airbnb
Booking Price Prediction

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Introduction

i. Background

There are plenty of benefits from Airbnb Sharing Economy, as the environmental benefits. It has become a greener way to travel. While there are several advantages to live in Airbnb, it comes with several difficulties for the operators and Property Owners. Online Airbnb websites have hundreds of rental housing available. Determining the right price for one accommodation becomes difficult because of too much house pricing on the list. To solve the supply and demand problem for housing, they need to know an optimal pricing strategy. The pricing Recommender system could help hosts by suggesting a probable list of suggested room price from which they can select the optimized one. The pricing recommender system could make operators aware of similar rental housings which are available to provide for customers. For this report, I will present a detailed and systematical analysis of building a price recommender system.

Method

1. Data Source

This “listings” dataset consists of 45053 observations with 17 variables. Each row corresponds to a customer booking history record. To bring the data into a consistent format, several steps of data cleaning are taken, including dropping unnecessary columns, checking for

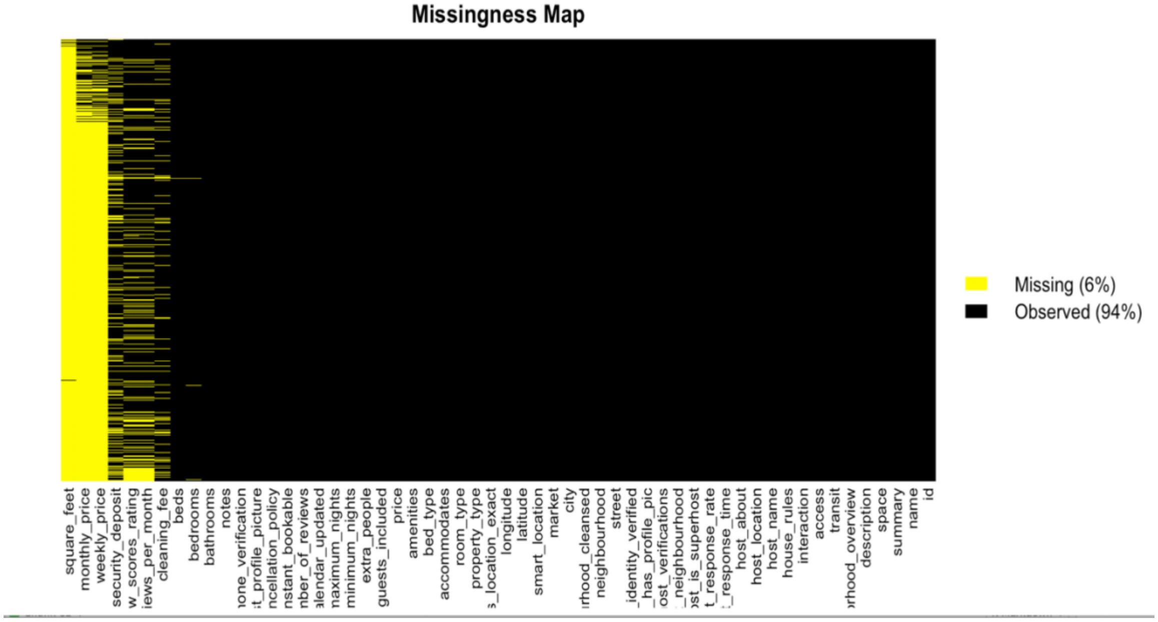


Table 2.1

checking for invalid data. Unnecessary columns including “scrape_id”,” review_scores_location”,” review_score_communication” which are irrelevant to the main content of data analysis and those variables are removed from the “listing” dataset. Those time variables, including “first review”, “last review”, “calendar_last_scraped” are invalid data since structure, are read in date number only. We see that in Table 1.1 there are too many missing values on variable “square_feet”, “monthly_price” and “weekly_price”. The rows with any of these missing values will, therefore, be removed. Finally, check columns names and make sure the name of each variable makes sense

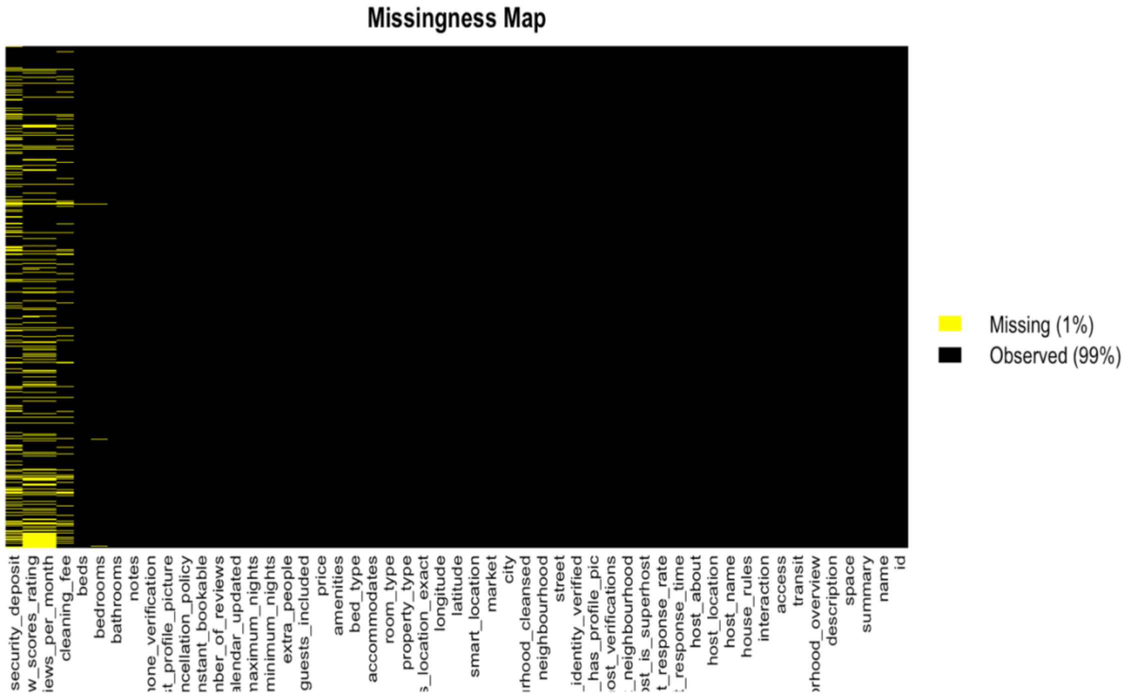


Table 2.2

Some essential variables that datasets provide are (after dropping duplicate records and deal with missing values and outliers):

- Bedrooms: Positive integer documenting the number of bedrooms in each booking record
- Neighborhood: the neighborhood of the listing
- Accommodates: the number of guests that the rental can accommodate

Another dataset named “reviews_final” contain customer reviews on Airbnb booking website.

2. Model Used

Models in this report include multiple regressions, logistic regression and multilevel regression. It is not likely that all observations coming from the same neighborhood group are similarly independent, and sometimes it might have skewed residuals. Multilevel Regressions are analyzed by different groups. Response variables measuring from each rental record can reasonably be assumed independent. Particular customers in specific neighborhood group tend to have a relatively high possibility of renting higher price of housing, so that know the average group price of renting makes it more likely that range of prediction price would somewhere near the average price in that particular group.

3. Visualization Used

1. univariate summary
   Uni-variate exploration includes bar plot, pie chart for price and covariate (security deposit, guests_included, cleaning fees. etc.) respectively
2. Bivariate summaries
3. Bivariate exploration includes an examination of numerical and graphical summaries of the relationship between price and covariate (security deposit, guests_included, cleaning_fees. etc.). Graphs include boxplot and scatter plot.

Result

For Exploratory Data Analysis, it includes several aspects, such as reviews text analysis, neighborhood analysis, group analysis, room type analysis, price analysis, mapping of restaurants, and property type analysis.

1. Reviews Text analysis

Customer reviews could offer tremendous insights into what customers like and dislike about the rental experience. Existing reviews always heavily influence the booking decision of new customers. Based on the variable concerning the customer reviews, the next step is to use the word cloud graph to identify the most frequently used words in the customer review.
While comparing words with different colors, we observe that top three most frequently used words in the customer review in table 2.1 are “stay”, “location”, “clean”, which gives us a reason to believe that most Airbnb houses’ comfortableness is essential. From these results, we can infer that location and cleanness might be crucial for customers to consider.

