

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)

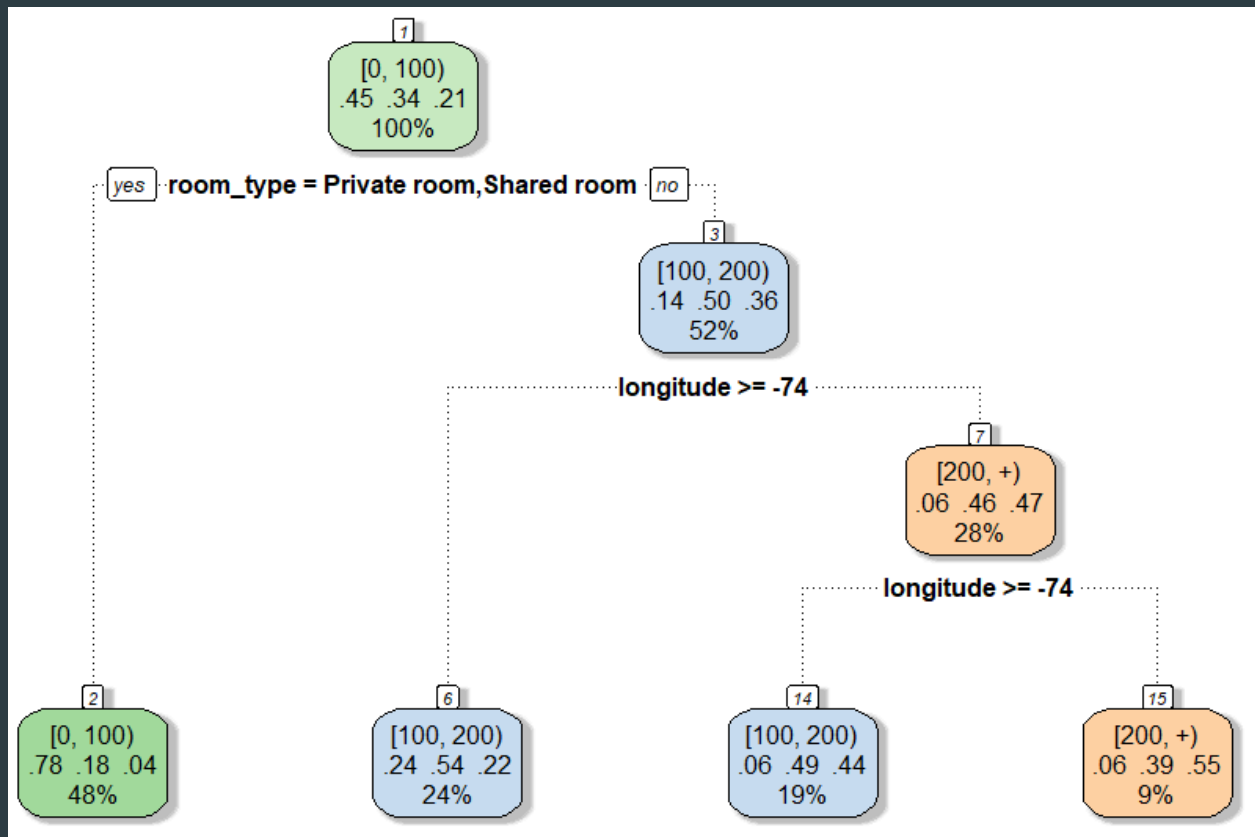
predict      [0, 100) [100, 200) [200, +)
[0, 100)      0.35285522 0.07779531 0.01724239
[100, 200)     0.07934420 0.17262844 0.06940791
[200, +)       0.01578117 0.10099947 0.11394588
> #Measure the accuracy
> accuracy <- function(x){sum(diag(x)/(sum(rowSums(x))))}
> print(paste("Accuracy:", accuracy(conf_matrix)))
[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		
pred	[0, 100)	[100, 200)	[200, +)
[0, 100)	5582	1242	309
[100, 200)	1039	3480	2038
[200, +)	22	344	609

