Airbnb Price Prediction

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***Abstract*— Airbnb is the world's most prominent online hospitality marketplace. It has a publicly available dataset, divided region wise which has been used in our predictions and analytics to determine how various features of property correlate to the price of the listing in the Airbnb website. In order to make our predictions more robust, we also used the text reviews by the customers and performed sentiment analysis on it, subsequently adding it as a feature for training the model. For the training part, we used data for Nashville, Tennessee but the model can be used for any region since the data structure is uniform throughout. For future work, we hope to collect more extensive and more diverse dataset to enhance its performance and generalizability.**

I. Introduction

Inside Airbnb provides the data for various listings of the property in the Airbnb website categorized region wise. Its prudent to have a good understanding of the features which are the driving factor in determining the price of a listing for the Airbnb as the business and homeowners as well. In order to determine how various housing attributed influence the pricing of a listing in Nashville, Tennessee, the models described in this paper makes a systematic analysis of several typical aspects using python and its libraries.

We started by cleaning the data based on various factors like removing the rows which had lots of missing values and removing the NaN values from the dataset, this followed by feature engineering based on domain research ad

II. Data Understanding

For our model, the data was downloaded from Inside Airbnb, which contains the database of various cities worldwide. The data utilizes public information compiled from the Airbnb website including the availability calendar for 365 days in the future, and the reviews for each listing, and hence seems a reliable source for our analysis.

We performed the analysis using data for Nashville, Tennessee, which can potentially be later replaced with data for any other city using the same source since the data for all the cities is structured in the same way.

The dataset for each city provides a *listing* file which contains all the listings on the Airbnb website for that particular city which contains about 96 features, ranging from listing id, listing URL, to information about the property, property type, host type, amenities.

The dataset used for the sentiment analysis on the text reviews was provided in CSV format. There are 6 features and almost three hundred thousand reviews. There are various reviews for a single property.

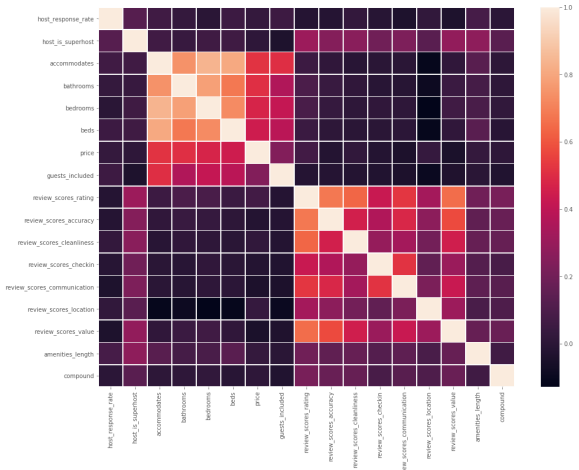
III. Data Preparation

For our model, the data was downloaded from the Inside Airbnb.The two datasets downloaded were *listing* and *reviews.*

The data preparation started with cleaning the data. Data was cleaned by removing the row with lots of missing values and also removing the NaN values.