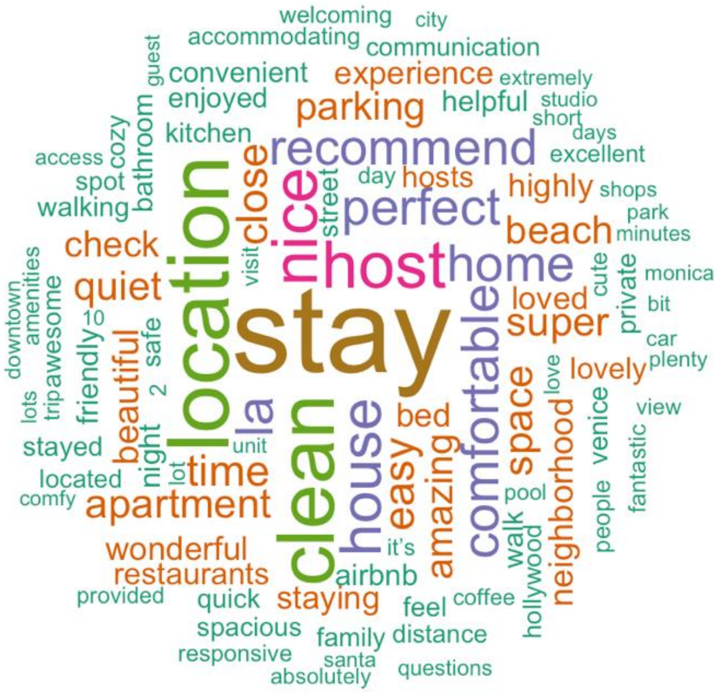
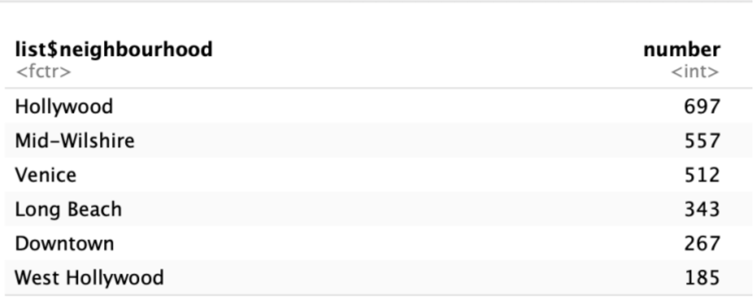


Table 3.1

2. Neighborhood Analysis

Now, looking at the graphs 2.2 below, we can see that the most significant number of booking is in the Hollywood area, which contains 697. Neighborhood analysis helps to understand the booking popularity in each neighborhood. Based on that, I would say that the larger the number of booking in that area is, the higher the demand for renting.



list$neighbourhood <fctr>	number <int>
Hollywood	697
Mid-Wilshire	557
Venice	512
Long Beach	343
Downtown	267
West Hollywood	185

Table 3.2

3.Group Analysis

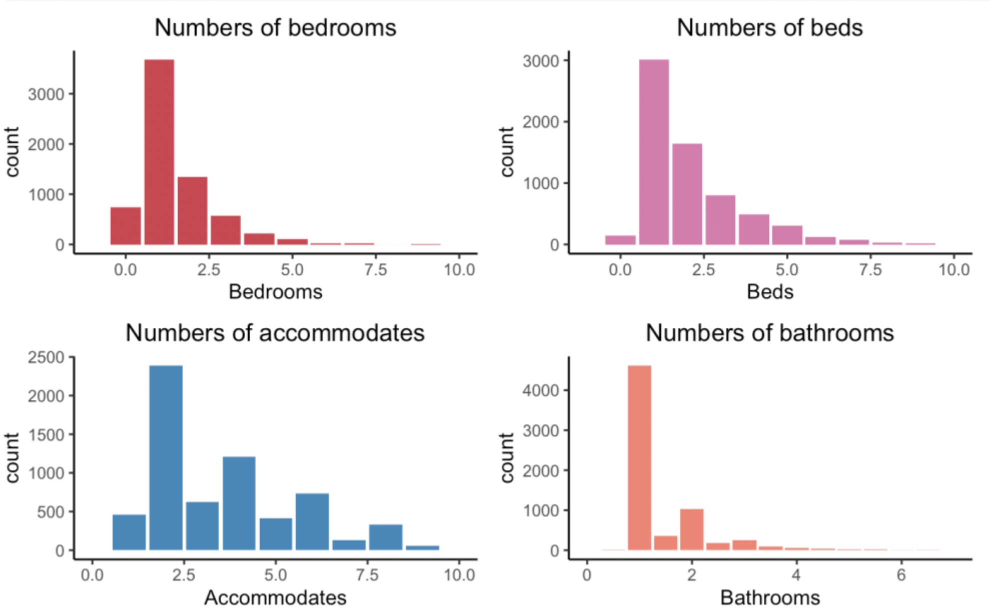
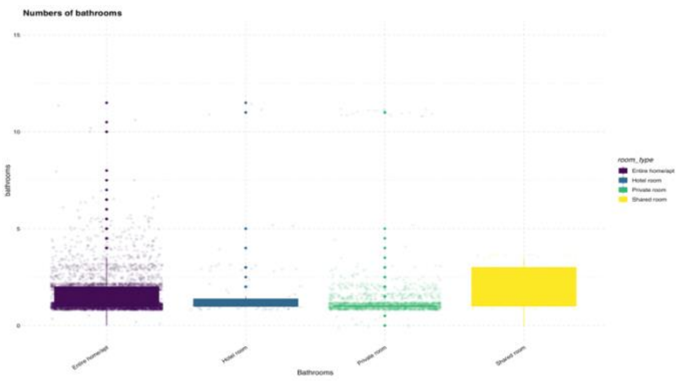
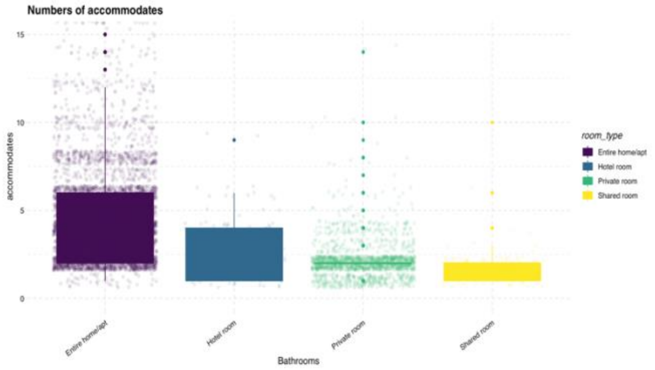


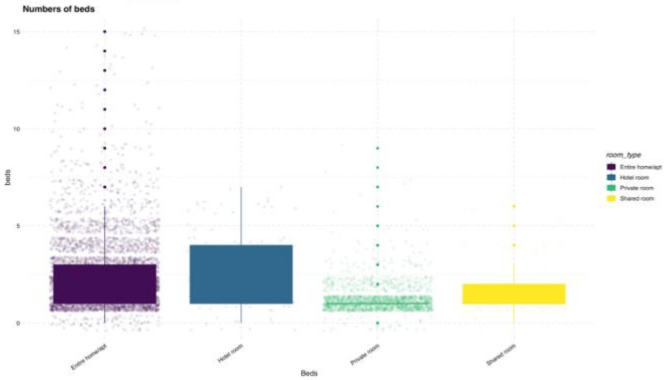
Table 3.3

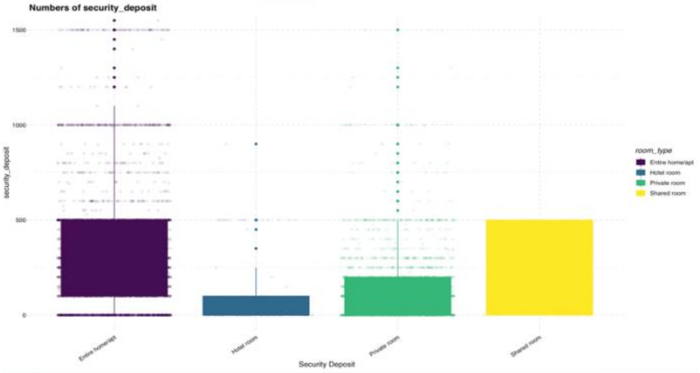
Each color indicates the distribution of one variable. There are four variables in this analysis, including bedrooms, beds, accommodates and bathrooms. To identify the total characteristics of booking, I count the number of observations of each group and plot bar graphs. An unusual situation can notice with the number of bedrooms and beds on the chart above, where we see that some of the housing does not have bedrooms or beds. It can be inferred that the demand for booking on Airbnb is not always belonged to the usual style of living. There might be tents in the living rooms etc. From the results, we observe that the majority number of beds, bedrooms and accommodates center at one and two. With the finding on the graph above, it would be promising for the host to try housing rental with a unique theme, which is also expected.

4. Room Type Analysis




Numbers of accommodates
15
10
5
0
accommodates
Entire home/apt
Hotel room
Private room
Shared room
Bathrooms
room_type
Entire home/apt
Hotel room
Private room
Shared room


Numbers of beds
15
10
5
0
beds
Entire home/apt
Hotel room
Private room
Shared room
Beds
room_type
Entire home/apt
Hotel room
Private room
Shared room


Numbers of security_deposit
1500
1000
500
0
security_deposit
Entire home/apt
Hotel room
Private room
Shared room
Security Deposit
room_type
Entire home/apt
Hotel room
Private room
Shared room

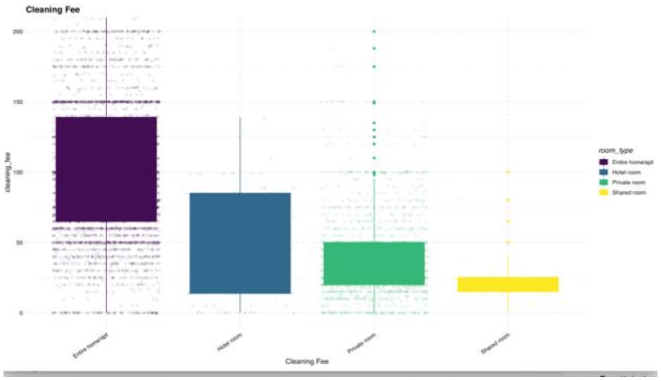
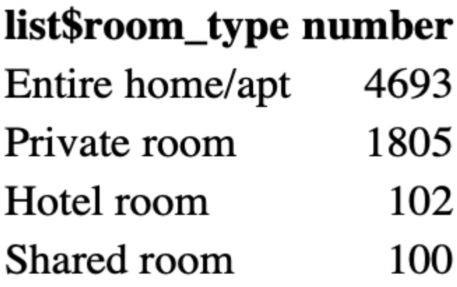


Table 3.4

From the boxplot above, entire home/apartment tend to have a more significant number of accommodates. The boxplot with cleaning fee shows higher cleaning fee is in a broader range. For the number of the security deposit, the shared room has more significant standard deviations from the center as compared to another room type. When looking at the boxplots on the number of beds and bedrooms, both private rooms have a short average compared to entire home/apt, and this may be because there are small varieties in private rooms.



list$room_type	number
Entire home/apt	4693
Private room	1805
Hotel room	102
Shared room	100

Table 3.5

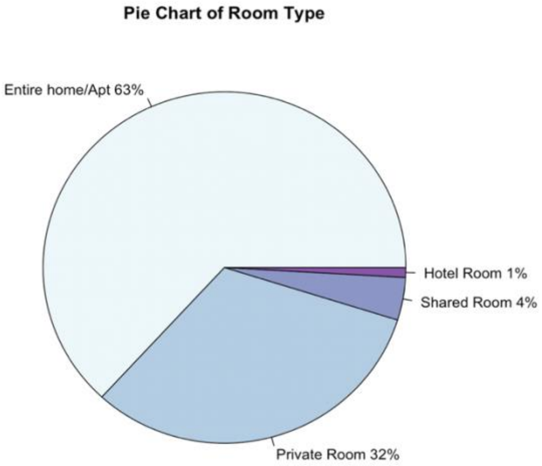


Table 3.6

I then visualized the number of booking record in each room type on the pie chart. Dark purple corresponds to the hotel room, which accounts for 1%, and light purple compares to a shared room with about four percent. The highest proportion of room type in the dataset for all bookings is about 63 percent, which belongs to the entire home/apt.

