAE: 76.066478 Test MdAE: 27.311435	Test R^2: 0.050012 Test MSE: 412278.382105 Test MAE: 158.279013 Test MdAE: 60.753428
Gradient Boost	Test R^2: 0.3413085 Test MSE: 152649.933 Test MAE: 87.8957 Test MdAE: 30.2264	Test R^2: 0.2638 Test MSE: 174211.7132 Test MAE: 91.3718 Test MdAE:34.2238


Linear Regression - Test dataset (Ridge Feature Selection)
Target Predicted
True Target
800
600
400
200
0
−200
0
2000
4000
6000
8000
10000


Linear Regression - Test dataset (Lasso Feature Selection)
Target Predicted
True Target
2500
2000
1500
1000
500
0
−500
0
2000
4000
6000
8000

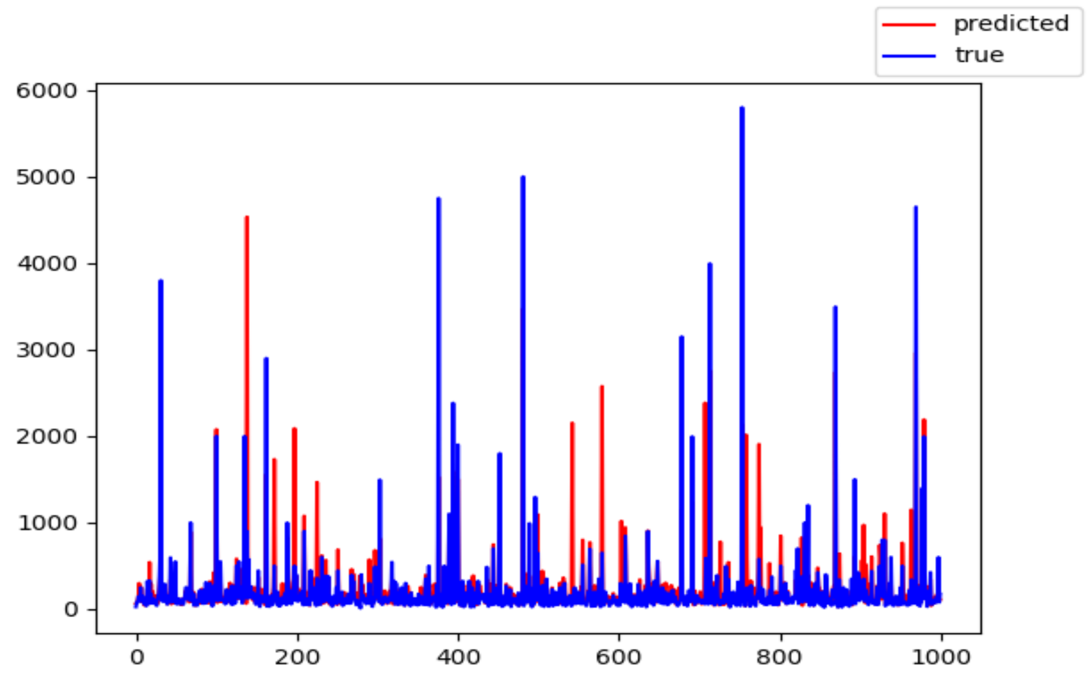


Figure 1: Random Forest

