

Analysis on New York Airbnb Rent

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Overview

- House price is different over time and location leads to high cost for compare lots of house price.
- Common expenses of compare different house price
 - Room type
 - Longitude and latitude
 - Neighborhood group
- Customer often compare the similar house.
- The reasons for house price fluctuations are similar.

Problem Description

Goal

- Help customer more fast to get the good price for rental a house.
- To show how the different reasons to effect the house price.
- Provide factors to the house owner with which they can improve the house price increase.

Problem Description

Summary

- Predict the price for a house from the different location.
- Factors considered
 - Room type
 - House's longitude and latitude
 - Neighborhood group
- Performed data preparation, data analysis & data modelling.
- Developed machine learning models to predict the attrition.

Approaches / Techniques Used

1. KNN (Zheng Liu)
2. kkNN (Qianyi Zhang)
3. Naïve Bayes (Ziming Zhang)
4. Decision Tree (Ziming Zhang)
5. SVM (Qianyi Zhang)
6. ANN (Zheng Liu)
7. Random Forest (Zichong Wang)
8. C5.0 (Zichong Wang)

Solution

- Read the data set and analyze the data for some absent value.
- Convert data based on the algorithm requirement.
- Normalize the data for certain algorithms.
- Apply algorithms.
- Train the data.
- Predict the price for the house.
- Create visualization for some models.

Supervised Learning

KNN - K - Nearest-Neighbor

- The data points are predicted based on how its k nearest neighbor data are classified.
- The target variable is the “price” of aribnb in NYC based on correlated featrues which are :
 - Latitude & Longitude (location)
 - room type
 - reviews & availability (popularity)
- Normalization : Min - Max Normalization

KNN - K - Nearest-Neighbor Result

```
# Get 70% data as training set, 30% data as testing set.  
idx <- sort(sample(nrow(data),as.integer(.3*nrow(data))))  
training <- data[-idx,] # train 70% of the data  
test <- data[idx,] # test 30% of the data
```

```
[1] "k = 5 accuracy = 0.667094565682499"  
[1] "k = 15 accuracy = 0.694765368706319"  
[1] "k = 25 accuracy = 0.69248324062188"  
[1] "k = 35 accuracy = 0.696191698759093"  
[1] "k = 45 accuracy = 0.694622735701041"  
[1] "k = 55 accuracy = 0.693196405648267"  
[1] "k = 65 accuracy = 0.690486378547996"  
[1] "k = 75 accuracy = 0.692197974611325"  
[1] "k = 85 accuracy = 0.691056910569106"  
[1] "k = 95 accuracy = 0.694052203679932"  
[1] "k = 105 accuracy = 0.691342176579661"  
[1] "k = 115 accuracy = 0.689630580516332"  
[1] "k = 125 accuracy = 0.689487947511054"  
[1] "k = 135 accuracy = 0.68863214947939"  
[1] "k = 145 accuracy = 0.687776351447725"  
[1] "k = 155 accuracy = 0.687633718442448"  
[1] "k = 165 accuracy = 0.684923691342177"  
[1] "k = 175 accuracy = 0.685066324347454"  
[1] "k = 185 accuracy = 0.684067893310512"  
[1] "k = 195 accuracy = 0.682926829268293"
```

- Total data tested = 7012 (30% of original dataset)
- Table of prediction
- K = 35 can get the best performance.
- Accuracy: ~69.6%

Supervised Learning

kkNN

- Investigate whether neighbourhood_group, neighbourhood, room_type have an impact on price_level

```
> summary(data)
   neighbourhood_group      neighbourhood      room_type      price_level
Bronx        : 1090    Williamsburg       : 3919  Entire home/apt:25407  [0, 100)  :21866
Brooklyn     :20095    Bedford-Stuyvesant: 3710  Private room    :22319  [100, 200):17233
Manhattan    :21660    Harlem            : 2658  Shared room     : 1158  [200, +)   : 9785
Queens       : 5666    Bushwick          : 2462
Staten Island:  373    Upper West Side   : 1971
                  Hell's Kitchen     : 1958
                  (Other)           :32206
```

- K = 3

```
table(test$price_level,fit)
      fit
      [0, 100] [100, 200] [200, +]
[0, 100)    4809     1667      56
[100, 200)   1214     3614     418
[200, +)     225      2200     462
```

Accuracy: 60.6%

- K = 10

```
table(test$price_level,fit)
      fit
      [0, 100] [100, 200] [200, +]
[0, 100)    5336     1135      61
[100, 200)   1280     3370     596
[200, +)     227      2045     615
```

Accuracy: 63.6%

Supervised Learning

Naïve Bayes

- Assume that all the features are independent of each other
- The dependent variable: neighbourhood_group, neighbourhood, latitude, longitude, room type.