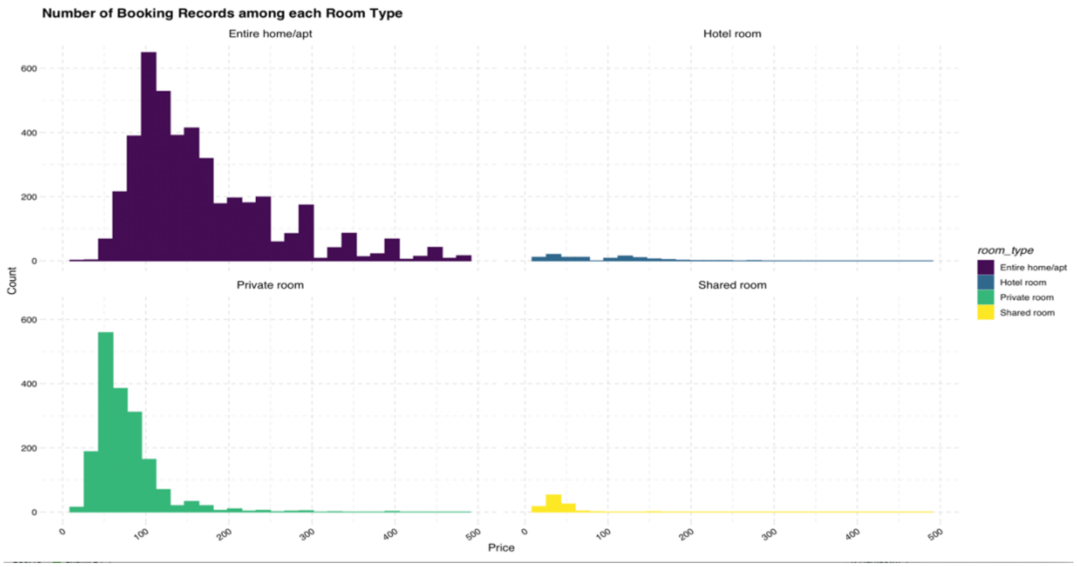


Table 3.7

The number of booking records based on room type is in the range between zero and five hundred as expected shows that most private room has priced in the range between zero and three hundred, with significant peaks in around seventy-five. Similarly, for the entire home/apt, there are lower price booking than the price which over three hundred. We can see a peak of around one hundred.

4. Price Analysis

The following plot shows the distribution of price lower than five hundred among all observations. As we know, the majority of housing would have a similar amount if they have the same location and size; this can also be inferred from the graph. The majority of the observations in the data frame are lower than two hundred and fifty.

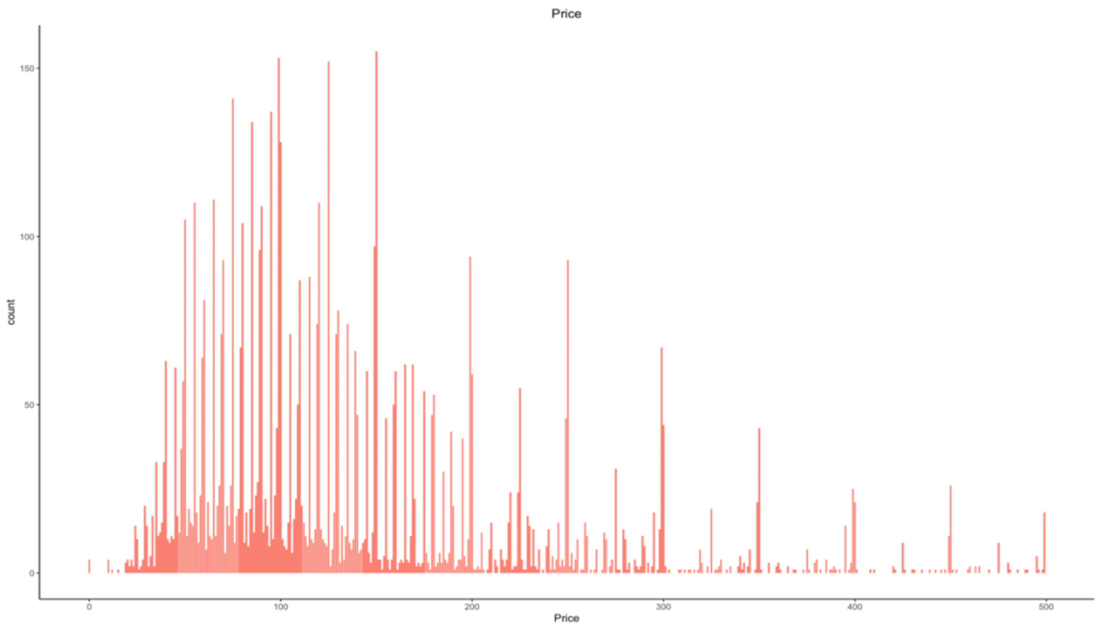


Table 3.8

6. Mapping of Rental Housing

The map below shows the location of Airbnb housing in Los Angela. There is a large number of certain house areas. This is likely to be correlated with surroundings. Since Hollywood, Mid-Wilshire and Venice are the most developed and popular area compared to other neighborhoods. Higher demand leads to a large amount of housing for rental.

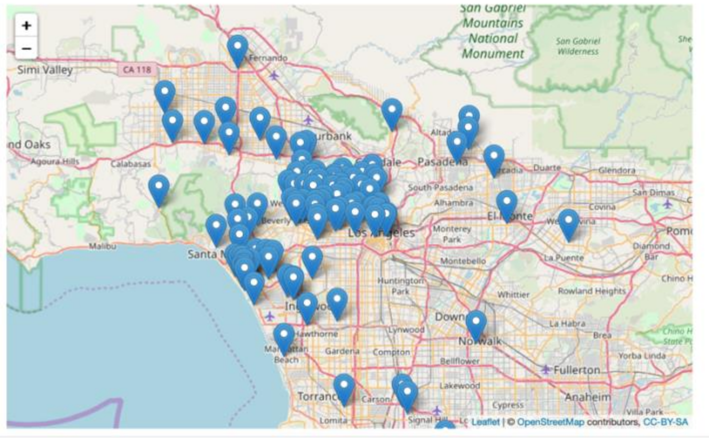


Table 3.9

7. Property Type Analysis

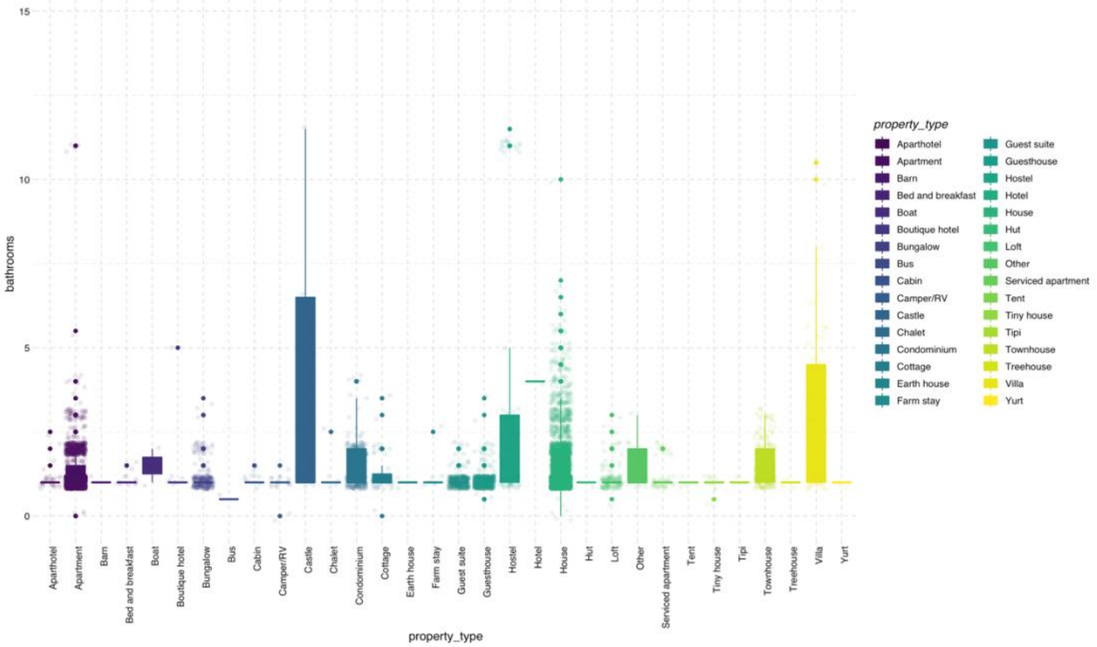


Table 3.10

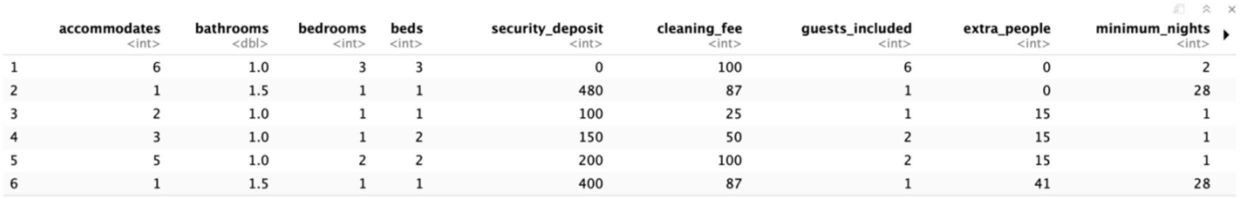
Instead of categorizing booking records based on room type, I would like to investigate the number of bathrooms grouped by property type. As you can see, the number of bathrooms in the castle has a more significant standard deviation from the mean.