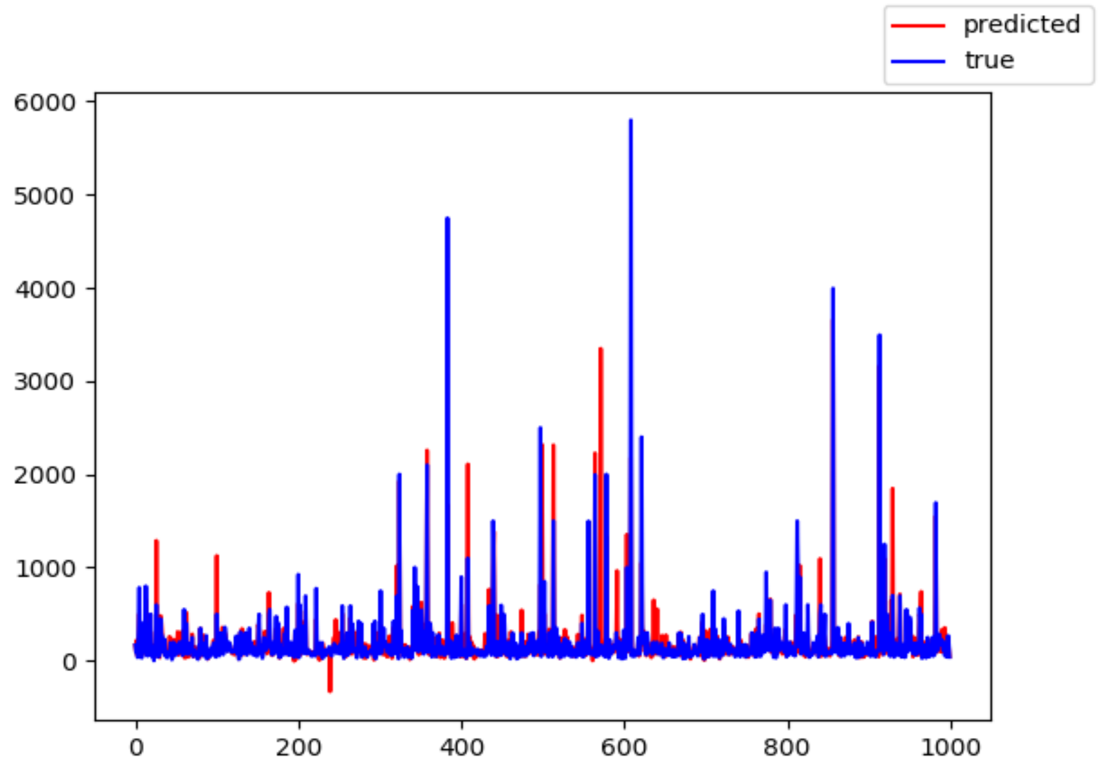


Figure 2: Gradient Boosting

Price

Number of Data

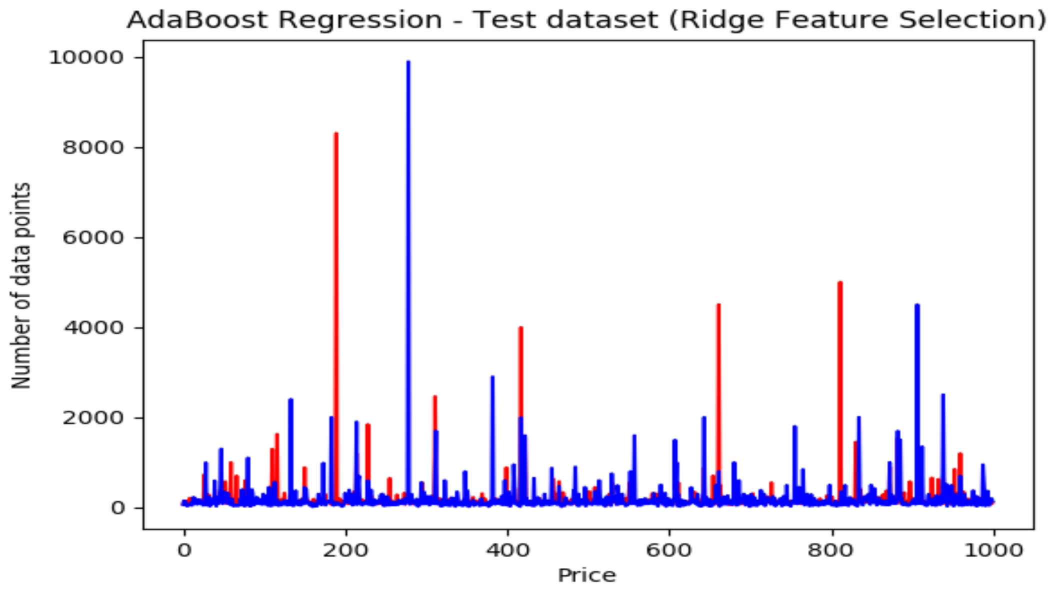
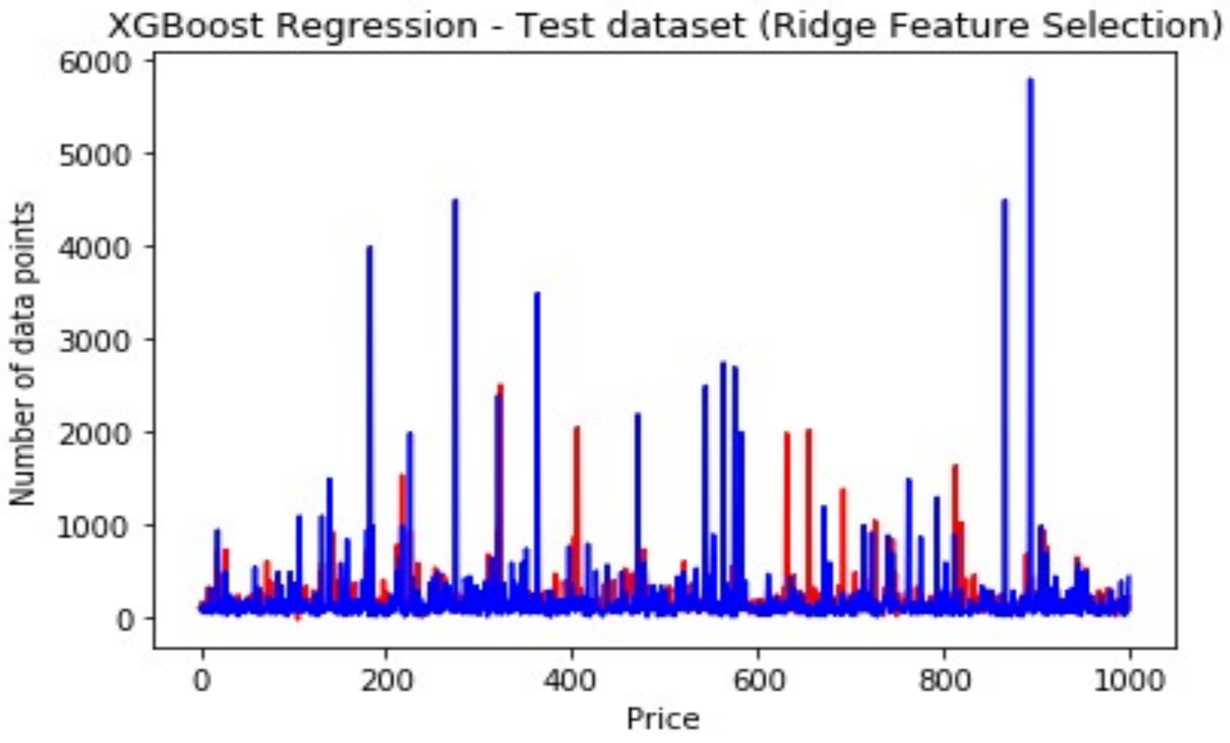

AdaBoost Regression - Test dataset (Ridge Feature Selection)
Number of data points
Price
0
2000
4000
6000
8000
10000
0
200
400
600
800
1000