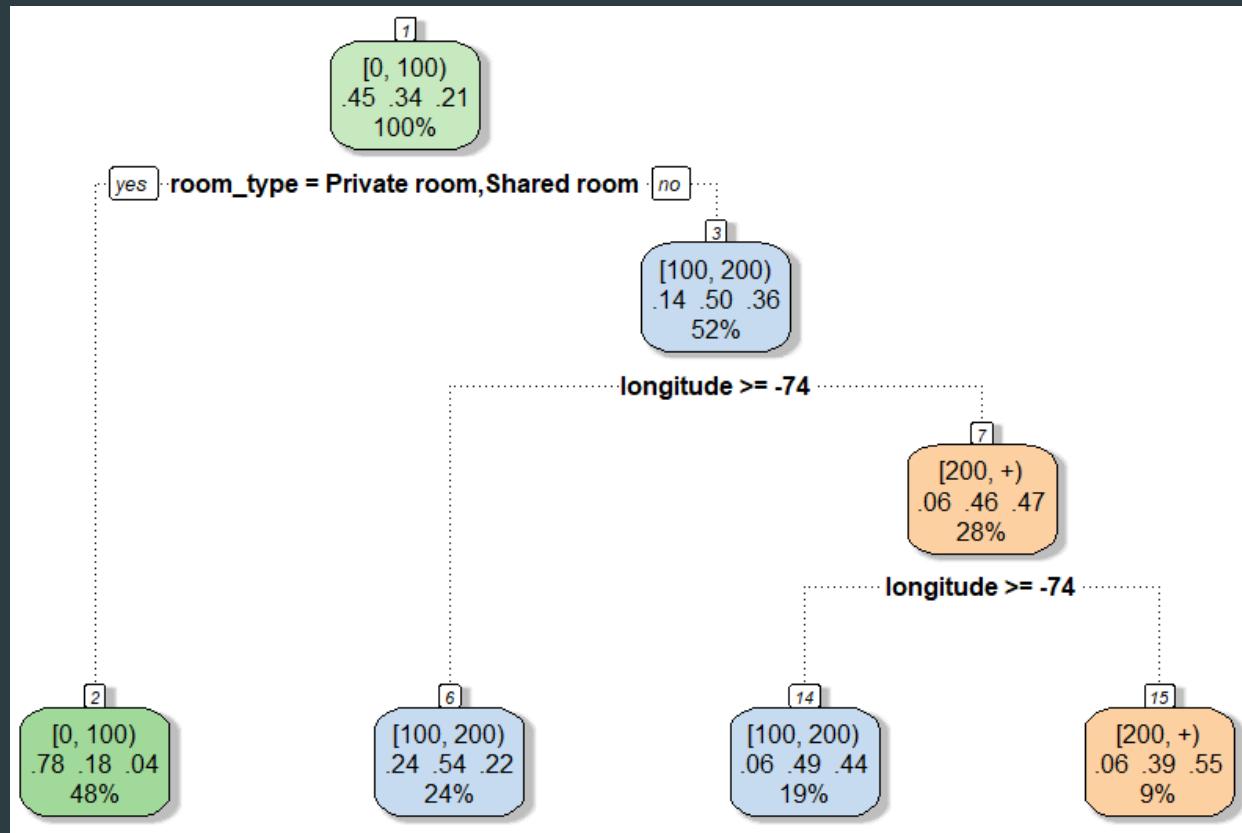
```
> conf_matrix  
  
predict      [0, 100] [100, 200] [200, +)  
[0, 100)      12074     2662     590  
[100, 200)    2715      5907     2375  
[200, +)      540       3456     3899  
  
> prop.table(conf_matrix)  
  
predict      [0, 100] [100, 200] [200, +)  
[0, 100)  0.35285522 0.07779531 0.01724239  
[100, 200) 0.07934420 0.17262844 0.06940791  
[200, +)   0.01578117 0.10099947 0.11394588  
  
> #Measure the accuracy  
> accuracy <- function(x){sum(diag(x))/(sum(rowSums(x)))}  
> print(paste("Accuracy:", accuracy(conf_matrix)))  
[1] "Accuracy: 0.639429540008183"  
>
```