Discussion

The task of the machine learning algorithms is to build models that for a given rental booking what price it is.

1. Multiple Regressions

I examine the factors predicting the Airbnb rental price at Los Angela’s. Table below are variables that might be considered into price prediction.



	accommodates	bathrooms	bedrooms	beds	security_deposit	cleaning_fee	guests_included	extra_people	minimum_nights
	<int>	<dbl>	<int>	<int>	<int>	<int>	<int>	<int>	<int>
1	6	1.0	3	3	0	100	6	0	2
2	1	1.5	1	1	480	87	1	0	28
3	2	1.0	1	1	100	25	1	15	1
4	3	1.0	1	2	150	50	2	15	1
5	5	1.0	2	2	200	100	2	15	1
6	1	1.5	1	1	400	87	1	41	28

Table 4.1

i. Model Selection

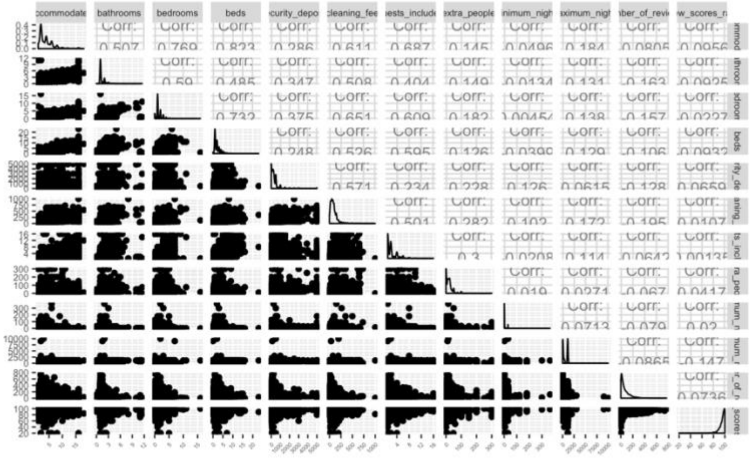


Table 4.2

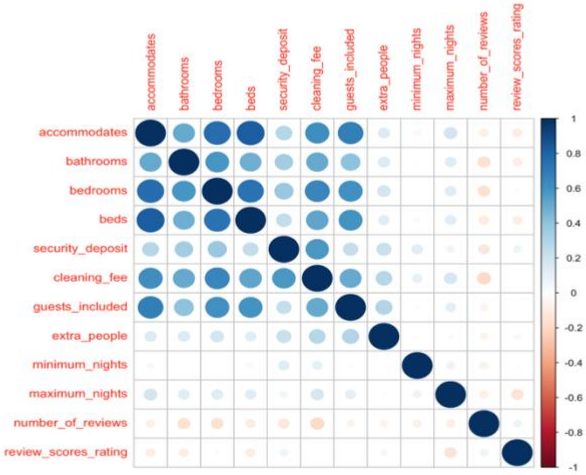
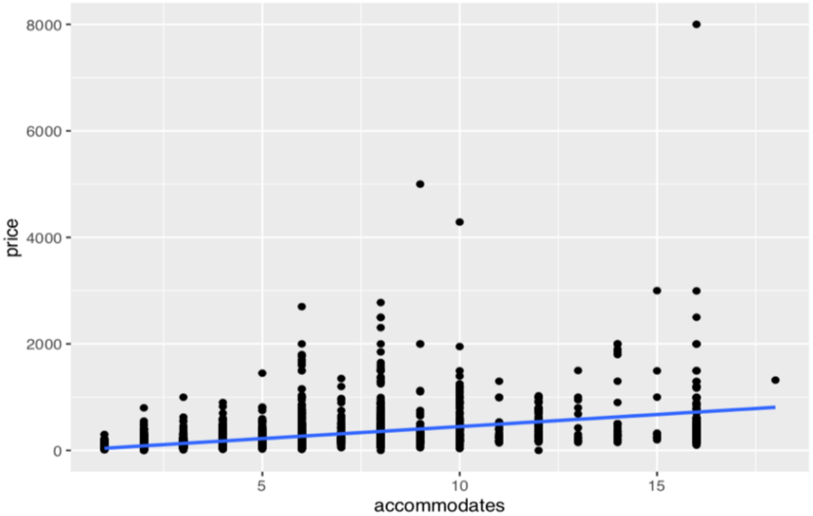


Table 4.3

After making correlation graphs among variables, I had about half of variables that have large correlations. Accommodates and beds/bedrooms are correlated positively based on the graph above. Additionally, we can notice that accommodates are not strongly correlated with some other variables, such as "number of reviews", "review scores rating" etc., Although there is no strong positive relationship among variables that I've mentioned above, they are not negatively correlated to each other.



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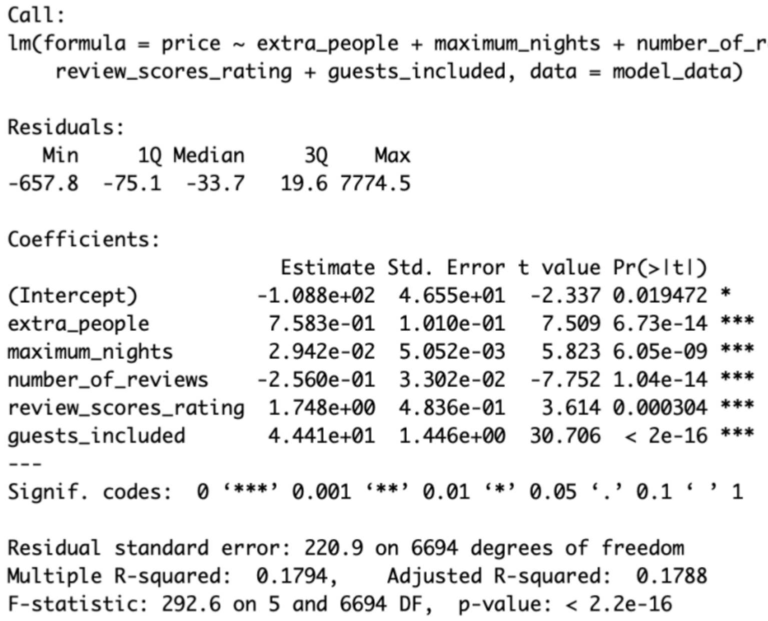
ii. Interpretation

The first attempt uses the following model to predict the prices:

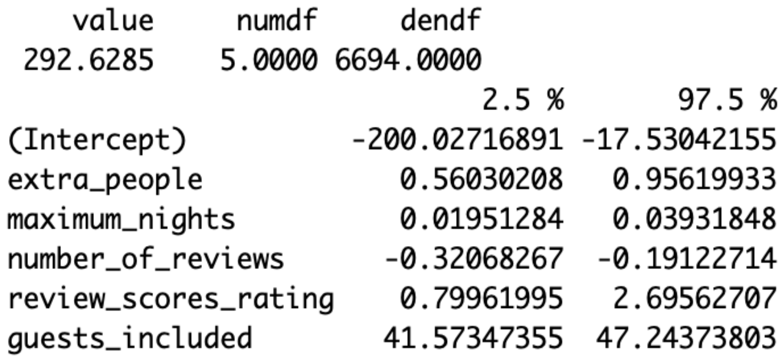


```
Call:
lm(formula = price ~ extra_people + maximum_nights + number_of_reviews +
    review_scores_rating + guests_included, data = model_data)

Residuals:
   Min     1Q Median     3Q    Max 
-657.8  -75.1  -33.7   19.6 7774.5 

Coefficients:
                       Estimate Std. Error t value Pr(>|t|)    
(Intercept)          -1.088e+02  4.655e+01  -2.337 0.019472 *  
extra_people          7.583e-01  1.010e-01   7.509 6.73e-14 ***
maximum_nights        2.942e-02  5.052e-03   5.823 6.05e-09 ***
number_of_reviews    -2.560e-01  3.302e-02  -7.752 1.04e-14 ***
review_scores_rating  1.748e+00  4.836e-01   3.614 0.000304 ***
guests_included       4.441e+01  1.446e+00  30.706  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 220.9 on 6694 degrees of freedom
Multiple R-squared:  0.1794,	Adjusted R-squared:  0.1788 
F-statistic: 292.6 on 5 and 6694 DF,  p-value: < 2.2e-16
```

Table 4.5

Coefficient of accommodates means if extra_people value increases by 1 unit, we'd expect our price variable to increase by 0.76 unit while keeping all other coefficients as constant; coefficient of maximun_nights means if maximun_nights value increases by 1 unit, we'd expect our price variable to increase by 0.0294 unit while keeping all other coefficients as constant; coefficient of number_of_reviews means if number_of_reviews value increases by 1 unit, we'd expect our price variable to decrease by 0.026 unit while keeping all other coefficients as constant; coefficient of review_scores_rating means if review_scores_rating increases by 1 unit, we'd expect our price variable to increase by 1.75 unit while keeping all other coefficients as constant; coefficient of guests included means if guests included value increases by 1 unit, we'd expect our price variable to increase by 44.4unit while keeping all other coefficients as constant; intercept means if all six variables equal to 0, then the expected value of earn would be -108.8.