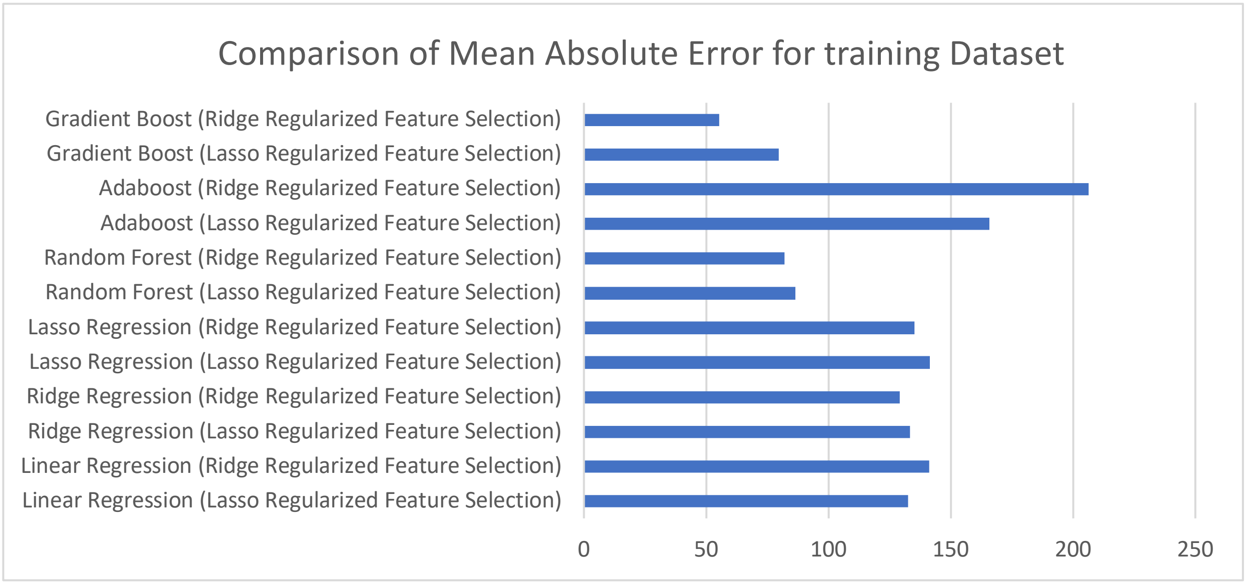
Figure 3

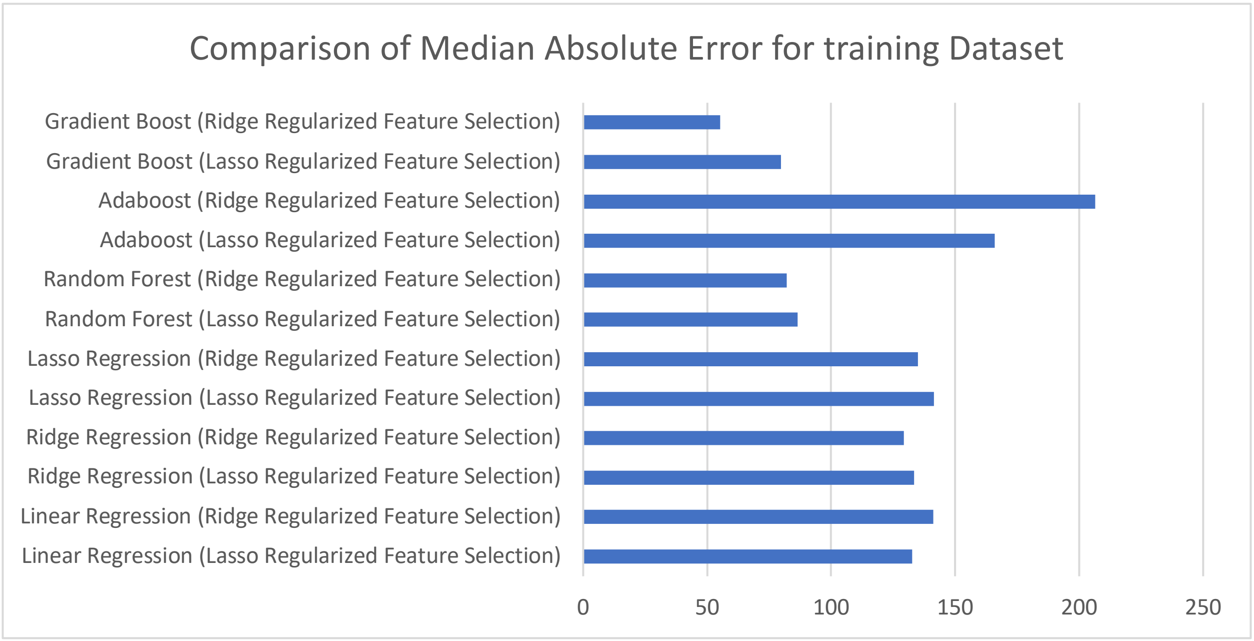

XGBoost Regression - Test dataset (Ridge Feature Selection)
Number of data points
Price
0
1000
2000
3000
4000
5000
6000
0
200
400
600
800
1000