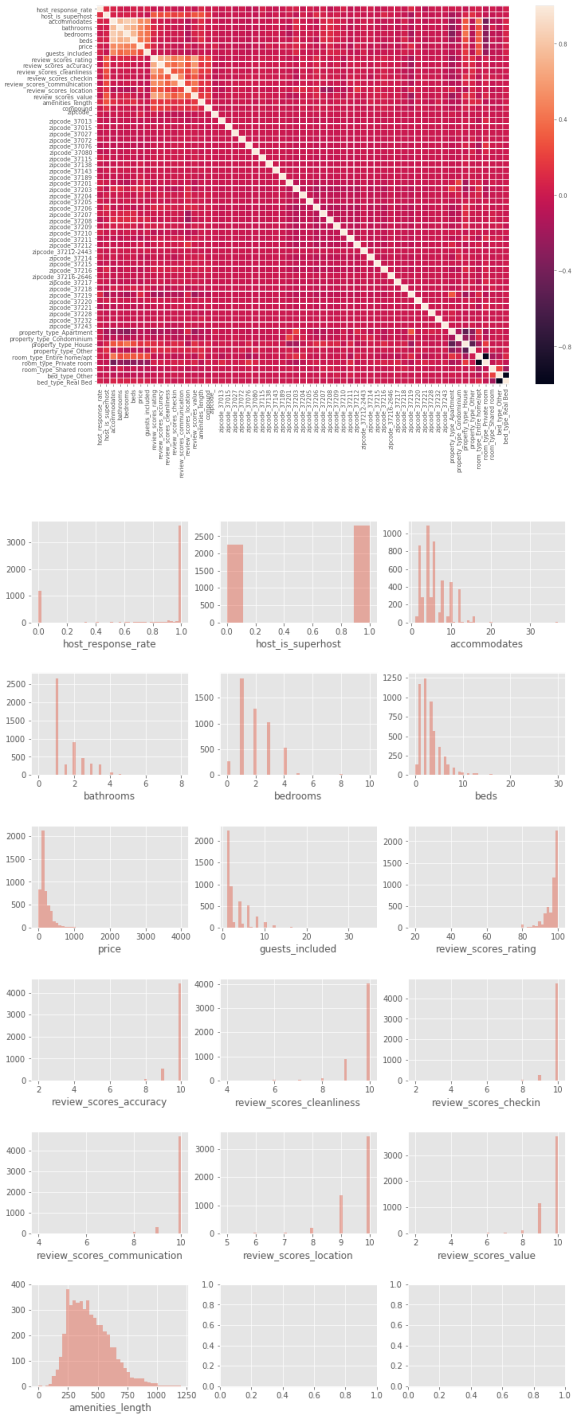
Features like *host_is_superhost, property_type, bed_type* are recoded to get uniform values.

After transformations and selecting the relevant features, we get the following correlation between the features.



Other variables like *zipcode, property_type, room_type, bed_type* are then converted to dummy variables in order to convert them into categorical variables.

After the above transformations, we get the following correlation between the features.



Feature Engineering

After cleaning the data, Pandas was used to describe various features and were evaluated on

various parameters like count,mean,median etc to determine its aptness to be used for the modeling.

We have used Vader module of NLTK to perform sentiment analysis and provide each review with a sentiment score. The These sentiment score was classified as positive, negative or neutral.

IV. Modeling & Evaluation

The target variable is the price of an airbnb property. Given the nature of our features after modifications and the problem at hand, a simple logistic regression algorithm is one very efficient way to predict our target variable. Due to our dataset-size and it's computationally inexpensive nature, this algorithm is a great choice for a baseline model. Logistic regression models are easily comprehensible and transparent in nature. We also used Decision trees, as they are known to be compatible with both types of tasks i.e regression and classification. Along with Logistic Regression and Decision trees, we applied a Random Forest model. The Random Forest model is a complex model and is suitable for both regression and classification tasks. Even though Random Forest is a complex algorithm,
its level of understanding of decision trees is quite simple.

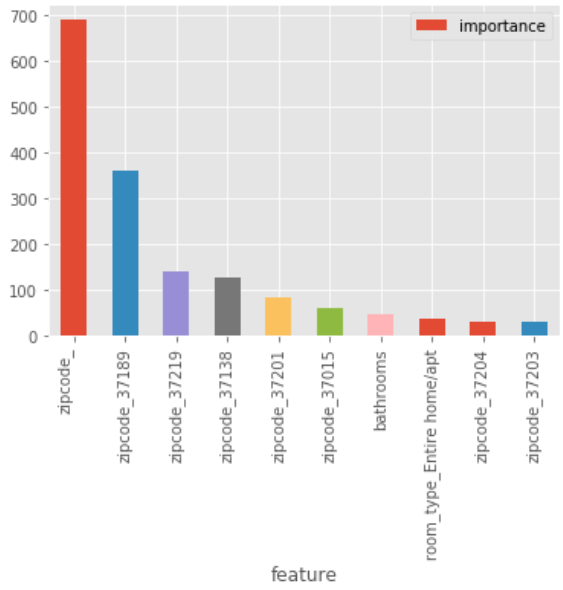
A. Regression

Since Logistic Regression has been proven to be very predictive when it comes to medium size dataset We applied our clean and feature engineered dataset to get the prediction on the prices.

We used cross-validation to deal with overfitting.

It gave us an Mean Squared Error value of 181.59

To better understand what is driving the predictive decisions, below is the weighting of the features in the regression model.



