Price Prediction Project

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Agenda

1. Objectives and Business Case
2. Data Overview and Preparation
3. Exploratory Analysis and Unsupervised Modeling
4. Supervised Modeling
5. Key Takeaways

Objective & Problem Statement

Why?

- To help new and existing owners fix the most competitive price
- This isn’t an easy ask

How?

- A ML model that uses several methods to predict the right price
- Saves huge time, effort and cost on the part of the owner

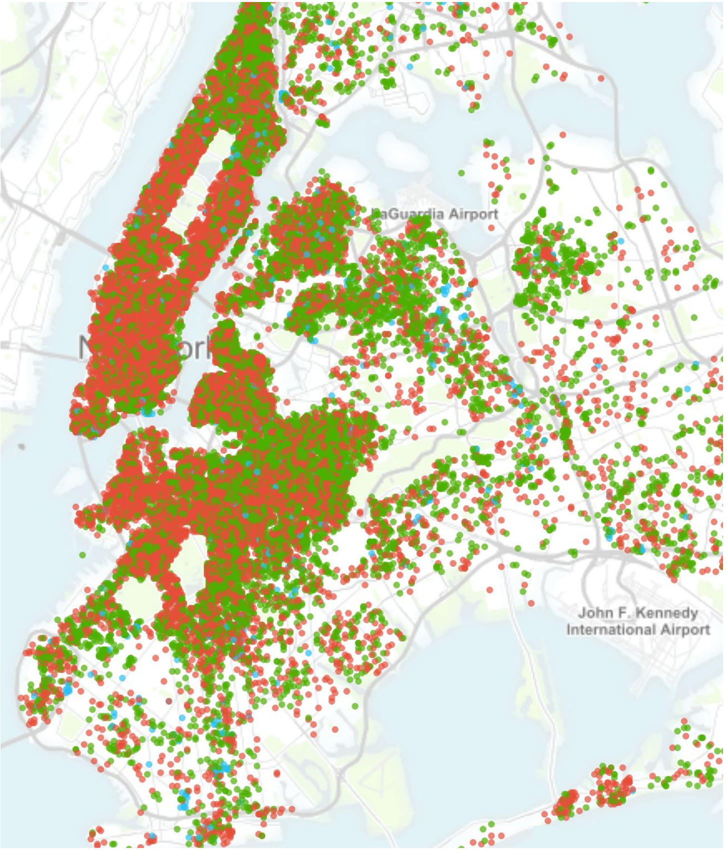
Who?

- To owners (or to hosts with multiple properties looking to list new ones)
- To a consulting firm in this business
- To Airbnb in order to improve their “suggested price” metric

Data Cleaning and Preparation

The Dataset

- New York dataset, with 50,600 Airbnb listings
- Contained a wide range of information including:
    - Location and neighborhood
    - Property and room type
    - No. of guests, bedrooms bathrooms
    - Amenities included (130 types)
    - Price, security deposit, cleaning fee
    - Reviews and rating
- Also contained a lot of additional information which we dropped:
    - Text data: listing name, summary, descriptions
    - URLs, pictures, etc



Data source: http://insideairbnb.com/get-the-data.html

Data Cleaning & Key Assumptions

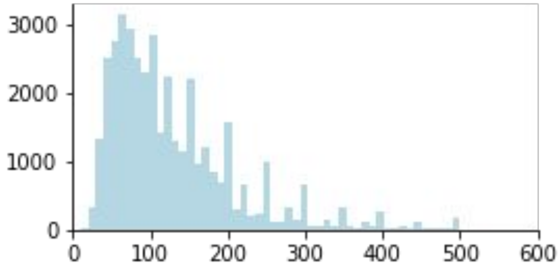
- Additional steps on cleaning and refining the data using Python.
  - Dropped all listings with 0 reviews in the last 12 months.
    Assumption: these are likely 'inactive' properties which don't reflect true price
  - Dropped outliers and listings with extremely high prices (2%), by filtering for price less than $500
  - Extensive missing values in square feet, security deposit and cleaning fee, so those columns were dropped.
    Assumption: security deposit and cleaning fees, are time independent (same amount charged regardless of the length of stay)
- For predictions, we focused on the daily price only, rather than weekly and monthly prices, as this was the most complete data.
- Final data dimensions were (28,268, 37) from (50,600, 107) originally.
- Created train and holdout validation samples with a 70:30 ratio.

Exploratory Analysis and Unsupervised Modeling

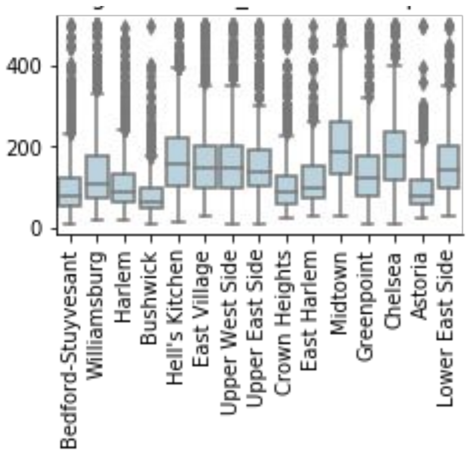
Exploratory Analysis

- Price skewed cheaper with a median of $100
- In the dataset given, 5.7% hosts manage 3 or more listings, which account for 24.7% of total listings in New York
- The most relevant variables are related to locations, quality of room, and amenities