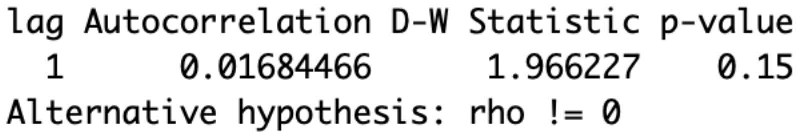
The adjusted R2 and AIC achieved by all multiple regression models are calculated, respectively. Comparing the results from each model, I finally choose the model with the lowest AIC or lowest adjusted R2 with no multicollinearity. Since multiple regression model is not the optimal algorithm for price prediction, the model result above is only one of the model (not the best one) that I've tried for all the algorithms.



```
   value     numdf     dendf
 292.6285    5.0000 6694.0000
                           2.5 %       97.5 %
(Intercept)         -200.02716891 -17.53042155
extra_people           0.56030208   0.95619933
maximum_nights         0.01951284   0.03931848
number_of_reviews     -0.32068267  -0.19122714
review_scores_rating   0.79961995   2.69562707
guests_included       41.57347355  47.24373803
```

Table 4.6

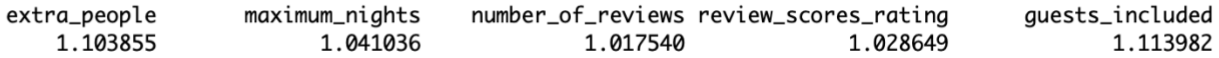
iii. Model Checking



```
lag Autocorrelation D-W Statistic p-value
  1      0.01684466      1.966227    0.15
Alternative hypothesis: rho != 0
```

Table 4.8

To make sure that the model above can be used, I did a model check to verify that models didn't violate any regression assumptions. Based on the result from Table 4.8, it is evident that DW statistics is closed to 2 and p-value is larger than 0.05. It is concluded that the assumption of independence of error is not able to be rejected.



```
 extra_people       maximum_nights     number_of_reviews review_scores_rating       guests_included
     1.103855             1.041036              1.017540             1.028649              1.113982
```

Table 4.9

Table 4.9 is used to check multicollinearity among each predictor. To make sure that variables that are used in the model are strongly correlated, I made a correlation matrix with all predictor variables and calculated variance inflation factor (VIF). Since all the number from each variable is not larger than 10, there is no multicollinearity.

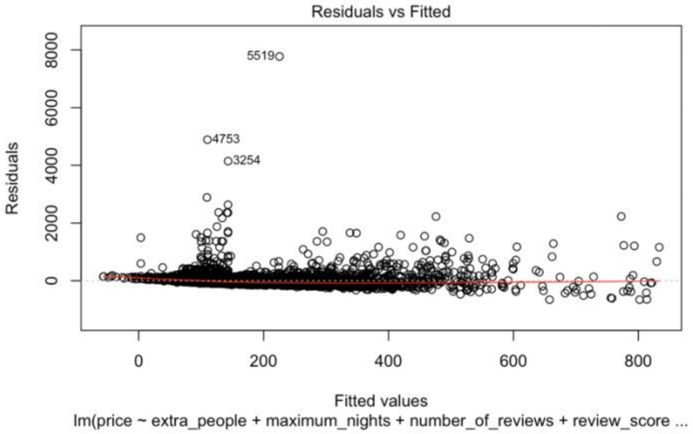


Table 4.10

Based on Table 4.10 above, it is the plot between fitted values and residuals. Residual dot is randomly placed around the horizontal zero. Also, the linearity assumption is satisfied since the red line is straight and horizontal.

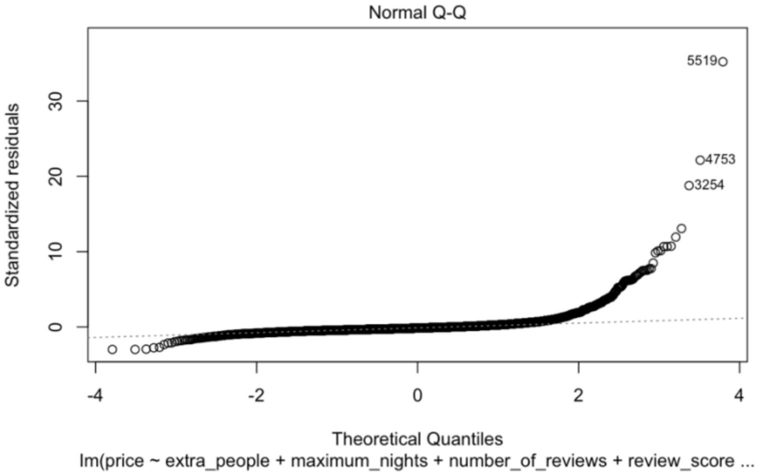


Table 4.11

Since normality assumption is based on the residuals, QQ plot would appropriate to analyze. On table 4.11, aside from three data points that have large residuals, most of the observations lie along the 45-degree line.

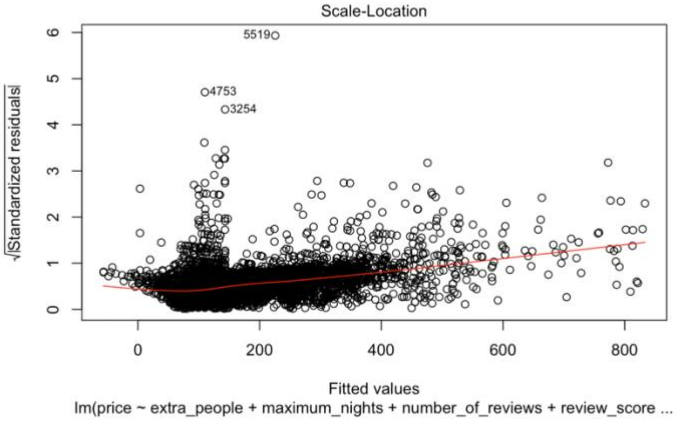


Table 4.12

Based on the scale-location plot above, the red line is almost flat and does not have a too apparent positive slope. And the data points are randomly spread out. After removing the observations 5519, 4753 and 3254, there would be more randomly spread on residuals.

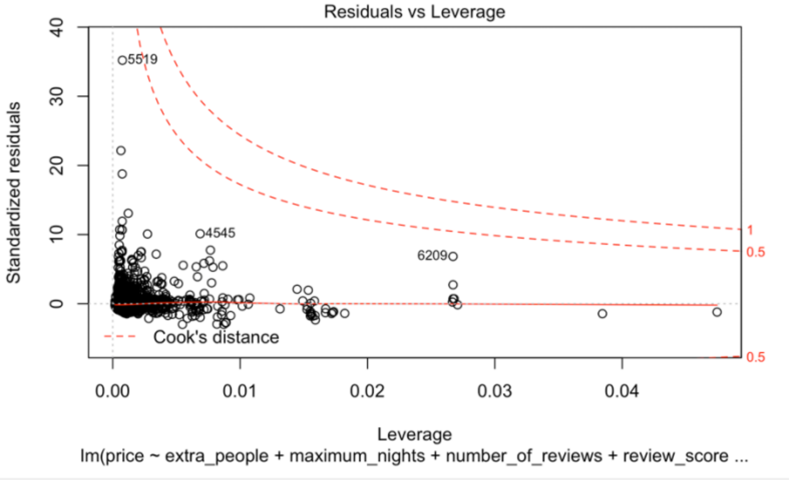


Table 4.13

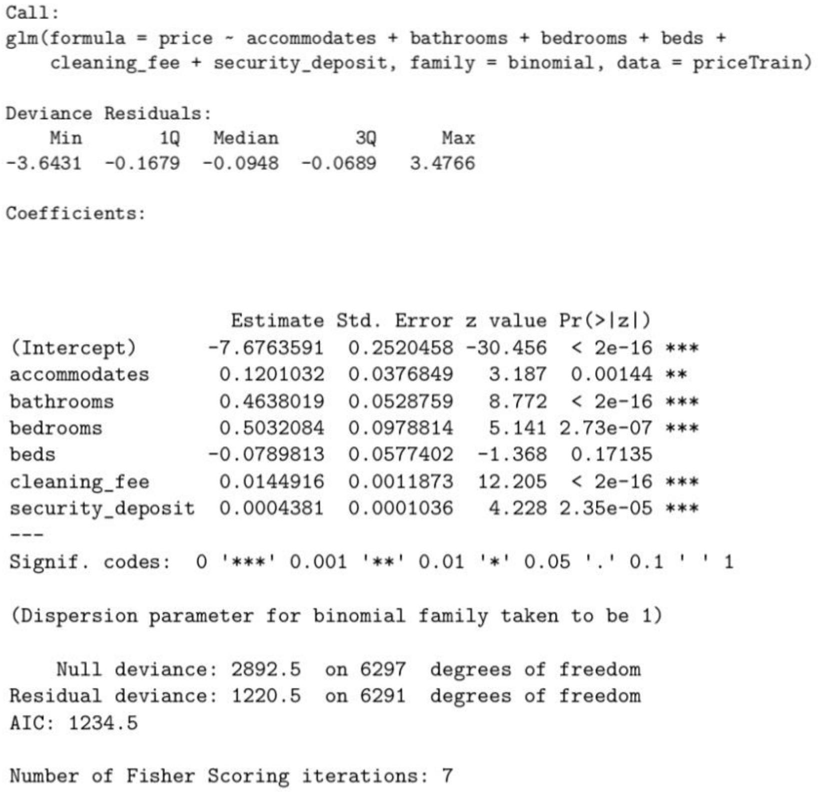
It can be noticed from the above graphs that there is red Cook's distance curved line contributing to influential data points. The situation presented above means that multiple regression might not be suitable enough for price prediction. Further changes on the multiple regression include removing outliers, make transformations on the variable. Perhaps I can achieve a higher result by making a transformation on particular variables.