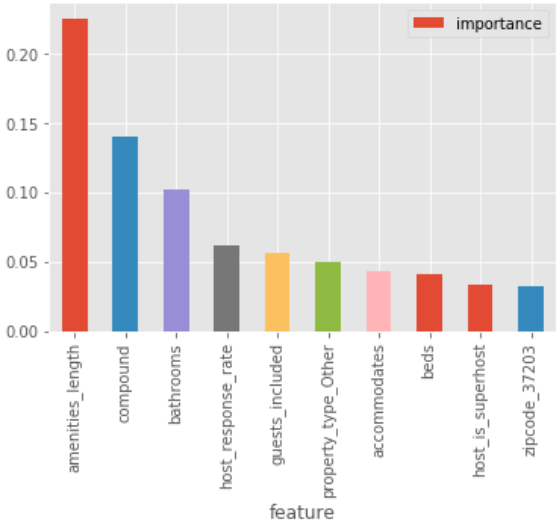
B. Decision Trees

Since decision trees have in-memory classification, are not computationally expensive and are easy to use, this model is our second choice to predict our target variable. One other important reason we used a decision tree is their capability to handle a dataset that contains a higher degree of errors and missing values. We applied a decision tree classifier from the Sklearn

library with varying maximum depths and a random state set to zero.

It gave us an Mean Squared Error value of 219.20

To better understand what is driving the predictive decisions, below is the weighting of the features in the decision tree.



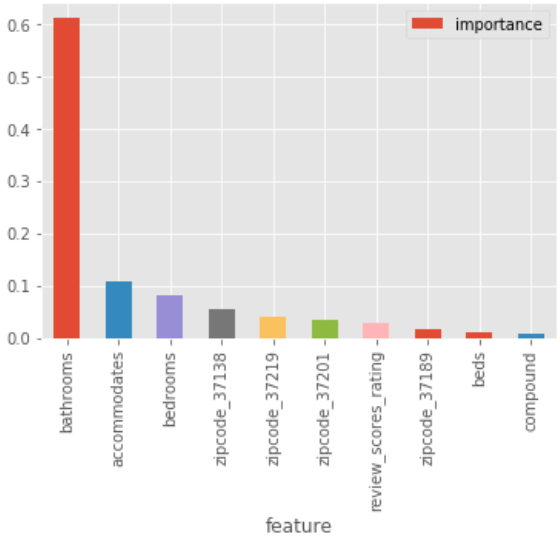
C. Random Forest

Random Forest is the ensemble of the decision tree. It generally gives a better result than a decision tree as it helps averages out the result of all the decision tree leading to canceling of the noise.

We used the same clean and featured engineered data to run this algorithm getting us the AUC of -

It gave us an Mean Squared Error value of 184.49

To better understand what is driving the predictive decisions, below is the weighting of the features in the random forest model.



V. Model Selection

Based on the models we get the below results-

Model Evaluation

```
In [242]: print("OLS MSE",ols_mse)
          print("Decision Tree MSE:", dtree_mse)
          print("Random Forest MSE:", rf_mse)

          OLS MSE 181.5949677637162
          Decision Tree MSE: 219.20719590570494
          Random Forest MSE: 184.49530715539314

In [243]: print("OLS R^2",ols_r2)
          print("Decision Tree R^2:", dtree_r2)
          print("Random Forest R^2:", rf_r2)

          OLS R^2 0.24619143080293515
          Decision Tree R^2: -0.09840642455473425
          Random Forest R^2: 0.22192027464735742
```

We see that the regression model has the lowest mean squared error and the highest R^2 value, thus indicating the best performance.

VI. Conclusion

From a business and implementation standpoint, we have succeeded in creating a

model that does a fair job in predicting the prices. A varied number of features were successfully cleaned, pre-processed and modeled on to get us our final regression models with optimized parameters.

VII. Appendix

For our model, the data was downloaded

A. References

1) https://nyudatabootcamp.gitbook.io/thebook/
2) http://insideairbnb.com/
3) F. Provost and T. Fawcett, Data Science for Business. Sebastopol, CA: O'Reilly, 2013

B. Project Link

https://github.com/dhruvkwal/Data-Bootcamp-Final-Project