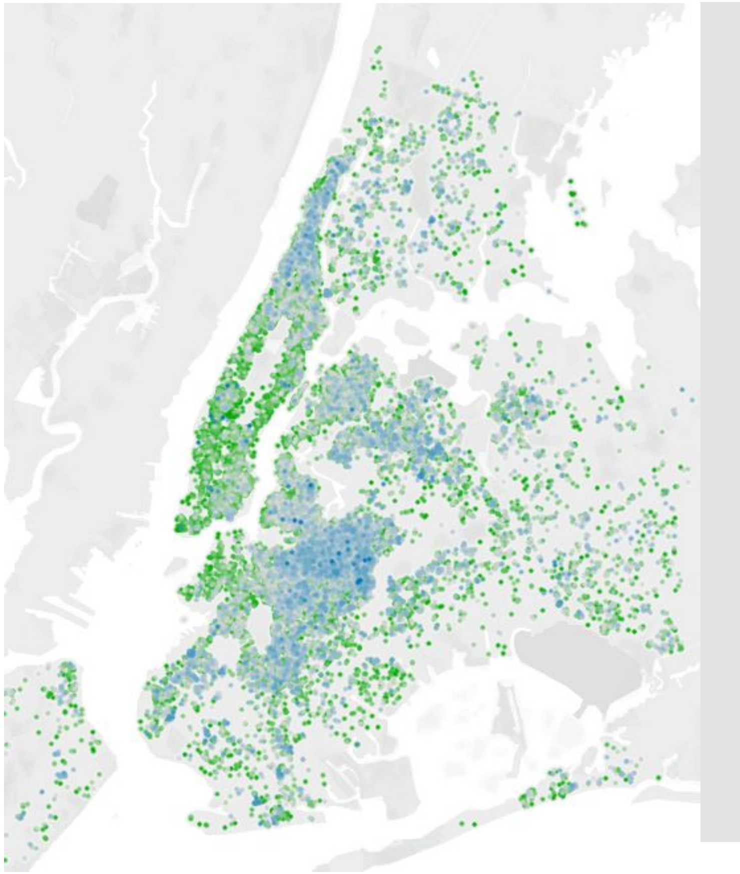
Price Distribution



Price by Neighborhood



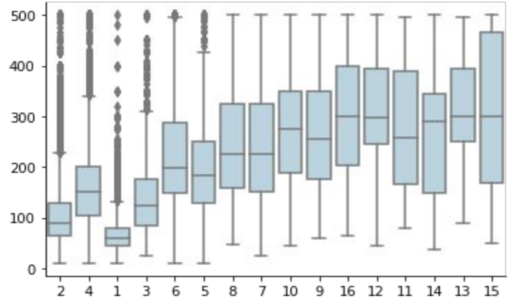
Price Distribution



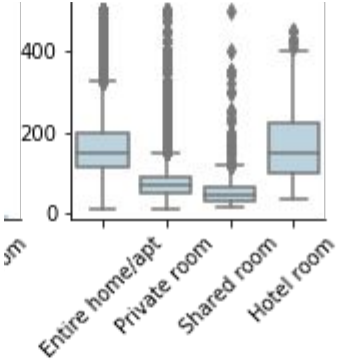
Exploratory Analysis

- The services offered is more relevant than guest rating and review count

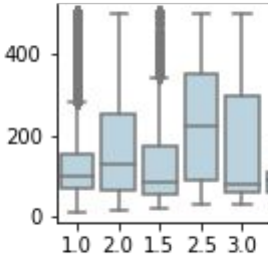
# of Guests



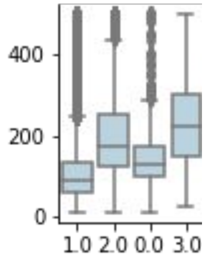
Price by Room Type



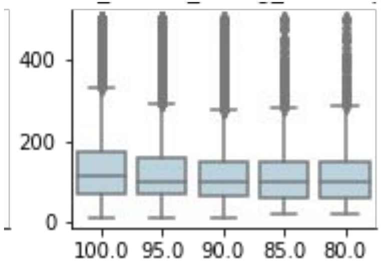
Bathroom



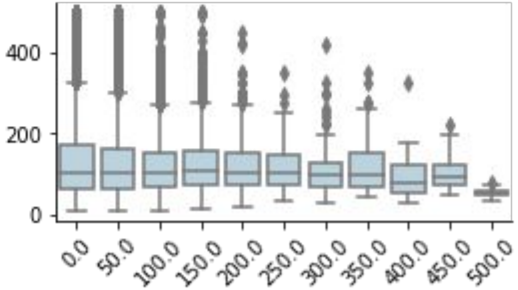
Bedrooms



User Ratings

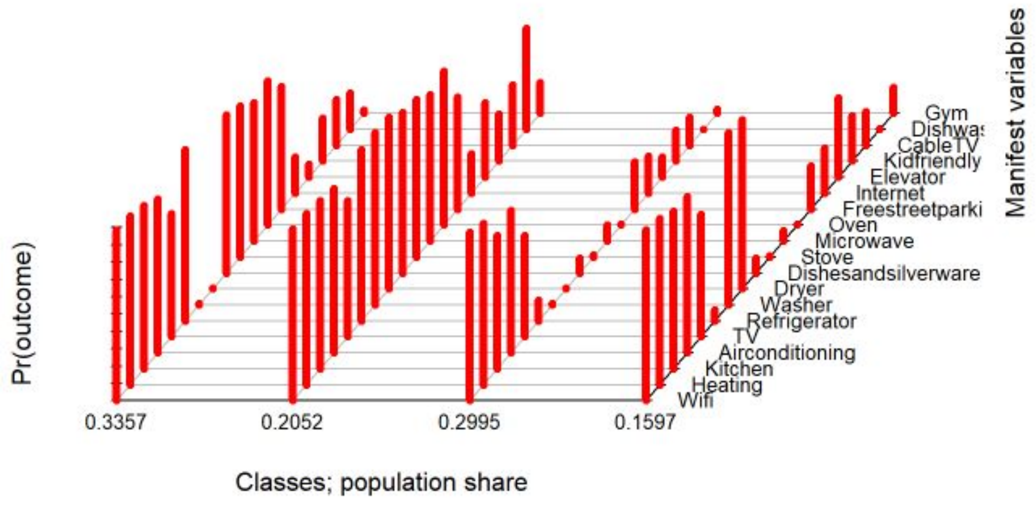


Historical Number of Reviews



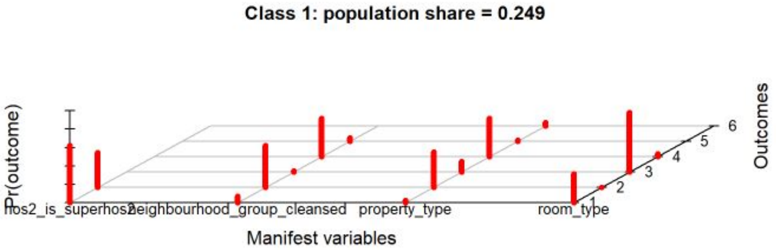
LCA on Amenities

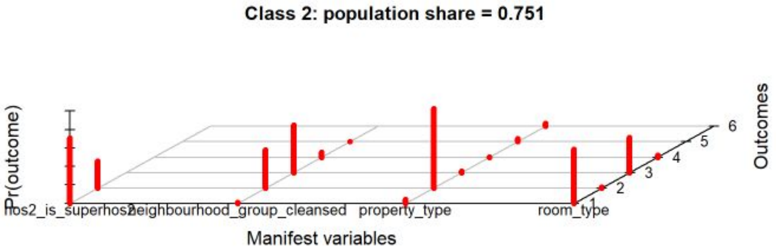
- Selected the 20 most frequent amenities across listings as well as amenities with the greatest effect on price.
- Optimal clustering at 4 clusters with relatively even population share across all classes.
- Cluster Descriptions:
    - Cluster 1 (33.57%): listings with all amenities available except washer and dryer.
    - Cluster 2 (20.52%): listings with all amenities available.
    - Cluster 3 (29.95%): listings that are private rooms with no additional amenities.
    - Cluster 4 (15.97%): listings with all amenities except kitchen related amenities.