The results for main data are as followed :

Model	**Lasso Regularization Feature Selection**	**Ridge Regularization Feature Selection**
Linear Regression	Train R^2: -0.2814879823316603 Train MSE: 153424.35443635285 Train MAE: 132.55971937161888 Train MdAE: 71.95548266110382	Train R^2: -0.3273716582342536 Train MSE: 121994.64264418682 Train MAE: 141.23332483869575 Train MdAE: 77.32151689019065
Ridge Regression	Train R^2: -0.25668206199 Train MSE: 148808.490143238 Train MAE: 133.30948186236418 Train MdAE: 72.45225402426422	Train R^2: -0.24068254203341644 Train MSE: 139204.5498635516 Train MAE: 129.18589469575332 Train MdAE: 70.46845449601551
Lasso Regression	Train R^2: -0.35199520770196946 Train MSE: 174248.30172211627 Train MAE: 141.5286187198581 Train MdAE: 76.88620349476787	Train R^2: -0.36931801893340577 Train MSE167249.8699284558 Train MAE: 135.07568486381757 Train MdAE: 73.17817032393305
Random Forest	Train R^2: 0.4224926575335006 Train MSE: 87617.63880580584 Train MAE: 86.50274063337751 Train MdAE: 43.26371684012834	Train R^2: 0.4477526330252414 Train MSE: 74379.69490052853 Train MAE: 81.99815229206335 Train MdAE: 39.45978848470595

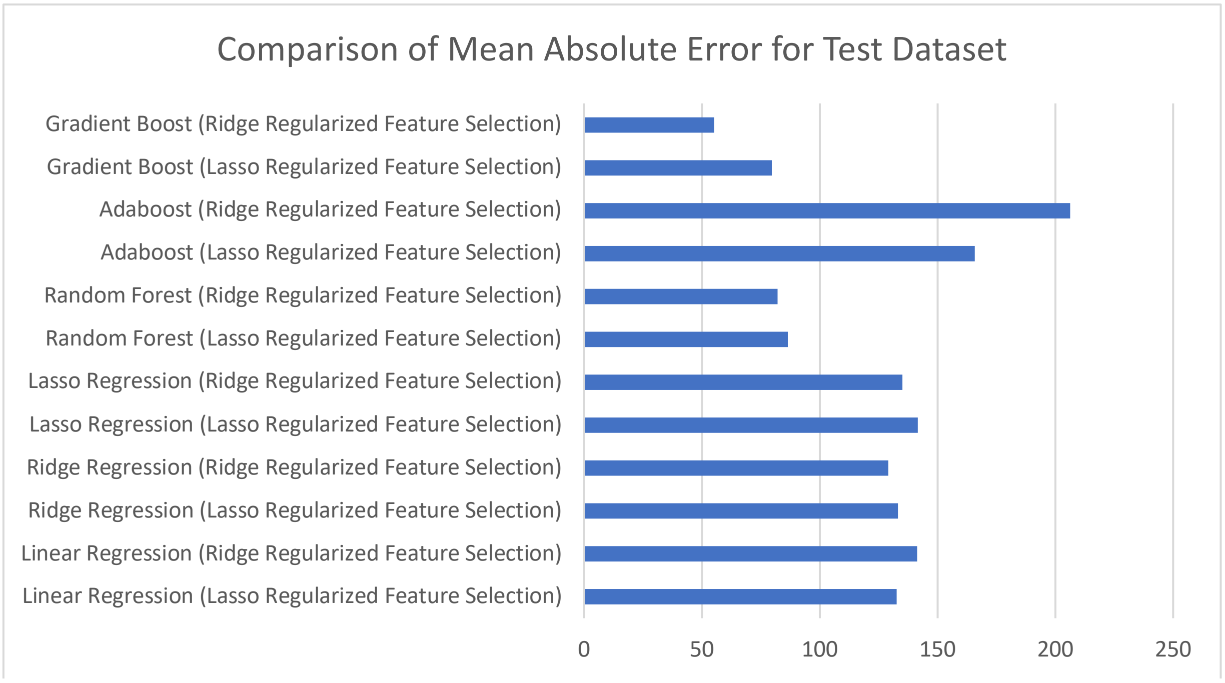
AdaBoost	Train R^2: 0.632454832971155 Train MSE: 113277.28102049492 Train MAE: 165.9149881947965 Train MdAE: 82.58897414336766	Train R^2: 0.5725548529721824 Train MSE: 99094.46515973457 Train MAE: 206.37796918422893 Train MdAE: 160.2516129032258
Gradient Boost	Train R^2: 0.557499853172446 Train MSE: 76383.0417928772 Train MAE: 79.74280724239341 Train MdAE:33.20358862805305	Train R^2: 0.8967316663193983 Train MSE: 23798.56641868538 Train MAE: 55.215840812925286 Train MdAE: 25.10667726703673