Accuracy: 63.94%

Supervised Learning

Decision Trees

- Decision tree is a basic classification and regression method. The decision tree model has a tree structure. It can be thought of as a collection of if-then rules.
- Use the CART algorithm.
- The dependent variable : latitude, longitude, room type.



```
> table(Actual=test_data[,4],CART=pred)
          CART
Actual      [0, 100) [100, 200) [200, +)
[0, 100)    12738     2329     193
[100, 200)   3050     8013    1137
[200, +)     645     4621    1492
> # Compare the prediction to actual data and calculate the accuracy
> right<- (test_data[,4]==pred)
> accuracy<-sum(right)/length(right)
> print(paste("Accuracy : ", accuracy))
[1] "Accuracy : 0.650037991700275"
```

Accuracy: 65.00%

Supervised Learning

Support Vector Machines (SVM)

- Investigate whether neighbourhood_group, neighbourhood, room_type have an impact on price_level

```
> summary(data)
   neighbourhood_group      neighbourhood      room_type      price_level
Bronx        : 1090    Williamsburg       : 3919  Entire home/apt:25407  [0, 100)   :21866
Brooklyn     :20095    Bedford-Stuyvesant: 3710  Private room     :22319  [100, 200):17233
Manhattan    :21660    Harlem            : 2658  Shared room      :1158   [200, +)    : 9785
Queens       : 5666    Bushwick          : 2462
Staten Island:  373    Upper West Side    : 1971
                  Hell's Kitchen      : 1958
                  (Other)           :32206
```

		true		
		[0, 100)	[100, 200)	[200, +)
pred	[0, 100)	5582	1242	309
	[100, 200)	1039	3480	2038
	[200, +)	22	344	609

Accuracy: 65.9%

Supervised Learning

Artifical Neural Network

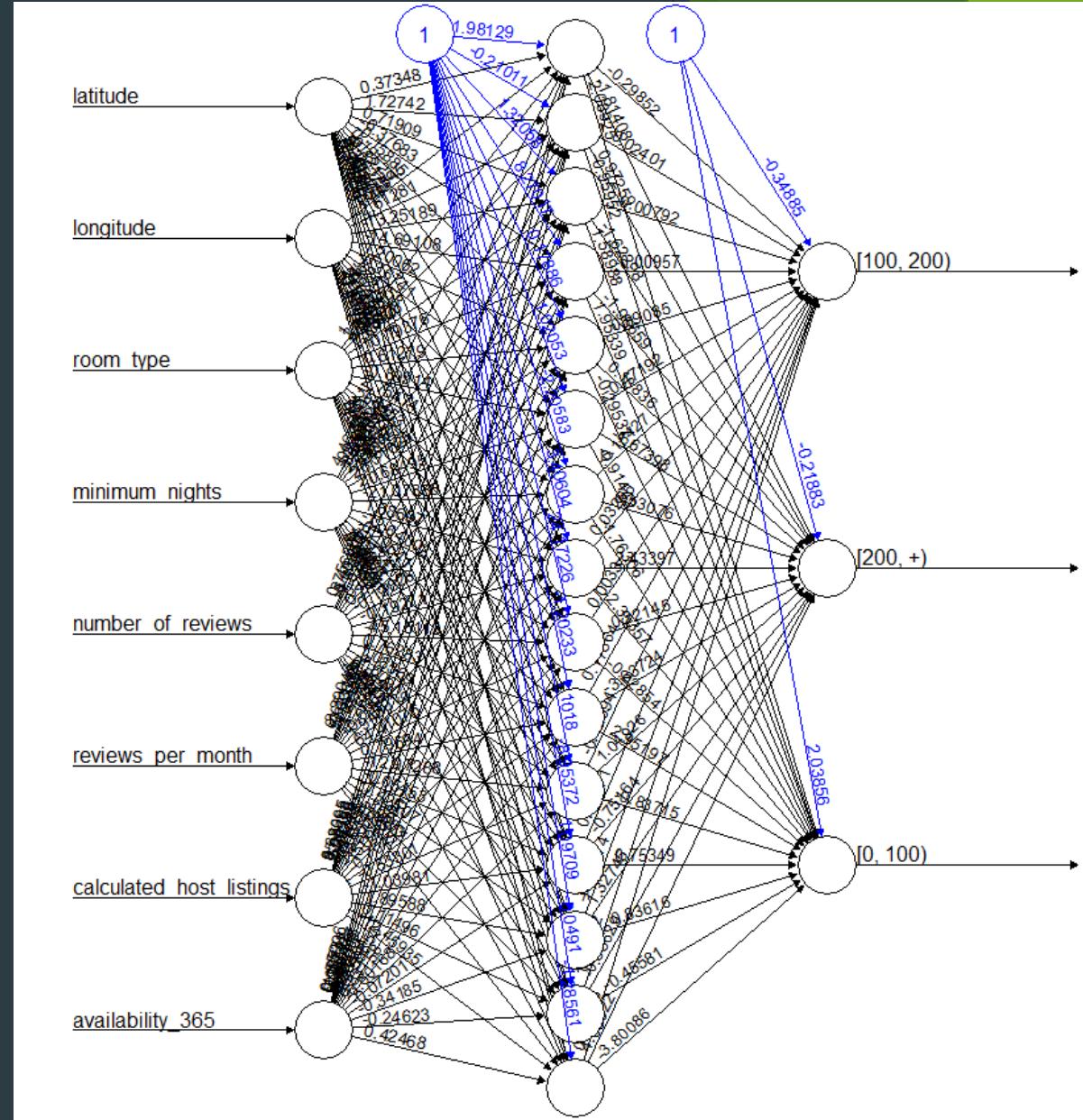
- Stimulate the behaviour of biological system composed of neurons.
- The target variable is the “price” of aribnb in NYC based on correlated featrues which are :
 - Latitude & Longitude (location)
 - room type
 - reviews & availability (popularity)
- Normalization : Min - Max Normalization
- Hidden Node : 15