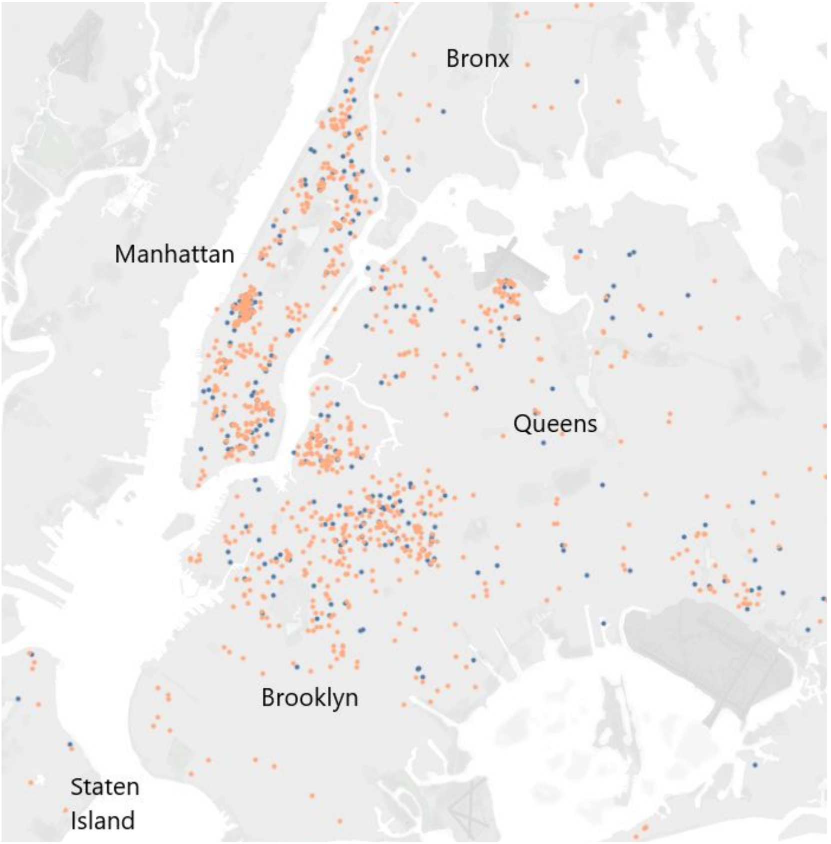


LCA on Property Type and Location

- Selected neighborhood, property type, and room type.
- Cluster Description:
  - Cluster 1 (24.9%): Even distribution of houses and apartments in Queens and Manhattan.
  - Cluster 2 (75.1%): Primarily apartments in Manhattan and Brooklyn





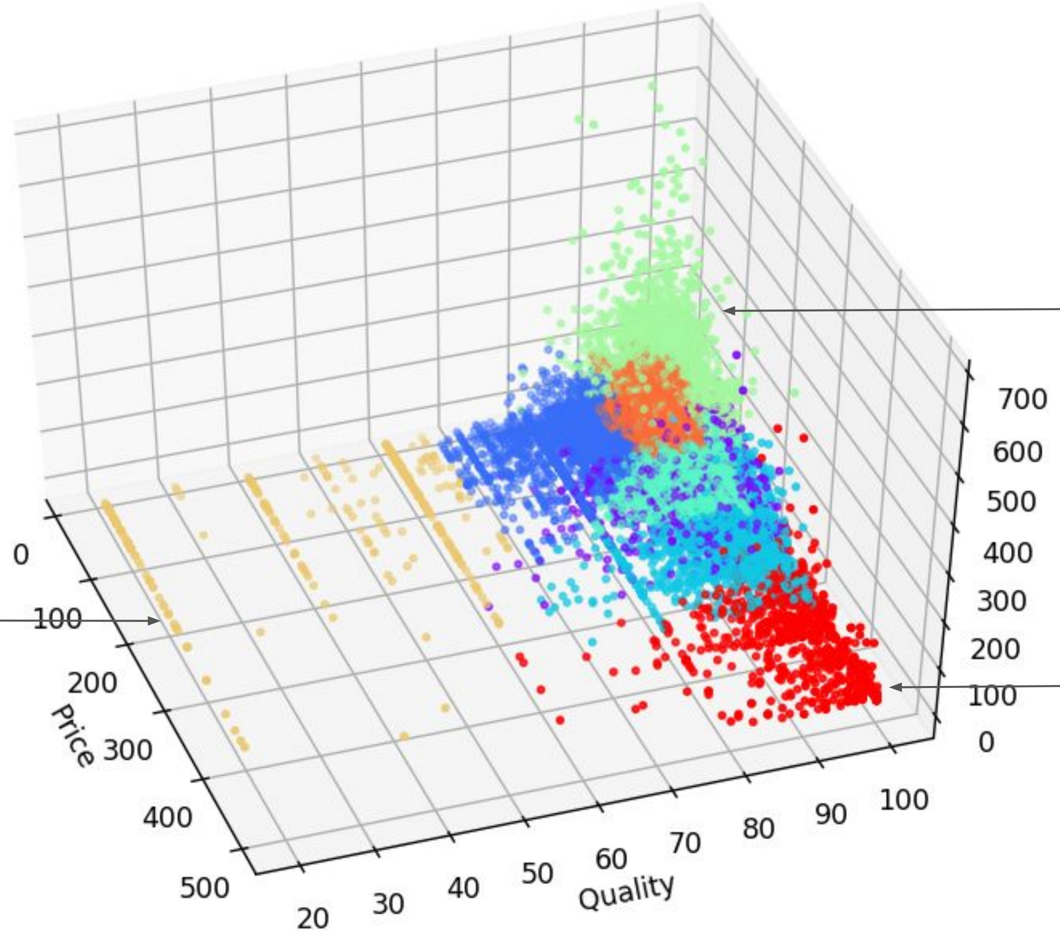


K-means Clustering

- Clustered listings based on the following variables: price, number of bedrooms, number of reviews, overall rating, number of guests.
- 8 clusters explaining ~85% of variance

Cluster	Price	Size	Quality	Occupancy	Number (proportion)
1	Average	Big	Above avg	Average	1746 (6.2%)
2	Very cheap	Small	Below avg	Very low	3150 (11.1%)
3	Very high	Average	Above avg	Very low	2520 (8.9%)
4	Average	Small	Above avg	Very low	6486 (22.9%)
5	Very cheap	Small	Above avg	Extremely high	2412 (8.5%)
6	Very cheap	Small	Terrible	Almost nil	389 (1.4%)
7	Cheapest	Smallest	Above avg	Very low	10623 (37.6%)
8	Ultra luxury	Huge	Above avg	Very low	942 (3.3%)

K-means Clustering



Cluster 5 (very cheap, good quality, highest occupancy)

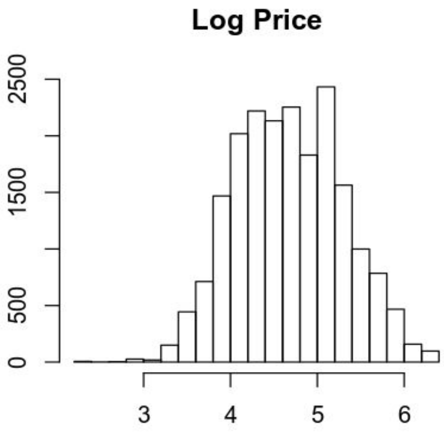
Cluster 6 (very cheap, worst quality, almost no occupancy)