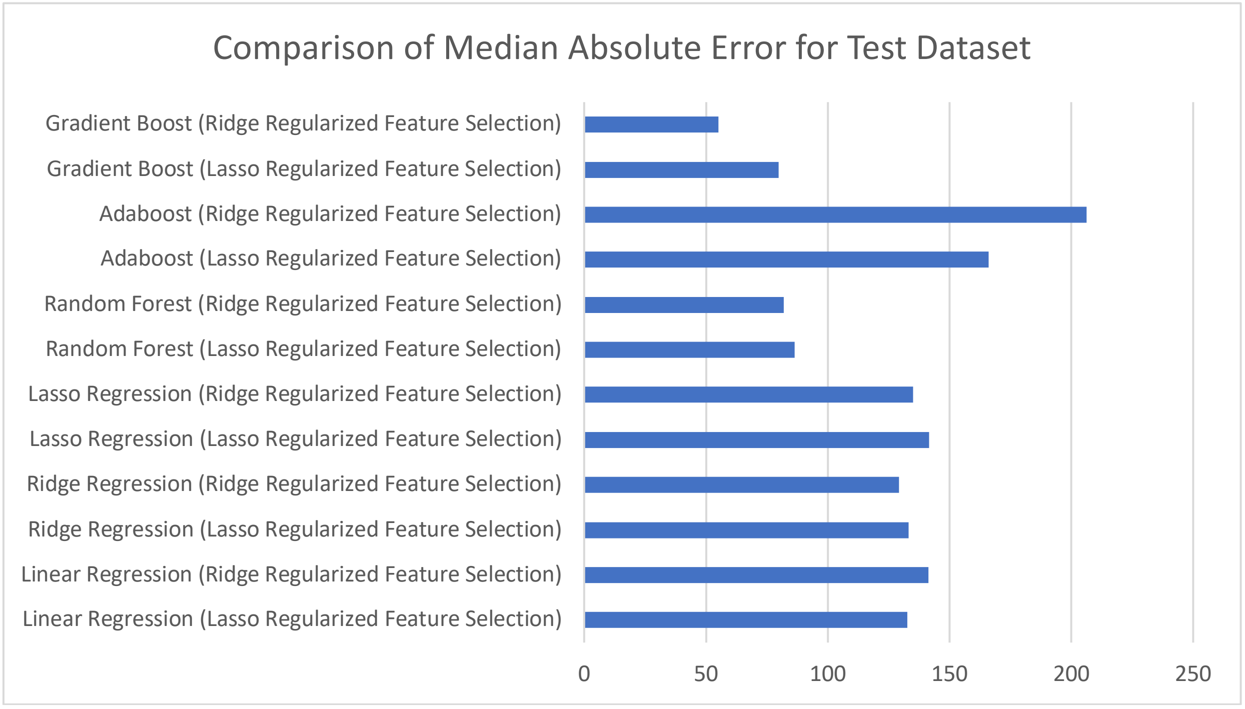

Comparison of Mean Absolute Error for training Dataset
Gradient Boost (Ridge Regularized Feature Selection)
Gradient Boost (Lasso Regularized Feature Selection)
Adaboost (Ridge Regularized Feature Selection)
Adaboost (Lasso Regularized Feature Selection)
Random Forest (Ridge Regularized Feature Selection)
Random Forest (Lasso Regularized Feature Selection)
Lasso Regression (Ridge Regularized Feature Selection)
Lasso Regression (Lasso Regularized Feature Selection)
Ridge Regression (Ridge Regularized Feature Selection)
Ridge Regression (Lasso Regularized Feature Selection)
Linear Regression (Ridge Regularized Feature Selection)
Linear Regression (Lasso Regularized Feature Selection)
0
50
100
150
200
250