Supervised Learning

Artifical Neural Network

Accuracy ~ 69.8%

```
prediction
Actual      [100, 200] [200, +)
[0, 100)      1      0
[100, 200)    2190    416
[200, +)     1695    2710
> wrong<- (test$price_level!=ann_cat)
> error_rate<-sum(wrong)/length(wrong)
> error_rate
[1] 0.3011979
> accuracy <- 1 - error_rate
> accuracy
[1] 0.6988021
```



Supervised Learning

Random Forest

- It is unexcelled in accuracy among current algorithms.
- It runs efficiently on large data bases.
- It can handle thousands of input variables without variable deletion.
- It gives estimates of what variables are important in the classification.
- It generates an internal unbiased estimate of the generalization error as the forest building progresses.
- It has an effective method for estimating missing data and maintains accuracy when a large proportion of the data are missing.

Prediction			
	[0, 100)	[100, 200)	[200, +)
[0, 100)	4503	959	68
[100, 200)	824	2688	787
[200, +)	153	1140	1099

Overall Statistics

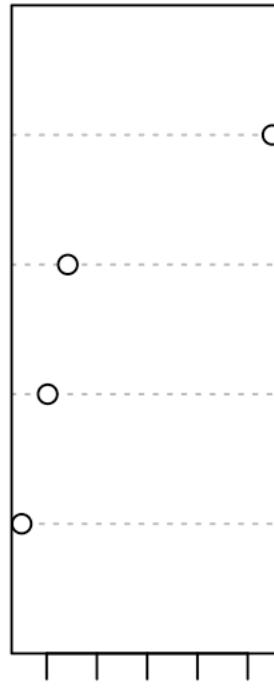
Accuracy : 0.6783
95% CI : (0.67, 0.6866)
No Information Rate : 0.4484
P-Value [Acc > NIR] : < 2.2e-16
Kappa : 0.4878