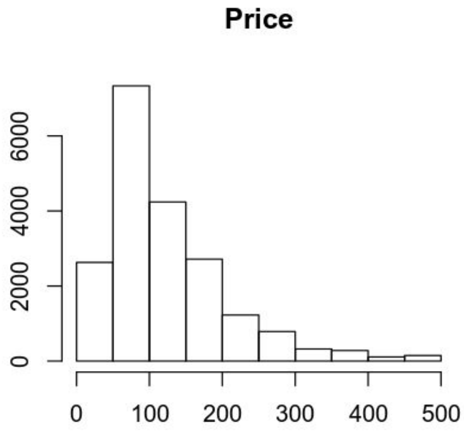
Cluster 8 (luxury, good quality, low occupancy)

Supervised Modeling

Linear Modeling

- Price was converted to logprice to stabilize variance
- Initial model with 11 variables was heavily overfitted and showed signs of multicollinearity.
- Final model: logprice ~ accommodates + zipcode + room_type





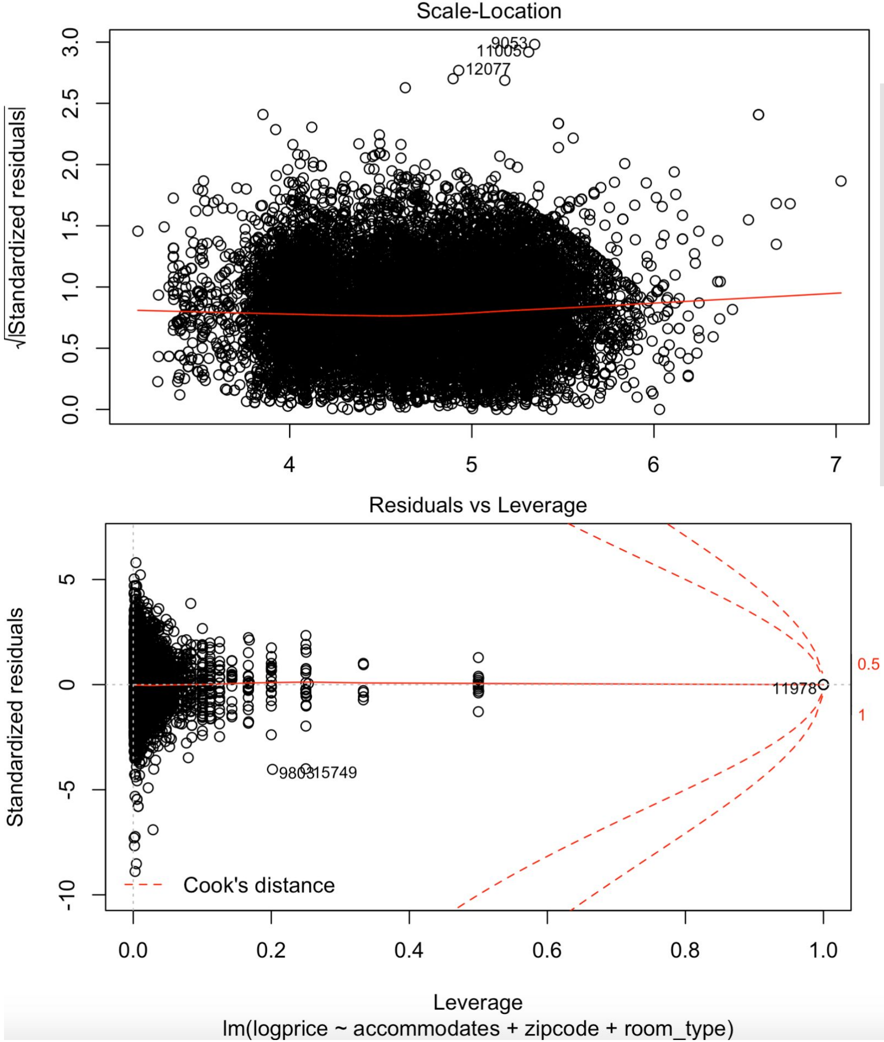
Model Performance

	R2
Train	0.59
Test	0.46

Linear Model Residuals

- The scale-location plot shows the square root of the standardized residuals as a function of the fitted values. The plot shows no obvious trend in this plot.

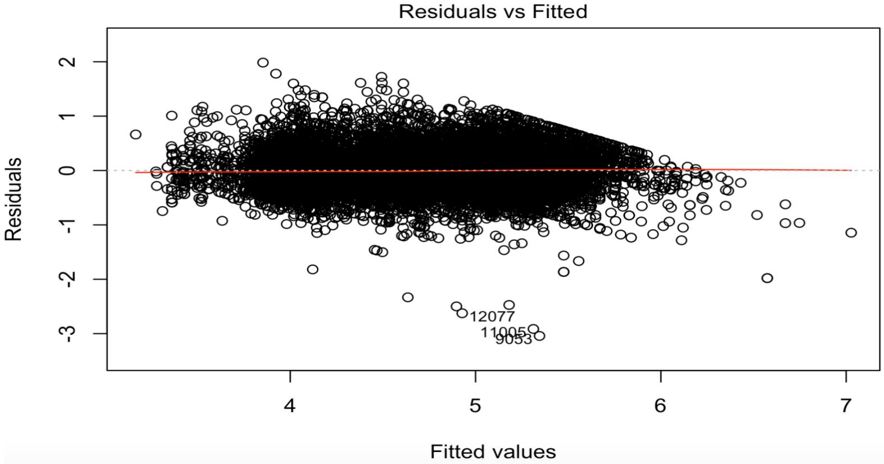
- The residual vs leverage plot shows that the smaller distances means that removing the observation has little effect on the regression results.

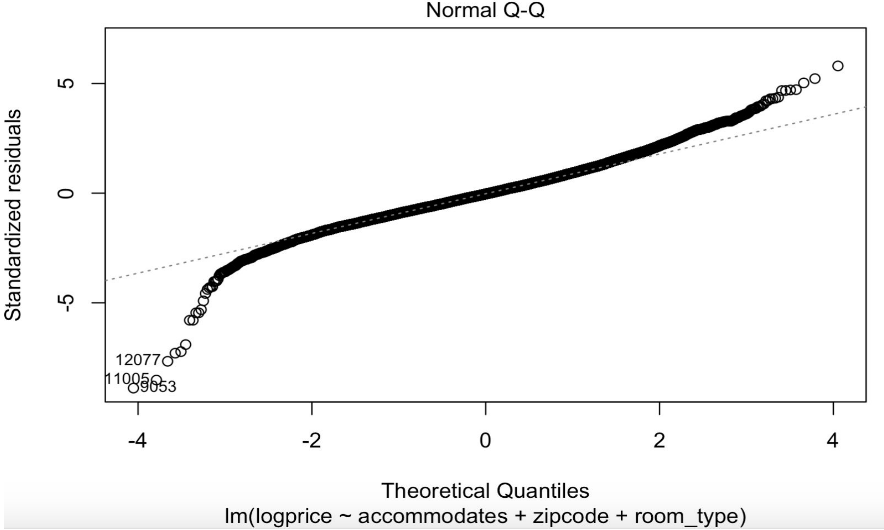


Linear Model Residuals

- The residual errors versus their fitted values show that the residuals are randomly distributed around the horizontal line representing a residual error of zero.