2. Logistic Regressions

i. Model Selection

To make the problem more tractable, I start by grouping prices into a few categories: price large than 400 and price small than 400. I spilt the dataset into a training set and a test set. To rate the success of the model, I calculate the accuracy score.

ii. Interpretation



```
Call:
glm(formula = price ~ accommodates + bathrooms + bedrooms + beds +
    cleaning_fee + security_deposit, family = binomial, data = priceTrain)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-3.6431  -0.1679  -0.0948  -0.0689   3.4766

Coefficients:



                   Estimate Std. Error z value Pr(>|z|)
(Intercept)      -7.6763591  0.2520458 -30.456  < 2e-16 ***
accommodates      0.1201032  0.0376849   3.187  0.00144 **
bathrooms         0.4638019  0.0528759   8.772  < 2e-16 ***
bedrooms          0.5032084  0.0978814   5.141 2.73e-07 ***
beds             -0.0789813  0.0577402  -1.368  0.17135
cleaning_fee      0.0144916  0.0011873  12.205  < 2e-16 ***
security_deposit  0.0004381  0.0001036   4.228 2.35e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 2892.5  on 6297  degrees of freedom
Residual deviance: 1220.5  on 6291  degrees of freedom
AIC: 1234.5

Number of Fisher Scoring iterations: 7
```

The logistic regression model and interpretation for this project is as below:

logit(P)= -7.68+0.12*accommodates*+0.46*bathrooms*+0.5*bedrooms-*0.07*beds+0.01*cleaning fee+0.0004*security deposit*

- Intercept: With all other variables equal to 0 would have log odds of -7.67 to have price over 400.
- Accommodates: With the same level of all the rest variables, when accommodates level increases by 1, then the expected value of the price's log odds would increase by 0.12 unit.
- Bathrooms: With the same level of all the rest variables, when bathrooms level increase by 1, the expected value of the price's log odds would increase by 0.46 unit.
- Bedrooms: With the same level of all the rest variables, when bedrooms level increases by 1, then the expected value of the price's log odds would increase by 0.5 unit.
- Beds: With the same level of all the rest variables, when beds level increases by 1, then the expected value of the price's log odds would decrease by 0.08 unit.
- Cleaning fee: With the same level of all the rest variables, when cleaning fee level increases by 1, then the expected value of the price's log odds would increase by 0.5 unit.
- Security deposit: With the same level of all the rest variables, when security deposit level increases by 1, then the expected value of the voter's log odds of support for Bush would increase by 0.0004 unit.

iii. Model Checking

As you can see, this logistic regression model does better than multiple regression. The model fits well based on marginal model plots.

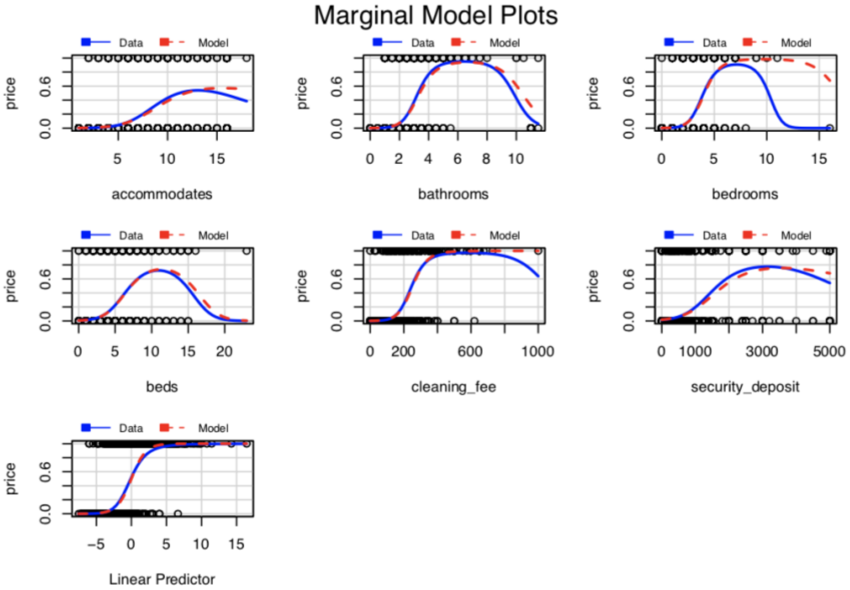


Table 4.14

Below is a plot of the binned residual between expected values and average residual. It shows that most of the points fall into the confidence bands.

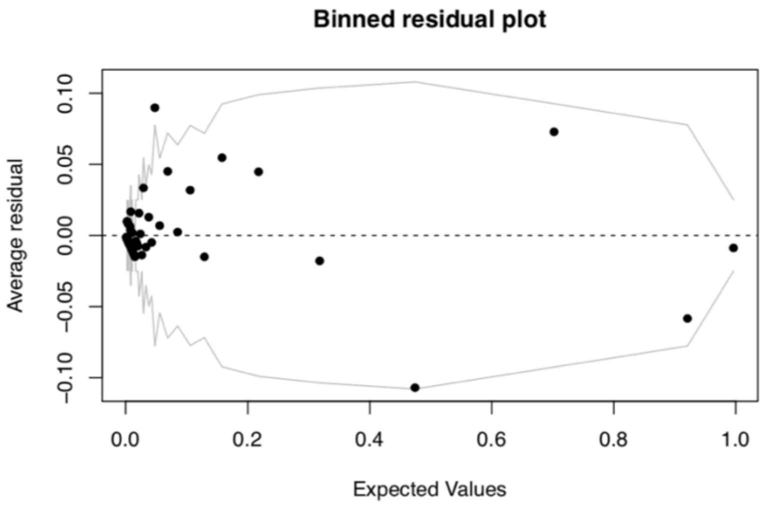


Table 4.15

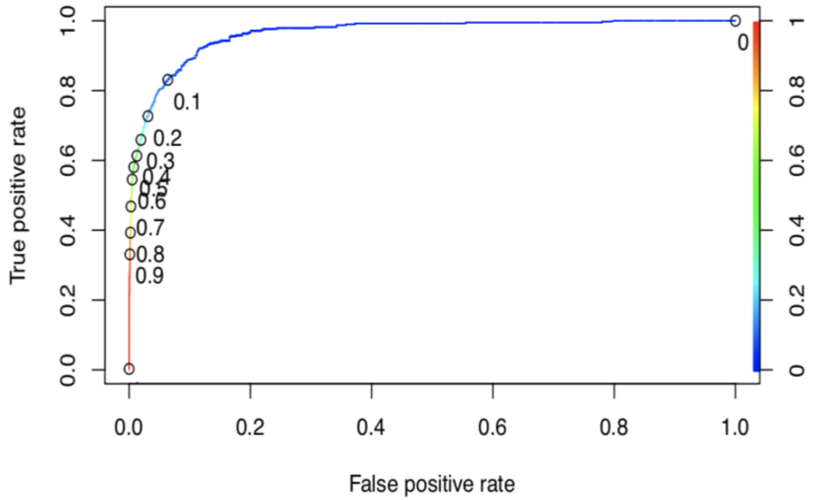


Table 4.16

I use the training set to feed into the logistic regression model. By graphing the ROC (Table 4.16) and getting confusion matrix based on the result of the logistic regression model, I obtain the accuracy of about 94.89. It allows us to have a better understanding of how the price would be predicted by setting the response variable into a binary outcome and running the logistic regression model.

3. Multi-level Regressions

i. Model Selection

A random forest is an algorithm that works to find the essential variables in building the multilevel regression. Referring to the table, we can see that variables “cleaning fee”, “guests included”, “security deposit”, “cancel policy”, “instant bookable” and “extra people” have a more significant decrease in MSE compared to other variables.

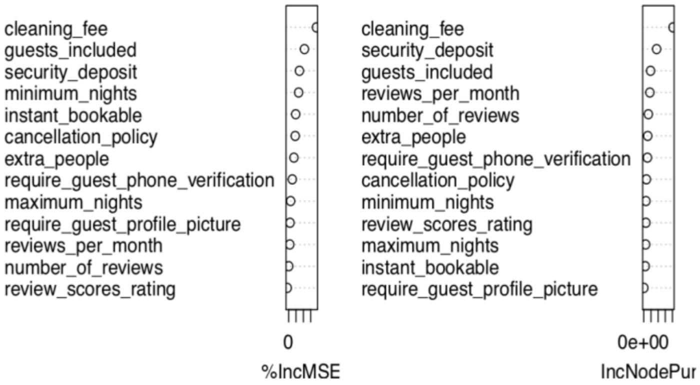
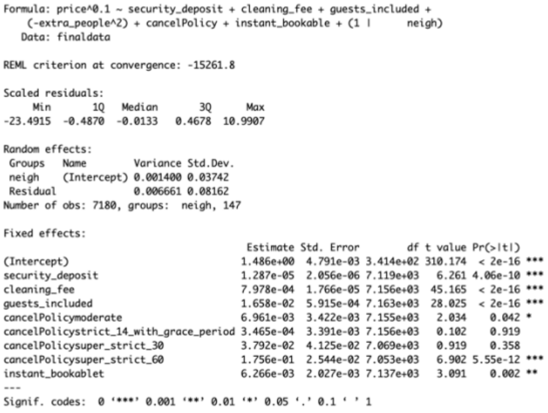