Comparison of Median Absolute Error for training Dataset
Gradient Boost (Ridge Regularized Feature Selection)
Gradient Boost (Lasso Regularized Feature Selection)
Adaboost (Ridge Regularized Feature Selection)
Adaboost (Lasso Regularized Feature Selection)
Random Forest (Ridge Regularized Feature Selection)
Random Forest (Lasso Regularized Feature Selection)
Lasso Regression (Ridge Regularized Feature Selection)
Lasso Regression (Lasso Regularized Feature Selection)
Ridge Regression (Ridge Regularized Feature Selection)
Ridge Regression (Lasso Regularized Feature Selection)
Linear Regression (Ridge Regularized Feature Selection)
Linear Regression (Lasso Regularized Feature Selection)
0
50
100
150
200
250

Model	Lasso Regularization Feature Selection	Ridge Regularization Feature Selection
Linear Regression	Test R^2: -0.9802267923058938 Test MSE: 211242.64378285082 Test MAE: 138.49505811232814 Test MdAE: 73.35424287382557	Test R^2: -0.020305724761928934 Test MSE: 173634.8543017877 Test MAE: 137.4722986766043 Test MdAE: 77.12418726086798
Ridge Regression	Test R^2: -1.0446320562887434 Test MSE: 231556.28012920715 Test MAE: 136.7893948618803 Test MdAE:71.012938184536	Test R^2: -2.6123885916133416 Test MSE: 156846.6845009356 Test MAE: 140.37919739192486 Test MdAE:66.75215283743577
Lasso Regression	Test R^2: 0.10568783638645152 Test MSE: 131103.97022778765 Test MAE: 137.38874849658103 Test MdAE: 78.03635659246538	Test R^2: -0.221952620892941 Test MSE: 156846.6845009 Test MAE: 139.6404856938470 Test MdAE: 74.4560377001344
Random Forest	Test R^2: 0.20824186439653047 Test MSE: 115001.40550877777 Test MAE: 91.60620320862277 Test MdAE: 42.42915080597352	Test R^2: -0.12013584914521847 Test MSE: 189181.89437012997 Test MAE: 95.04562021580199 Test MdAE: 38.96292271635451
AdaBoost	Test R^2: 0.3124977166677271 Test MSE: 144811.86730471934 Test MAE: 172.19095106734986	Test $R^{2:}$ 0.22453751161206315 Test MSE: 216741.17709803724 Test MAE: 218.43505588071022 Test MdAE: 160.9939968056397

	Test MdAE: 82.58897414336766	
Gradient Boost	Test R^2: 0.3828900722944142 Test MSE: 121342.91331865962 Test MAE: 84.08776943213483 Test MdAE: 32.33825657765277	Test R^2: 0.5505589141900278 Test MSE: 97786.77322384185 Test MAE: 72.20184344842117 Test MdAE: 25.90042367237018




Comparison of Median Absolute Error for Test Dataset
Gradient Boost (Ridge Regularized Feature Selection)
Gradient Boost (Lasso Regularized Feature Selection)
Adaboost (Ridge Regularized Feature Selection)
Adaboost (Lasso Regularized Feature Selection)
Random Forest (Ridge Regularized Feature Selection)
Random Forest (Lasso Regularized Feature Selection)
Lasso Regression (Ridge Regularized Feature Selection)
Lasso Regression (Lasso Regularized Feature Selection)
Ridge Regression (Ridge Regularized Feature Selection)
Ridge Regression (Lasso Regularized Feature Selection)
Linear Regression (Ridge Regularized Feature Selection)
Linear Regression (Lasso Regularized Feature Selection)
0
50
100
150
200
250