- The standard Q-Q plot shows the residual errors are normally distributed.





Conclusion

- The linear model has an R squared of 0.59 on the training data, but does not perform well in holdout and drops to 0.46. As a result, the Mean Absolute Percentage Error of the model is 52%, whereas the desirable MAPE has to be less than 20%.

- Therefore, we can make this model further rigorous by using more advanced models.

Model Performance

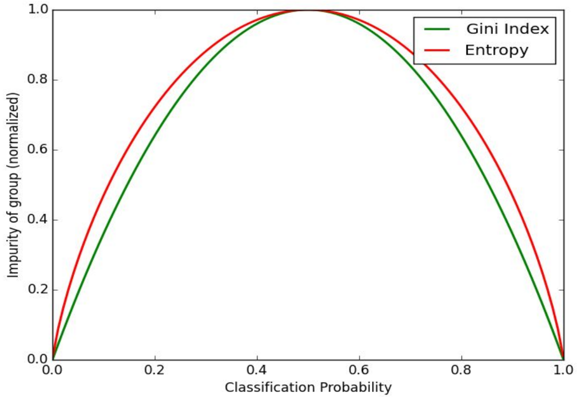
	Initial model	**Final model**
Train	0.72	**0.59**
Test	0.13	**0.46**

Decision Tree

Model Performance (R^2)

	Gini Index	Entropy
Train	0.653	0.653
C.V.	0.601	0.594
Test	**0.604**	0.599

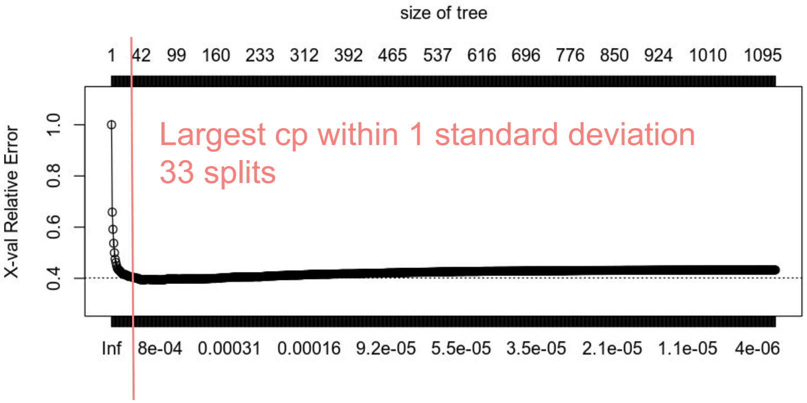
Scaled Gini Index v.s. Entropy



- Gini Index as the loss function
  - Similar performance on the train set; the Gini index stands out on the test set
  - Entropy for classification, Gini for regression
- Conservative selection of the complexity parameter
- 9 features used out of 98
- Advantages of rpart
  - Easy parameter tuning with cp (complexity parameter); printcp presents the threshold cp to avoid heuristic search for the best set of parameters
  - No dummification required as in sklearn
  - Feature selection not required (but could benefit the model) to reach decent performance

Decision Tree

Complexity Parameter Tuning



Feature Importance

1. Room_type
2. Accommodates
3. Neighbourhood_cleansed
4. Guests_included
5. Host_neighbourhood
6. Bedrooms
7. Bathrooms
8. Host_location
9. Property_type

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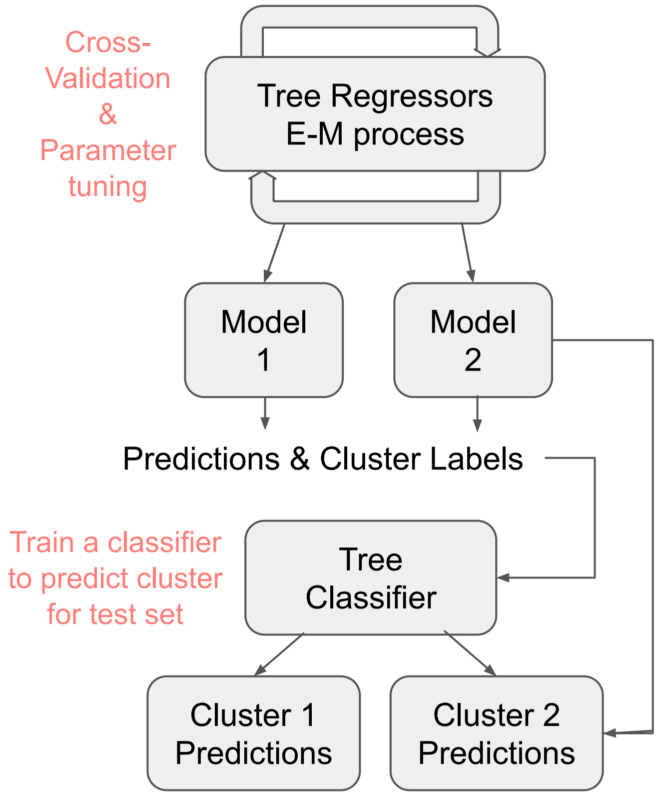
Cluster-wise Decision Tree



Model Performance

	Class 1 R2	Class 2 R2	**Overall R2**	Class Acc.
Train	0.877	0.753	**0.839**	0.978
Test	0.741	0.661	**0.734**	0.948

- The model performance depends on...
  - Performance of the multi-class classifiers
  - Discrepancy among predictive models of different clusters
    - R2 is -0.79 for the 5% misclassified samples
- Strengths
  - Highly effective
  - Insights into clusters of study subjects
- Weaknesses:
  - Prolonged training time
  - Painstaking parameter tuning and feature selection

Random Forest

- Full model trained with all predictors, ntrees = 1000
- Hyperparameters using GridSearch with cross-validation.
  - Ntrees = 1250, max depth = 60, min sample split = 5, min samples per leaf = 2
- Further improvements were possible by subsetting the data again to include only those listings with >5 reviews in the last 12 months.
- High training R2 values are an indicator that RandomForest is quite prone to overfitting.