Accuracy: 65.9%

Supervised Learning

Artificial Neural Network

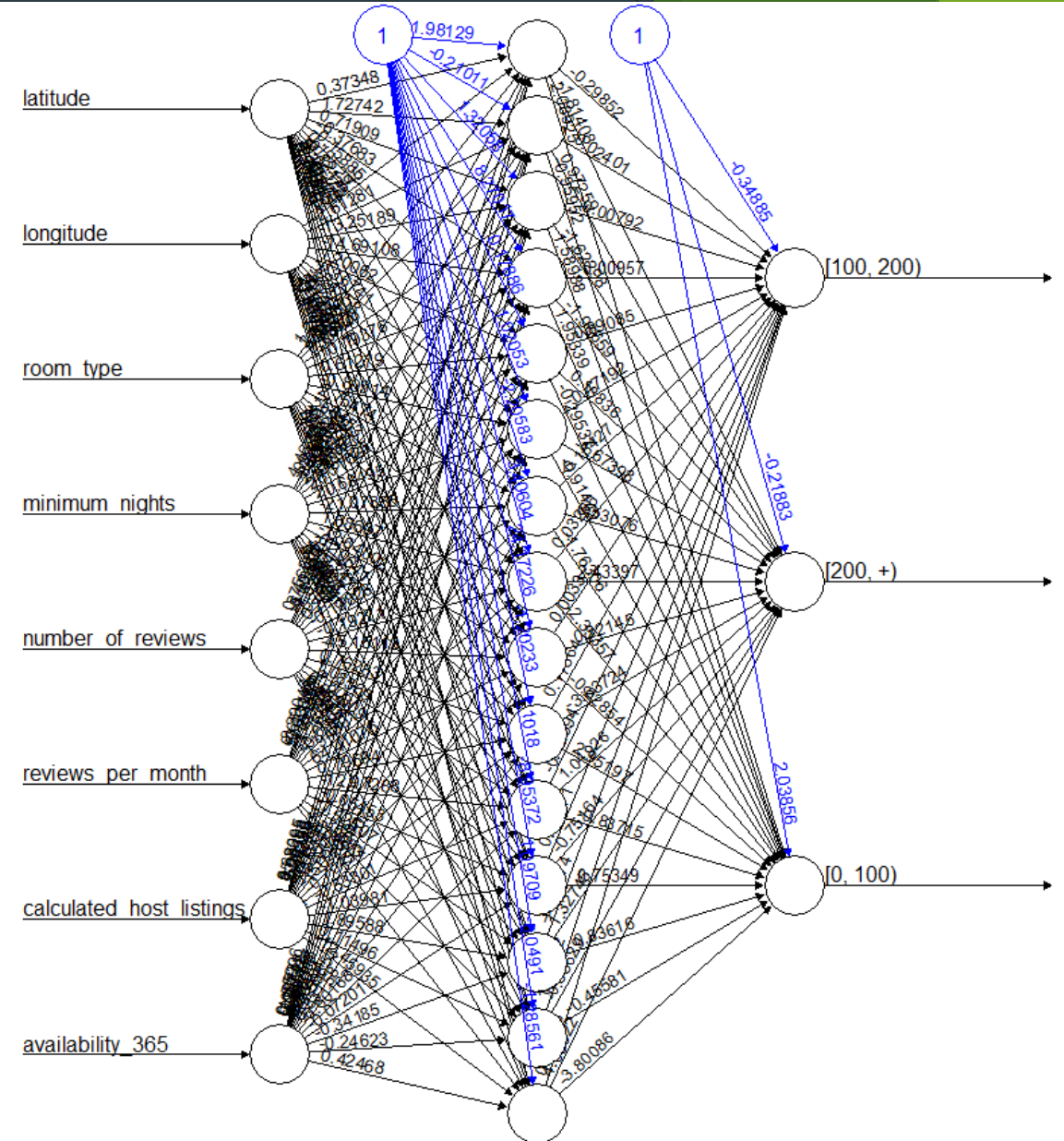
- Stimulate the behaviour of biological system composed of neurons.
- The target variable is the “price” of aribnb in NYC based on correlated featrues which are :
 - Latitude & Longitude (location)
 - room type
 - reviews & availability (popularity)
- Normalization : Min - Max Normalization
- Hidden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