5. Final Results and Interpretation

1. The results of feature selection for the dataset showed that not all the features were necessary. We can introduce sparsity using lasso and ridge regularization and decrease the number of features.
2. The use of regularization has huge impact in improving the performance. This implies that the low performance of linear regression is not due to poor generalization but due to the inherent inability of the chosen model to not fit the data completely.
3. Tree based regressors are fairly simple but they produce noisy & weak regressors. The good thing is they are fairly robust to outliers but the regression accuracy might not as good as other models.
4. Using bagging one can fit many large trees to bootstrap resampled versions of the training data and classify by mean of the each region created.
5. The ability of decision trees to fit nonlinear relationships enables better performance than linear regressor. Boosting techniques enhances this performance.
6. Tuning the parameters, our final model is a Gradient boost regressor with ridge feature selection, with parameters max_depth=4 and n_estimators=200 gives us a good model. We can see that it fairly fits well to the variation of the data by checking the R2 score. The test R2 is fairly close to the training R2 and they are both above 0.5. This is good because Gradient boost regressor tend to overfit the data, in our case it did not. It outperformed all of the other classifiers giving around 25 median absolute error. Thus, this suggests Gradient boost regressor tends to work better with lower dimensional data since our lasso feature selection outputs around 100 features whereas Ridge outputs around 250.
7. Our results suggest that our Linear, Lasso and Ridge Regression algorithms mostly fail to predict the Airbnb price well enough, this is expected since Linear Regression based models are tend to work with linear data. We have lots of categorical features and outliers in our data. Hence, our data is non-linear in it's nature. Trying to use polynomial regression with a penalizer would work in this case but it was computationally very demanding, so it's not used.
8. In addition, its seen that the Tree based regressors are fairly simple, but they produce noisy and somewhat weak regressors. The good thing is they are fairly robust to outliers, which we can see from the results of Random Forest and Gradient Boost algorithms. In order to reduce the variance bagging/boosting methods are used to resample from the training data with replacement and average out each resulting model to get a more robust the final model.
9. Using bagging one can fit many large trees to bootstrap resampled versions of the training data and the regression output is the mean of each region created.
10. Using boosting one may fit many large/small trees to reweighted versions of the training data and the regression output is again the mean of the regions created. But, for boosting predictors are made sequentially.

11. Gradient boost is a stage wise additive technique where the original Adaboost problem is posed as an optimization problem, where the loss function is minimized using gradient descent procedure. A possible pitfall for our problem could be Gradient boosting might overfit for our data, but we see that using parameter tuning we are able to find a Gradient boosting regressor gives a fairly good result.
12. We think that main reason behind the other algorithms didn’t give the expected result is the possible outliers in the data. We also see that the exploratory data analysis worked in our favor. Our results from exploratory data analysis matches the results for our main dataset. The best performers in exploratory dataset also worked well with the main dataset.

6. Future Work

1. The current formulation does not use the reviews by previous users while developing the model. This could be a key component in the process of house price prediction. But this requires Natural Language Processing, which is outside the scope of this course.
2. Future work can include more parameter fine tuning to get more accurate model.
3. Also, RFECV Feature selection method can be explored to check it's results with the different models.
4. Clustering with K-means algorithm can be used to cluster the listings according to zipcode or neighborhood and then predict the prices. This method has not been explored but has potential to improve results.
5. Also, Neural Network approach has not been explored to fit the dataset. As Neural Networks can learn detailed patterns, hence it can be a good algorithm to explore.

7. References

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5. Explanation of gradient tree boosting : Quora discussion
6. Difference between Gradient and XGBoosting : Stack Exchange
7. Chopra, Sumit et. al. Discovering the hidden structure of house prices with a non parametric latent manifold model.
8. Zhang, Pan, Shi et al. The Prediction of Booking Destination on Airbnb Dataset

8. Student Contributions

Omer: Data Pre-processing on exploratory data, visualizations using exploratory data, modelling (exploratory and main data)using Lasso Regression and Ridge Regression and interpretations of the final results for those models.

Tamoghna: Data Pre-processing on main dataset, visualizations using exploratory data, modelling modelling (exploratory and main data)using Linear Regression and AdaBoost and interpretations of the final results for those models.

Rohan: Data Pre-processing on main dataset, visualizations using exploratory data, modelling modelling (exploratory and main data)using Gradient Boosting and Random Forest and interpretations of the final results for those models.