Model Performance

	Initial Model	GridSearch Xval	Reviews >5
Train	0.957	0.923	**0.961**
Test	0.654	0.661	**0.694**
Avg. Error	$32.01	$31.41	**$30.22**

Random Forest - Variable Importances

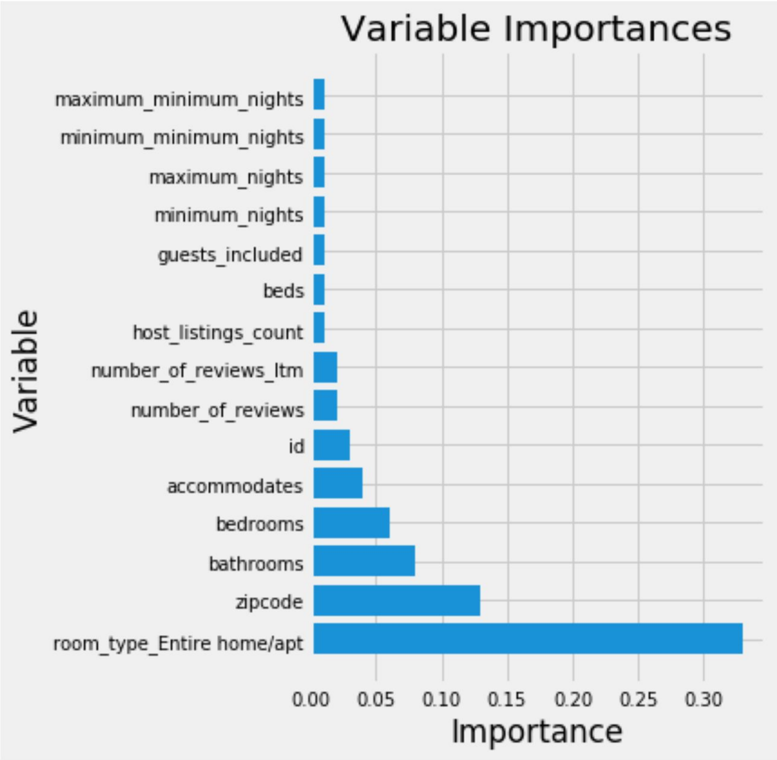
Checking for variable importances in the RandomForest model, we find some interesting results:

- Room type (entire apartment), zipcode, bathrooms and bedrooms are the most important variables
- Number of reviews are important, confirming our initial intuition
- Dishwasher and Dryer are the only important amenities

Retraining the model with just the most important variables, we get a slight drop in R2 and accuracy:

Test R2: 0.652, Accuracy: 71.2%, Avg. Error: $32.68

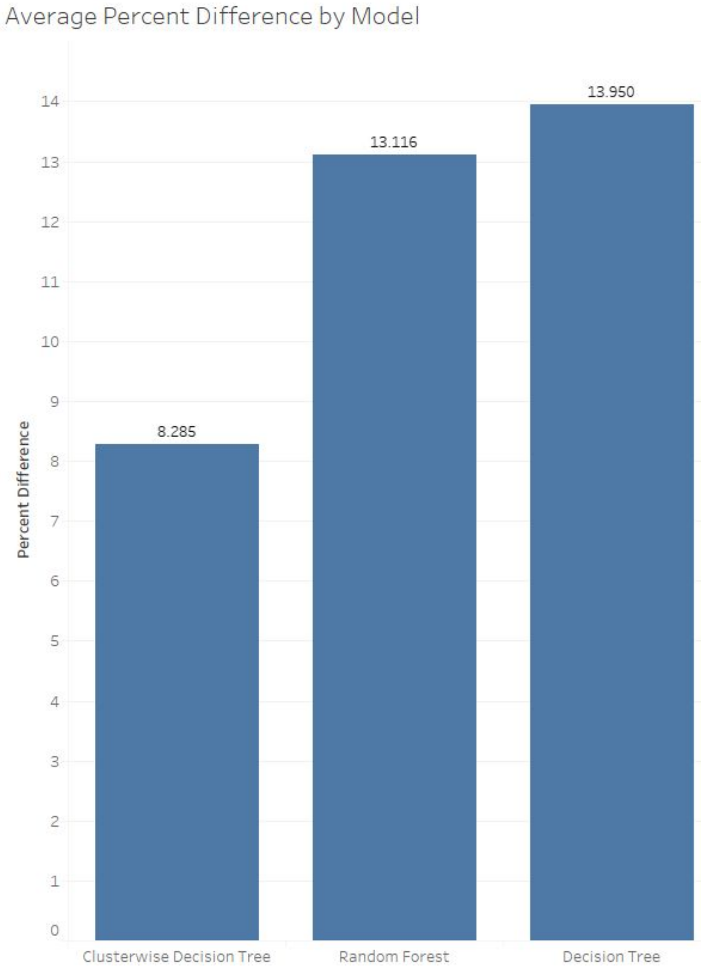
But we have a more interpretable model



Residual Analysis

- Analyzed the percent difference between actual price and predicted price on holdout set across all models.

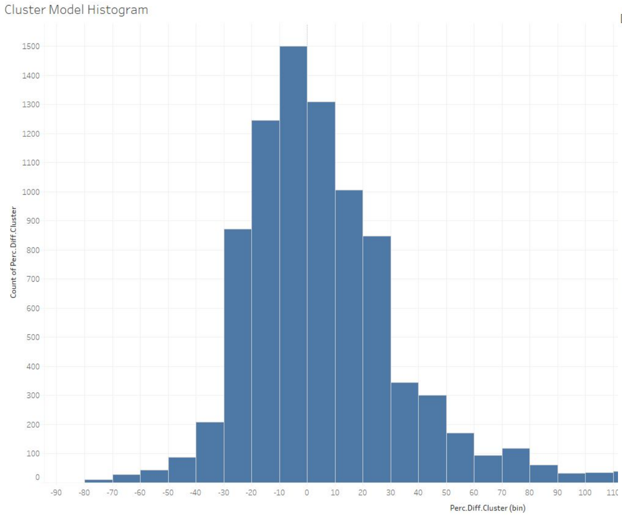
- Cluster-wise Decision Trees returned the smallest percent difference.
  - Cluster-wise Decision Tree: 8.285%
  - Random Forest: 13.116%
  - Decision Tree: 13.950%



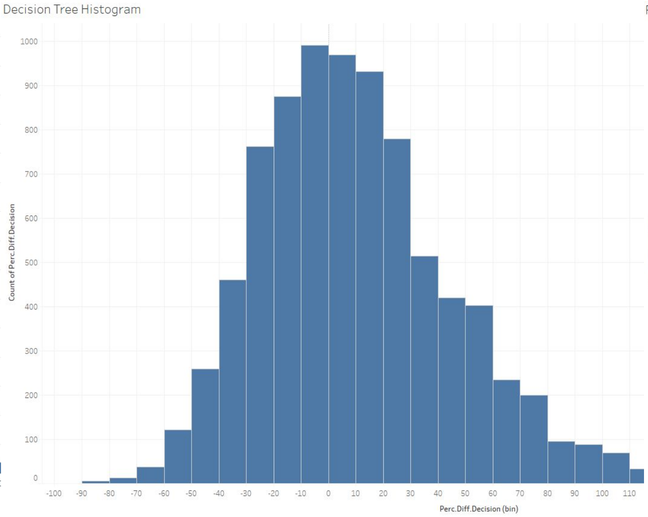
Residual Analysis

- Residuals across all models were normally distributed.