Accuracy: 67.83%

Supervised Learning

randomForest_class

room_type



MeanDecreaseAccuracy

room_type

longitude

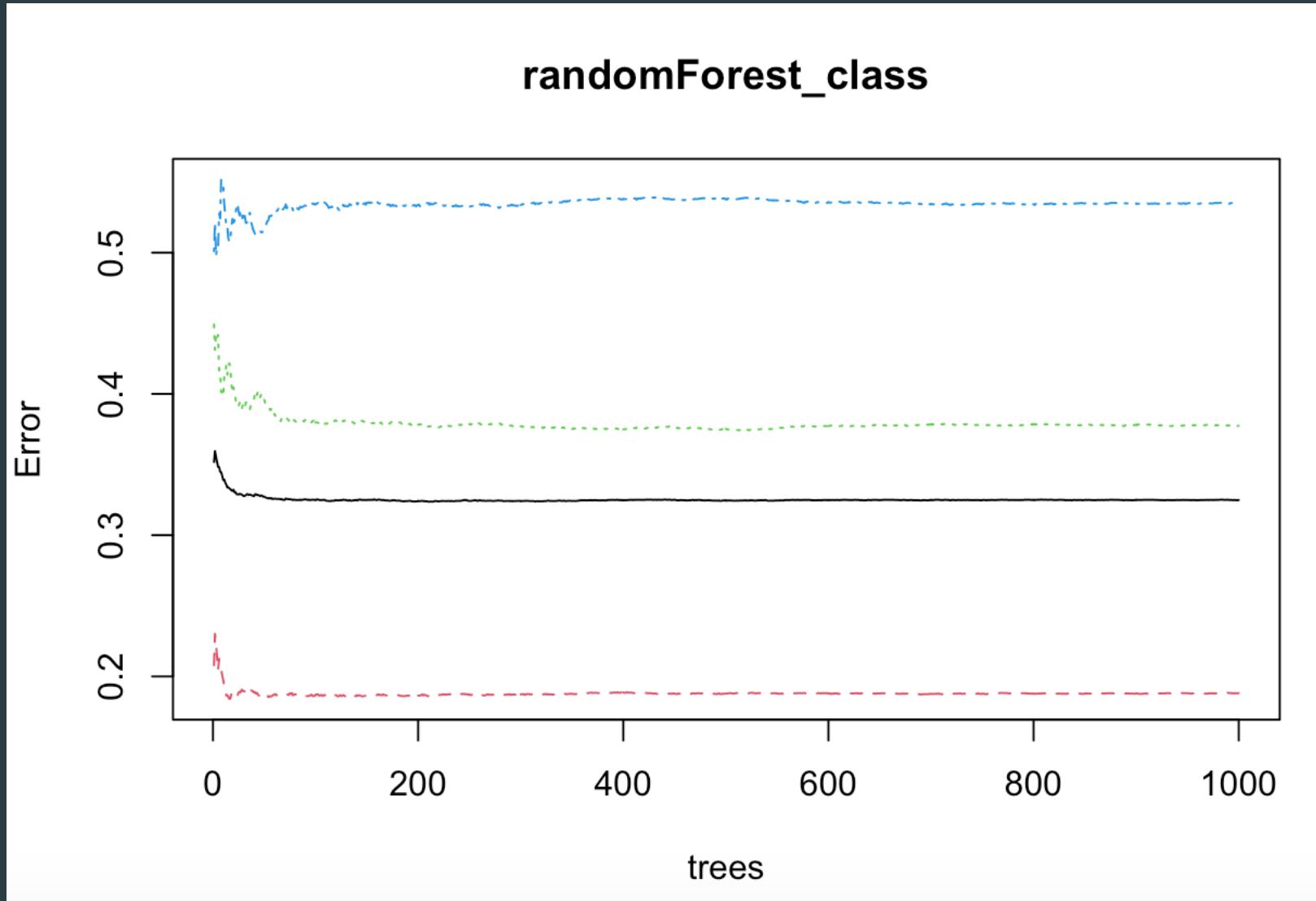
latitude

neighbourhood_group



MeanDecreaseGini

Supervised Learning



Supervised Learning

C5.0

- C5.0 is a classification algorithm that C4.5 is applied to large data sets, mainly in terms of execution efficiency and memory usage.
- It works by splitting the sample based on the field that provides the maximum information gain.
- Use Boosting to improve model accuracy.
- The C5.0 model is very good to fix the missing data and many input fields.