Supervised Learning

Artificial Neural Network

Accuracy ~ 69.8%

```
Actual      predition
[0, 100)    [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

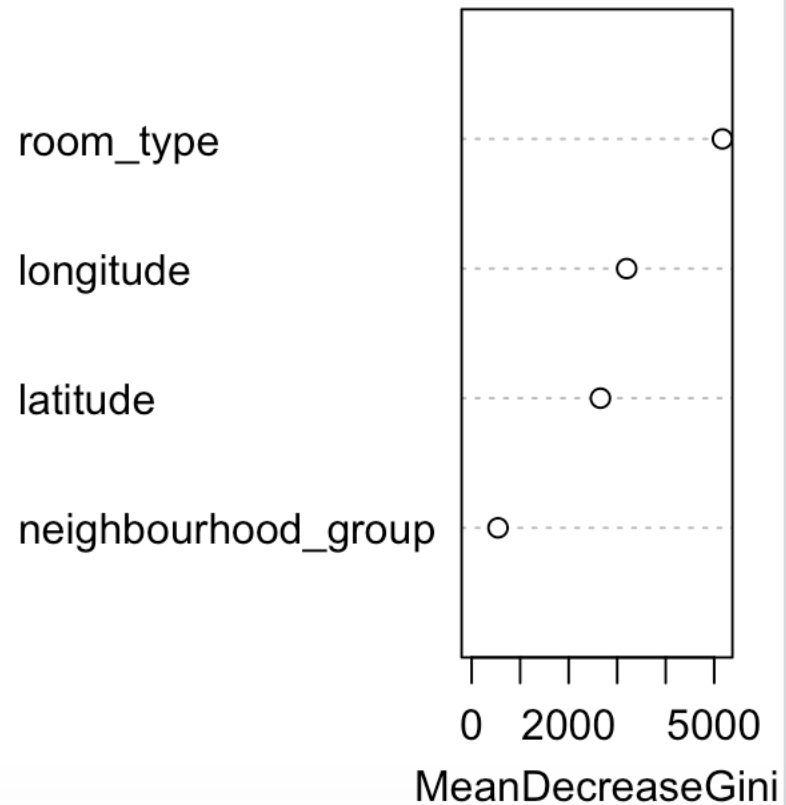
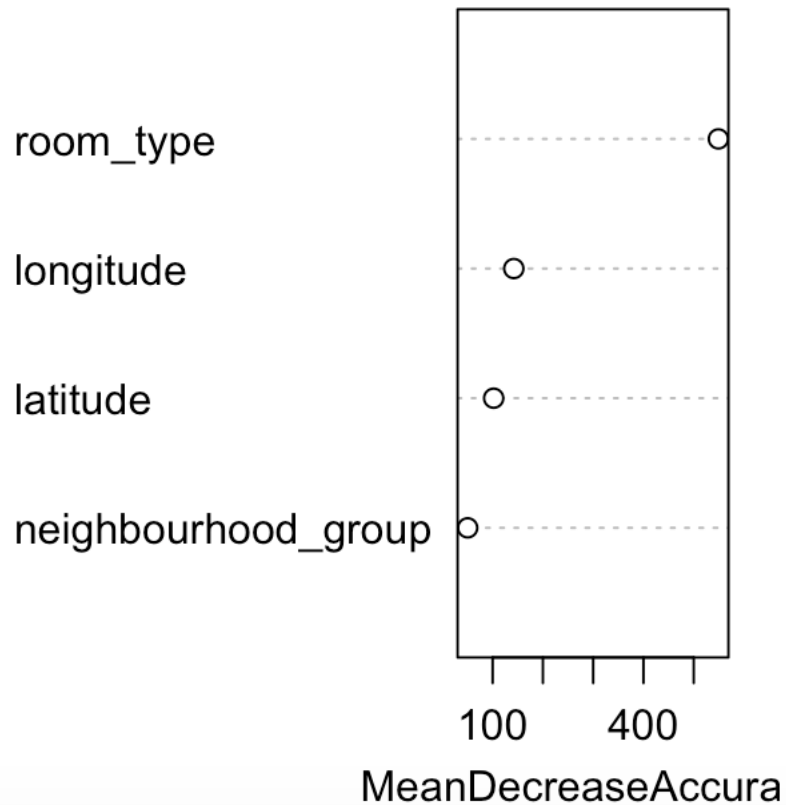