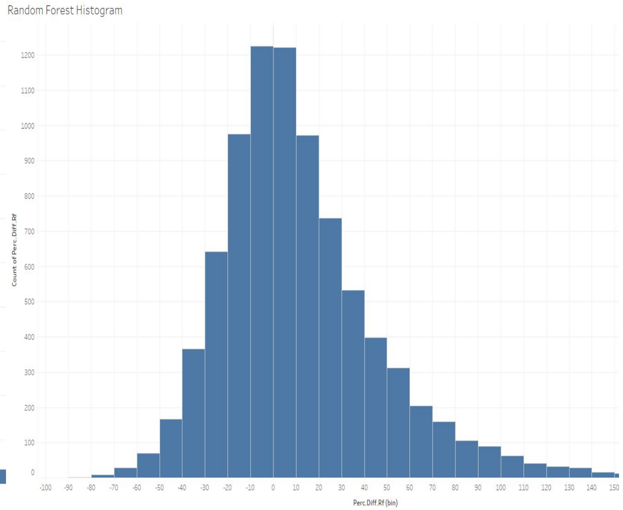
Cluster-wise Decision Tree



Decision Tree

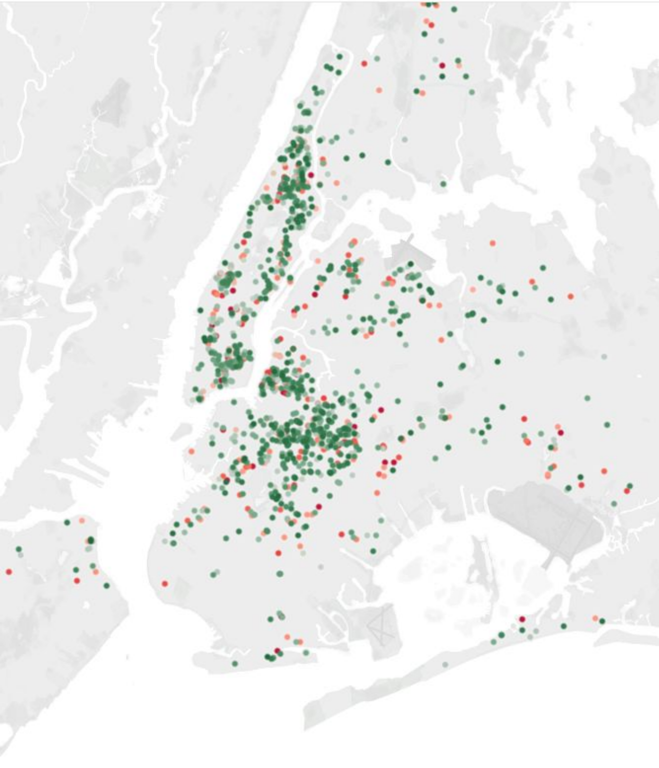


Random Forest

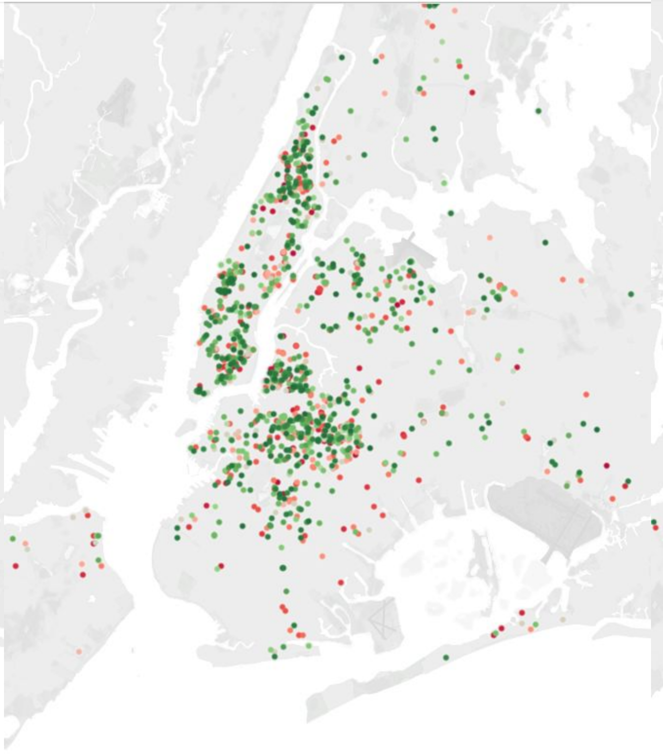


Heat Map of Overpredicted Prices

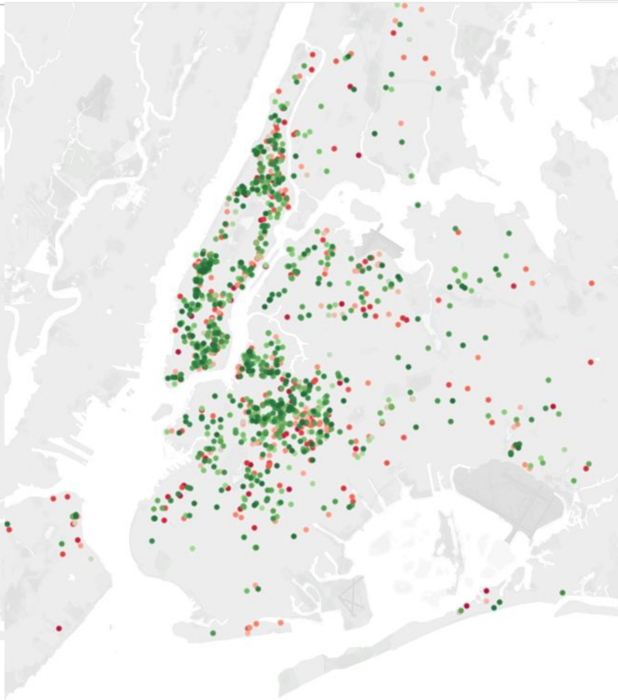
Cluster-wise Decision Tree



Decision Tree

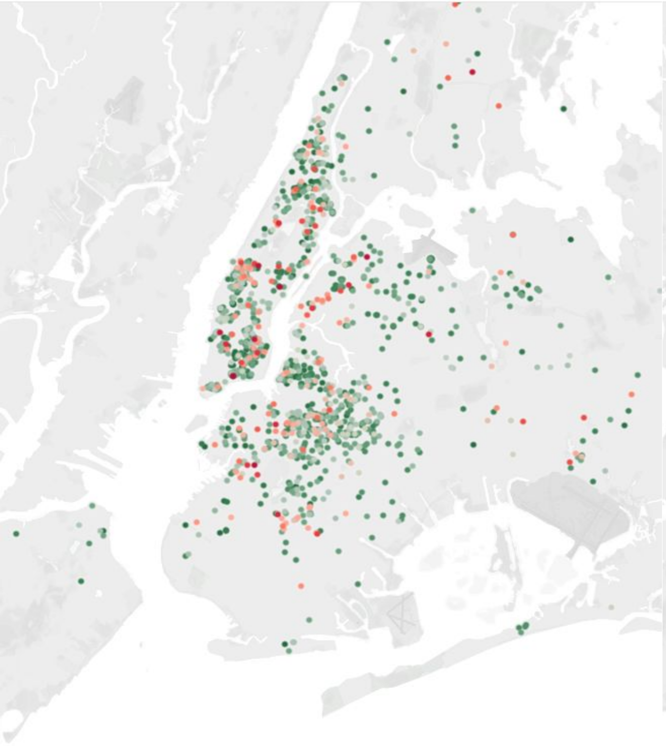


Random Forest

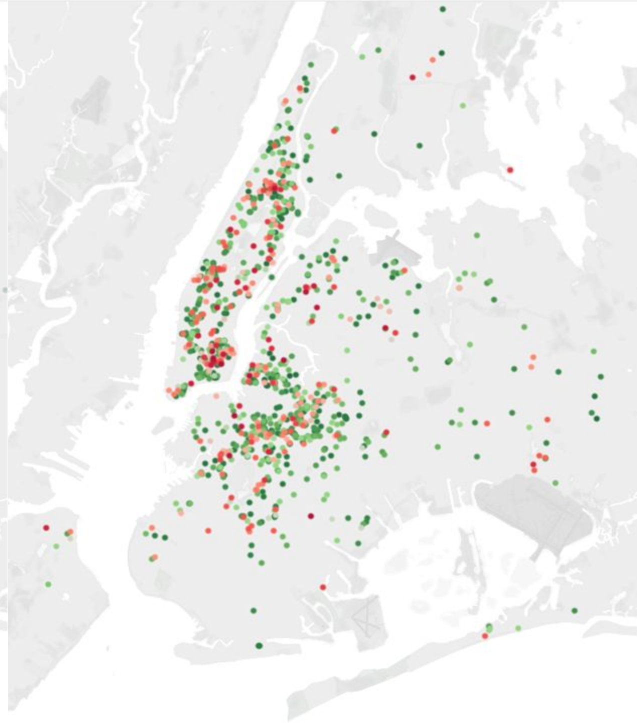


Heat Map of Underpredicted Prices

Cluster-wise Decision Tree



Decision Tree



Random Forest

Key takeaways

Model comparisons and summaries

Linear Model

Avg. Error: $47.21

Test R2: 0.46

- Poor results overall
- Too simplistic to capture the relationship between price and the predictors
- Prone to overfitting

Decision Trees

Avg. Error: $36.07

Test R2: 0.604

- Heavily overfitted
- Train/Test split impacts accuracy greatly

Cluster-wise Decision Trees

Avg. Error: $25.75

Test R2: 0.734

- Best R2
- Relatively stable between train and test results
- Performance dependent on cluster classification

Random Forest

Avg. Error: $31.61

Test R2: 0.661

- Decent performance
- Shows signs of overfitting

Key insights

1. Offer the entire apartment, instead of a private room
2. Always ask guests to leave a review
3. Offer a washer and dryer
4. Offer more beds within your listing

Limitations & Improvement