Accuracy: 68.1%

Confusion Matrix and Statistics

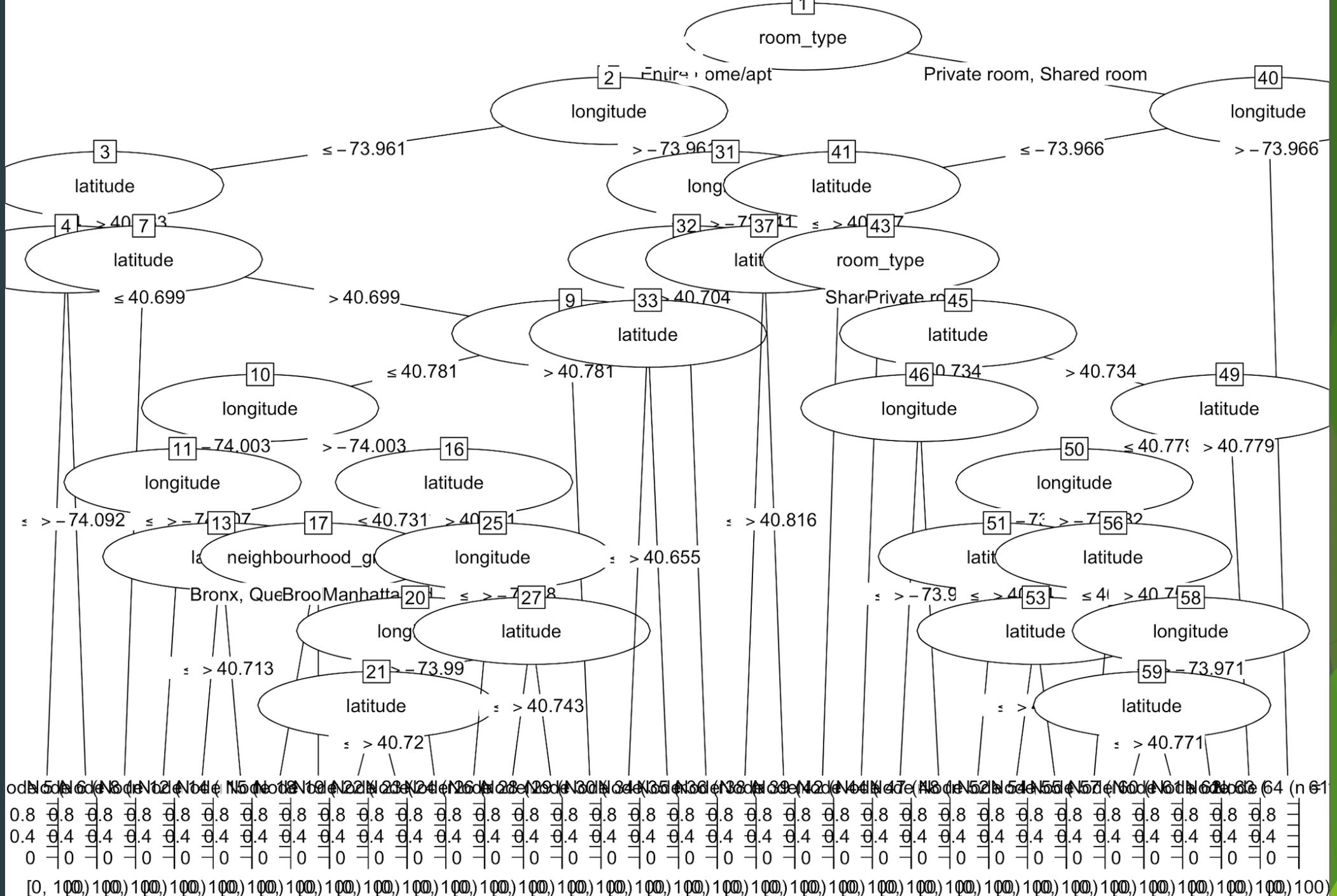
Prediction	Reference		
	[0, 100)	[100, 200)	[200, +)
[0, 100)	4571	903	56
[100, 200)	926	2619	705
[200, +)	158	1150	1133

Overall Statistics

Accuracy : 0.681
95% CI : (0.6727, 0.6893)
No Information Rate : 0.4627
P-Value [Acc > NIR] : < 2.2e-16

Kappa : 0.4911

McNemar's Test P-Value : < 2.2e-16



Conclusion

- ◀ We should choose the reasonable model based on the characteristics of the data. The difference in the results of the same data using different models may be very large.
- ◀ The training set with more data can make model be more accurate.
- ◀ When we filtered the data first, we have initially selected several important factors that may affect rental prices
- ◀ It can be known from the results predicted by the models, the location(neighborhood group) and neighborhood are the two main factors leading to different rental prices.
- ◀ The effect of room type on rental prices is obvious.

Future Work

- ◀ We can estimate a reasonable price based on various information about the house for new landlords.
- ◀ We can quickly match suitable house according to tenants' various requirements for house.
- ◀ When more and more features are added to the house, we can try new machine learning techniques to discover new features affecting rental prices.