Accuracy : 0.6783
95% CI : (0.67, 0.6866)
No Information Rate : 0.4484
P-Value [Acc > NIR] : < 2.2e-16

Kappa : 0.4878

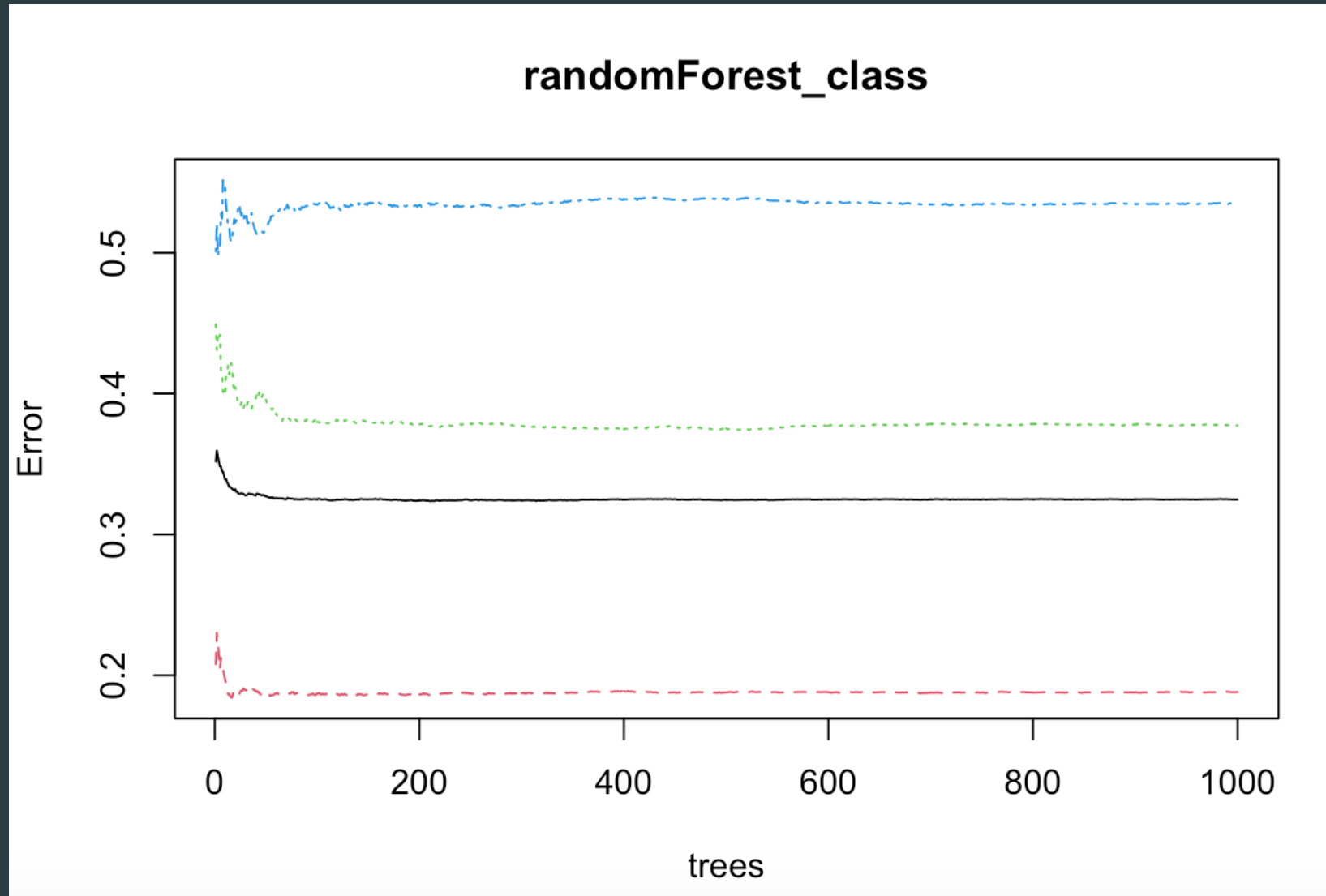
Accuracy: 67.83%

Supervised Learning

randomForest_class