Limitations

- Predicts a fixed price instead of a seasonal/special price (a concert in the vicinity presents an opportunity for a spike)
- Does not take duration of stay into account (prediction only for a single night)
- Not accurate for super luxury listings (price > $500 excluded)
- On an average, prediction is off by $30
- External validity: probably inaccurate for smaller cities with limited training data
- Price prediction is for the whole of NYC, not neighbourhood-wise

Improvement

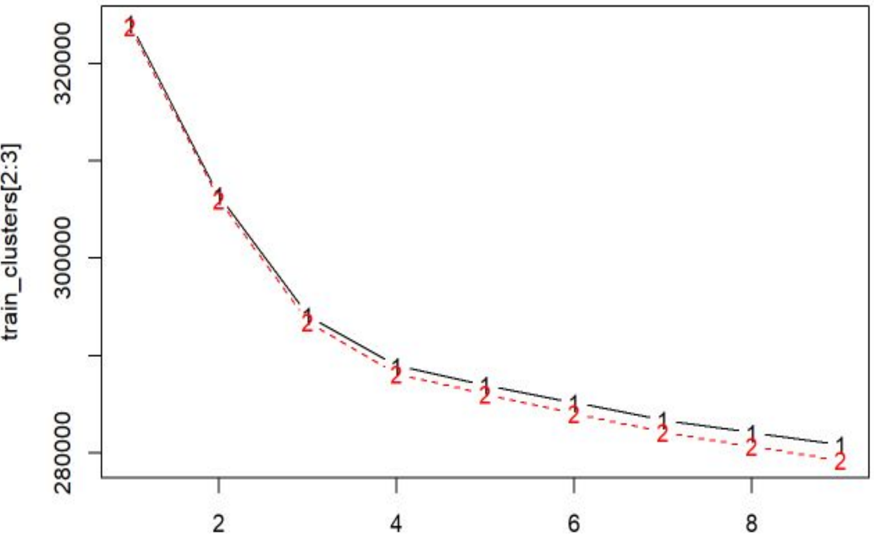
- Give a range of price, instead of a precise number
- Possible model improvements - feature selection in decision tree model, more clusters in cluster-wise decision tree model
- Neighbourhood-wise prediction instead of city-wise prediction (problem of limited data)

Appendix

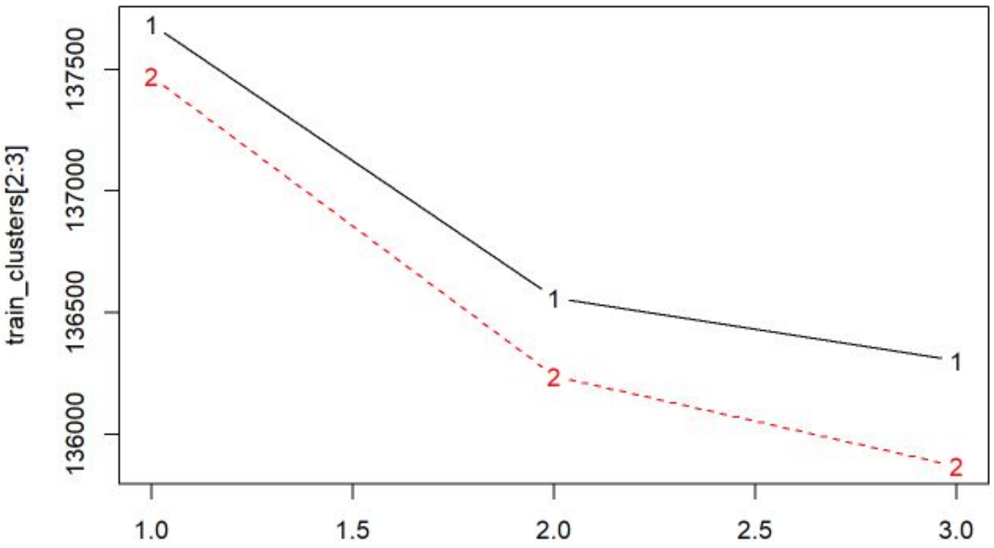
LCA Scree plots

- LCA AIC/BIC Plots

Amenities



Property Type



Regression Model Diagnostics

```
## Evaluate collinearity
vif(LinearModelFinal)
##                    GVIF  Df GVIF^(1/(2*Df))
## accommodates  1.409156   1        1.187079
## zipcode       1.305534 195        1.000684
## room_type     1.660918   3        1.088240
```

The result of vif () shows the GVIF value of each attribute is less than 5 which means the multicollinearity does not exist.