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

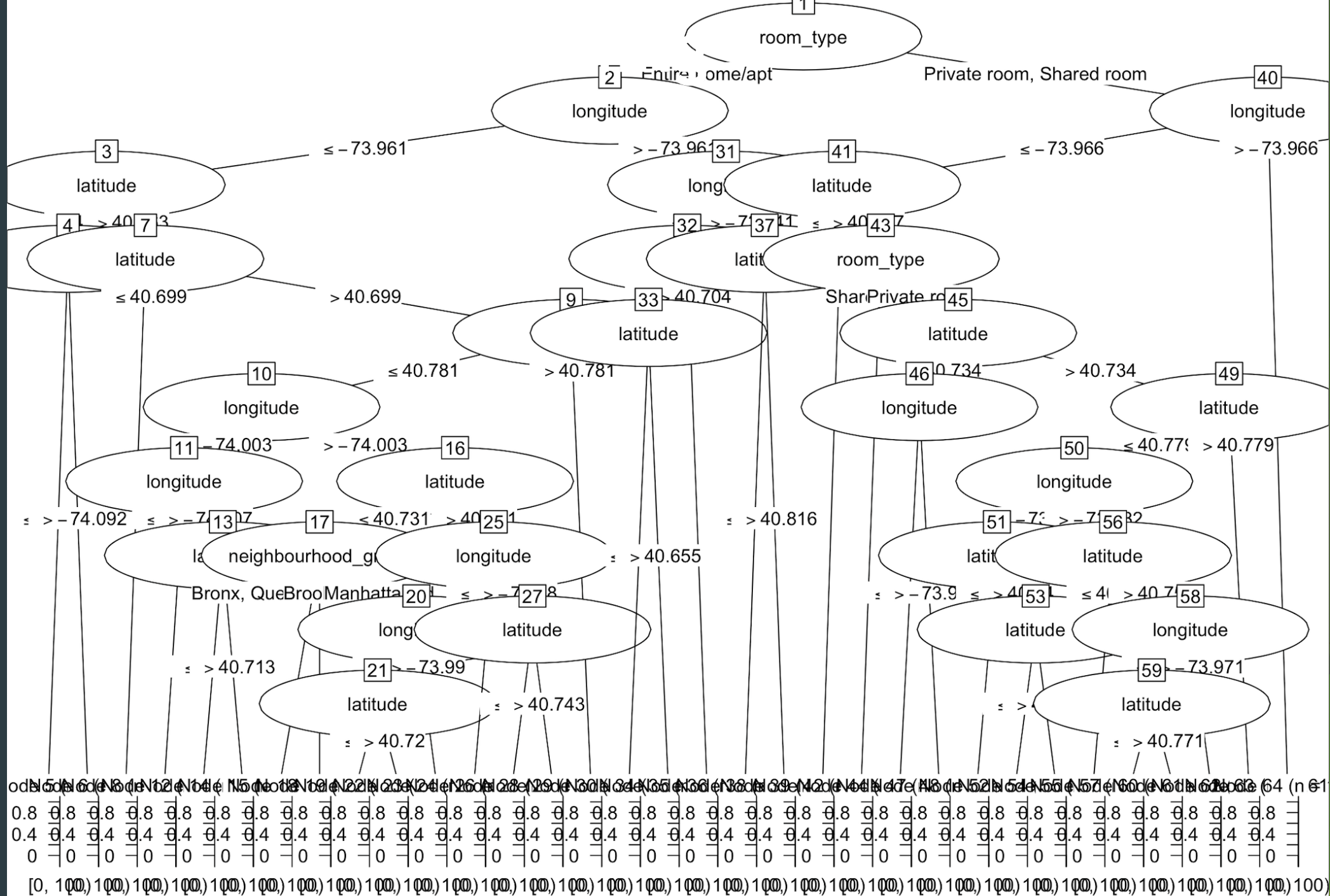
	Reference		
Prediction	[0, 100)	[100, 200)	[200, +)
[0, 100)	4571	903	56
[100, 200)	926	2619	705
[200, +)	158	1150	1133

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.