Table 4.17

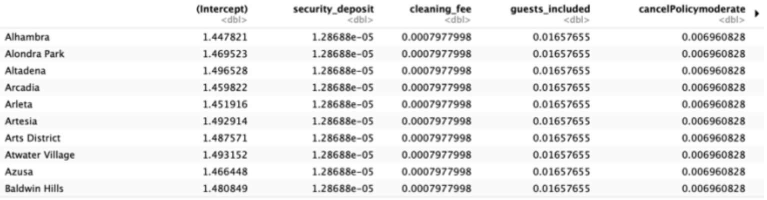
ii. Interpretation

1. Random intercept



```
Formula: price^0.1 ~ security_deposit + cleaning_fee + guests_included +
    (-extra_people^2) + cancelPolicy + instant_bookable + (1 |      neigh)
   Data: finaldata

REML criterion at convergence: -15261.8

Scaled residuals:
     Min       1Q   Median       3Q      Max
-23.4915  -0.4870  -0.0133   0.4678  10.9907

Random effects:
 Groups   Name        Variance Std.Dev.
 neigh    (Intercept) 0.001400 0.03742
 Residual             0.006661 0.08162
Number of obs: 7180, groups:  neigh, 147

Fixed effects:
                                    Estimate Std. Error        df t value Pr(>|t|)
(Intercept)                        1.486e+00  4.791e-03 3.414e+02 310.174  < 2e-16 ***
security_deposit                   1.287e-05  2.056e-06 7.119e+03   6.261 4.06e-10 ***
cleaning_fee                       7.978e-04  1.766e-05 7.156e+03  45.165  < 2e-16 ***
guests_included                    1.658e-02  5.915e-04 7.163e+03  28.025  < 2e-16 ***
cancelPolicymoderate               6.961e-03  3.422e-03 7.155e+03   2.034    0.042 *
cancelPolicystrict_14_with_grace_period 3.465e-04  3.391e-03 7.156e+03   0.102    0.919
cancelPolicysuper_strict_30        3.792e-02  4.125e-02 7.069e+03   0.919    0.358
cancelPolicysuper_strict_60        1.756e-01  2.544e-02 7.053e+03   6.902 5.55e-12 ***
instant_bookablet                  6.266e-03  2.027e-03 7.137e+03   3.091    0.002 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Table 4.18



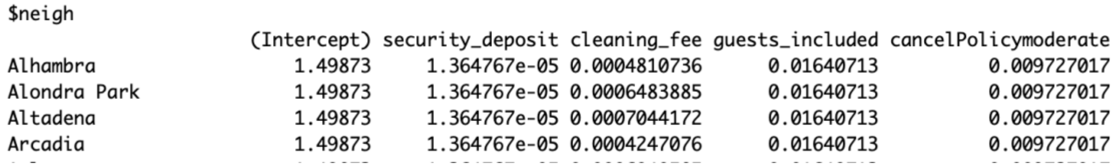
	(Intercept) <dbl>	security_deposit <dbl>	cleaning_fee <dbl>	guests_included <dbl>	cancelPolicymoderate <dbl>
Alhambra	1.447821	1.28688e-05	0.0007977998	0.01657655	0.006960828
Alondra Park	1.469523	1.28688e-05	0.0007977998	0.01657655	0.006960828
Altadena	1.496528	1.28688e-05	0.0007977998	0.01657655	0.006960828
Arcadia	1.459822	1.28688e-05	0.0007977998	0.01657655	0.006960828
Arleta	1.451916	1.28688e-05	0.0007977998	0.01657655	0.006960828
Artesia	1.492914	1.28688e-05	0.0007977998	0.01657655	0.006960828
Arts District	1.487571	1.28688e-05	0.0007977998	0.01657655	0.006960828
Atwater Village	1.493152	1.28688e-05	0.0007977998	0.01657655	0.006960828
Azusa	1.466448	1.28688e-05	0.0007977998	0.01657655	0.006960828
Baldwin Hills	1.480849	1.28688e-05	0.0007977998	0.01657655	0.006960828

Table 4.19

Among fixed effects:
Coefficient of security_deposit means if security_deposit value increases by 1 unit, we’d expect our price variable to increase by 1.28e^-5 unit while keeping all other coefficients as constant; coefficient of cleaning_fee means if cleaning_fee value increases by 1 unit, we’d expect our price variable to increase by 7.97e^-4 unit while keeping all other coefficients as constant; coefficient of guests_included means if guests_included value increases by 1 unit, we’d expect our price variable to decrease by 1.65e-2 unit while keeping all other coefficients as constant; coefficient of instant_bookablet means if instant_bookablet increases by 1 unit, we’d expect our price variable to increase by 6.266e^-3 unit while keeping all other coefficients as constant

Among random effects:
The model with random intercept effects for the first neighborhood (Alhambra) is 1.458 as table shows above.

2. Random slope



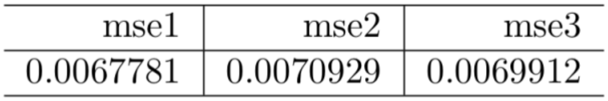
```
$neigh
                   (Intercept) security_deposit cleaning_fee guests_included cancelPolicymoderate
Alhambra               1.49873     1.364767e-05 0.0004810736      0.01640713          0.009727017
Alondra Park           1.49873     1.364767e-05 0.0006483885      0.01640713          0.009727017
Altadena               1.49873     1.364767e-05 0.0007044172      0.01640713          0.009727017
Arcadia                1.49873     1.364767e-05 0.0004247076      0.01640713          0.009727017
```

Table 4.20

Among fixed effect:

Coefficient of security_deposit for Alhambra means if security_deposit value increases by 1 unit, we’d expect our price variable to increase by 1.36e^-5 unit while keeping all other coefficients as constant; coefficient of guests_included means if guests_included value increases by 1 unit, we’d expect our price variable to increase by 1.65e-2 unit while keeping all other coefficients as constant; intercept means if all variables equals to 0,then the expected value of earn would be 1.499

Among random effects:
The model with random slope effects on cleaning_fee for the first neighborhood (Alhambra) is 4.8e^-4 as table shows above.



mse1	mse2	mse3
0.0067781	0.0070929	0.0069912

Table 4.21

By using the cross-validation method on multi-level models and compare the result of MSE on three models (random intercept, random slope, random intercept and slope), we found that the first model has the smallest result on MSE. It is concluded that the model with the random intercept grouped by neighborhood would be the optimized model among all other multi-level regression models.

iii. Model Checking

The QQ plot of residuals/parameters and residual plots from Table 4.18-4.20 give us generalized information about normality and independence of residuals. Errors in both multilevel models are not related to each other. The computation of residuals relies on the assumption of independence. Similarly, there are equal variance if criterion at different levels of predictor, which make the parameter estimates optimal.

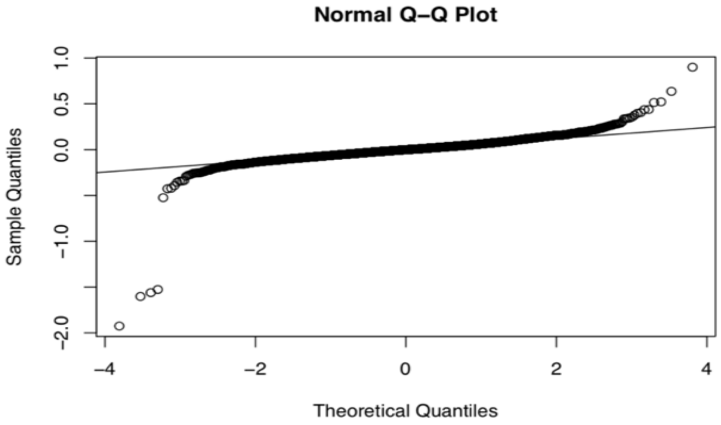


Table 4.22

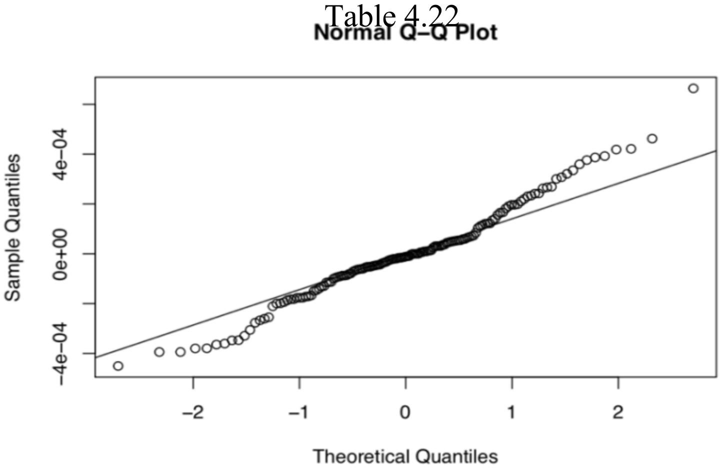


Table 4.23

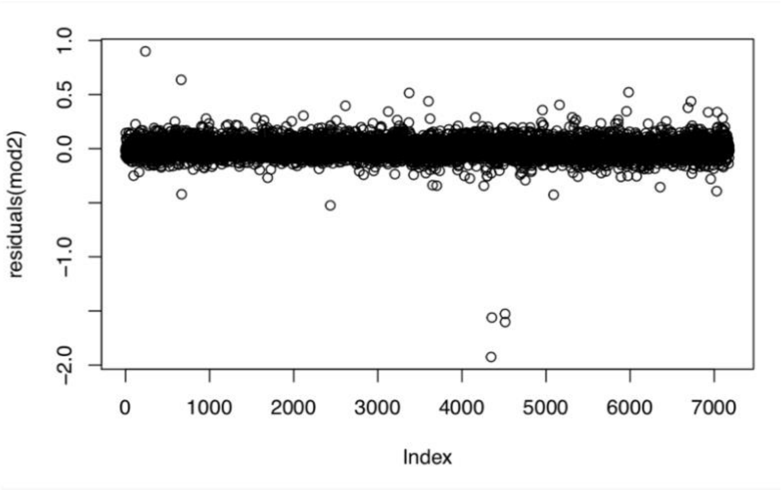


Table 4.24

Conclusion

i. Implication

With the end goal to make booking price prediction, this comprehensive exploratory data analysis and statistical modelling on their open-source dataset helped us to understand the underlying patterns and characteristics of different levels of predictors and how do predictors affect the price.

ii. Limitation

When I worked on model check for multiple regression, there are some data points which have large residuals. I did not remove these points at the beginning since I thought it might not be the influential outliers. However, the model fit better after I adjusted the original model.

iii. Future Direction

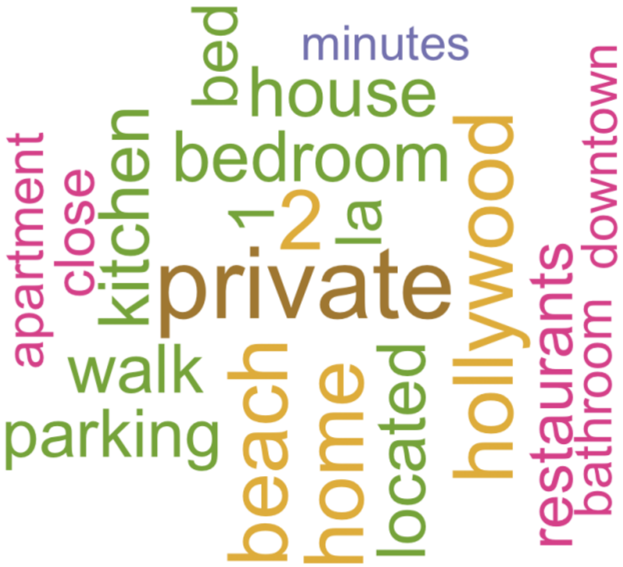
Building upon current data analysis, it would be interesting to work on the booking records from other cities in the US. Would it be appropriate to use logistic regression as well in different places, or is it only feasible in Los Angela's? The inferences would be solidified by further analysis. Airbnb sharing economy should have much more tremendous positive influence not only on travelers but property owners.

Reference

https://bookdown.org/roback/bookdown-bysh/

Appendix:

Other EDA:



R code:

```
knitr::opts_chunk$set(echo = TRUE)

library(randomForest)
library(lmerTest)
library(car)
library(ggplot2)
library(gridExtra)
library(stats)
library(lmtest)

list=read.csv("listings.csv")
list<-list[,-
c(2,3,4,9,16,17,18,19,20,21,23,28,30,31,33,34,41,43,44,47,48,70,71,72,73,74,75,77,78,79,80,81,
82,84,85,86,88,89,90,91,92,93,94,95,96,98,102,103,104,105)]

list_sum<-read.csv("listings_sum.csv")
```

```
#review_final<-read.csv("reviews_final.csv")
# Select 5000 random rows
#review<-review_final[sample(nrow(review_final), 5000), ]
#write.csv(review,file="review.csv")
review<-read.csv("review.csv")
library(Amelia)
#Check any NA
missmap(list,col=c('yellow','black'),y.at=1,y.labels='',legend=TRUE)
#drop irrelevant columns
list<-list[,-c(39,41,42)]
#check proportition of NA in whole dataset
missmap(list,col=c('yellow','black'),y.at=1,y.labels='',legend=TRUE)
list$host_since<-list_sum$host_since
list[list==""]<-NA
#drop missing values completely
list<-na.omit(list)
write.csv(list,file="list.csv")
#remove rows that have N/A in "host_response_time","host_response_rate""
library(dplyr)
list = filter(list, host_response_time != "N/A" & host_response_rate != "N/A")
#write.csv(list,file="airbnb.csv")
#Display the data dimensions
dim(list)
# Display the column names
colnames(list)
# Display the data structures
str(list)
#review/summaries text analysis
library(gridExtra)
library(grid)
par(mfrow=c(4,4))
library(plotly)
library(ggthemes)
g<-ggplot(data = list) +
  geom_bar(aes(x = bedrooms),fill="#D53E4F") +
  xlab('Bedrooms') +
  labs(title = "Numbers of bedrooms")+xlim(-1, 10)+
  theme(plot.title = element_text(hjust = 0.5,size=13),panel.grid.major =element_blank(),
panel.grid.minor = element_blank(),
panel.background = element_blank(),axis.line = element_line(colour = "black"))
h<-ggplot(data = list) +
  geom_bar(aes(x = beds),fill="#DE77AE") +
  xlab('Beds') +
  labs(title = "Numbers of beds")+xlim(-1, 10)+
  theme(plot.title = element_text(hjust = 0.5,size=13),panel.grid.major =element_blank(),
panel.grid.minor = element_blank(),
panel.background = element_blank(),axis.line = element_line(colour = "black"))

j<-ggplot(data = list) +
  geom_bar(aes(x = accommodates),fill="#3288BD") +
  xlab('Accommodates') +
  labs(title = "Numbers of accommodates")+xlim(0, 10)+
  theme(plot.title = element_text(hjust = 0.5,size=13),panel.grid.major =element_blank(),
panel.grid.minor = element_blank(),
panel.background = element_blank(),axis.line = element_line(colour = "black"))

i<-ggplot(data = list) +
  geom_bar(aes(x = bathrooms),fill="#FB8072") +
  xlab('Bathrooms') +
  labs(title = "Numbers of bathrooms")+xlim(0, 7)+
  theme(plot.title = element_text(hjust = 0.5,size=13),panel.grid.major =element_blank(),
panel.grid.minor = element_blank(),
panel.background = element_blank(),axis.line = element_line(colour = "black"))

grid.arrange(g, h, j,i ,ncol=2)

#price analysis
ggplot(data = list) +
  geom_bar(aes(x = price),fill="#FB8072") +
  xlab('Price') +
  labs(title = "Price")+xlim(-1, 500)+
  theme(plot.title = element_text(hjust = 0.5,size=13),panel.grid.major =element_blank(),
panel.grid.minor = element_blank(),
panel.background = element_blank(),axis.line = element_line(colour = "black"))

#neighborhood analysis
library(dplyr)
library(kableExtra)
list1<-list%>%group_by(list$neighbourhood) %>% summarise(number =
n())%>%arrange(desc(number))
head(list1)
Latitude<-list[,28]
Latitude<-data.frame(Latitude)
Latitude$long<-list[,29]

Latitude_sample<-Latitude[sample(nrow(Latitude), 100), ]

# get the location of housing
#library(leaflet)
#Latitude_sample %>%
  #leaflet() %>%
 # addTiles() %>%
 # addTiles() %>%
#addMarkers(popup="sites")

#property type analysis

list$property_type = as.factor(list$property_type)
ggplot(aes(x = property_type, y = bathrooms,color=property_type,fill=property_type), data =
list) +
  geom_boxplot() +
  geom_jitter(alpha = 0.1)+
  coord_cartesian(ylim=c(0,15))+
theme( axis.text.x  = element_text(angle=90, hjust=1, vjust=0.9))+
 scale_fill_viridis_d(option = "viridis") +
 scale_color_viridis_d(option = "viridis") +
 theme_pander()

#room type analysis
par(mfrow=c(4,4))
list$room_typee = as.factor(list$room_type)
ggplot(aes(x = room_type, y = bathrooms,color=room_type,fill=room_type), data = list) +
  geom_boxplot() +
  geom_jitter(alpha = 0.1)+
  coord_cartesian(ylim=c(0,15))+
theme( axis.text.x  = element_text(angle=35, hjust=1, vjust=0.9))+
 xlab('Bathrooms') +
  labs(title = "Numbers of bathrooms")+
  scale_fill_viridis_d(option = "viridis") +
 scale_color_viridis_d(option = "viridis") +
 theme_pander()

ggplot(aes(x = room_type, y = accommodates,color=room_type,fill=room_type), data = list) +
  geom_boxplot() +
  geom_jitter(alpha = 0.1)+
  coord_cartesian(ylim=c(0,15))+
theme( axis.text.x  = element_text(angle=35, hjust=1, vjust=0.9))+
 xlab('Bathrooms') +
  labs(title = "Numbers of accommodates")+
  scale_fill_viridis_d(option = "viridis") +
 scale_color_viridis_d(option = "viridis") +
 theme_pander()

ggplot(aes(x = room_type, y = beds,color=room_type,fill=room_type), data = list) +
  geom_boxplot() +
  geom_jitter(alpha = 0.1)+
  coord_cartesian(ylim=c(0,15))+
theme( axis.text.x  = element_text(angle=35, hjust=1, vjust=0.9))+
 xlab('Beds') +
  labs(title = "Numbers of beds")+
  scale_fill_viridis_d(option = "viridis") +
 scale_color_viridis_d(option = "viridis") +
 theme_pander()

ggplot(aes(x = room_type, y = bedrooms,color=room_type,fill=room_type), data = list) +
  geom_boxplot() +
  geom_jitter(alpha = 0.1)+
  coord_cartesian(ylim=c(0,15))+
theme( axis.text.x  = element_text(angle=35, hjust=1, vjust=0.9))+
 xlab('Bedrooms') +
  labs(title = "Numbers of bedrooms")+
  scale_fill_viridis_d(option = "viridis") +
 scale_color_viridis_d(option = "viridis") +
 theme_pander()

ggplot(aes(x = room_type, y = security_deposit,color=room_type,fill=room_type), data = list) +
  geom_boxplot() +
  geom_jitter(alpha = 0.1)+
  coord_cartesian(ylim=c(0,1500))+
theme( axis.text.x  = element_text(angle=35, hjust=1, vjust=0.9))+
 xlab('Security Deposit') +
  labs(title = "Numbers of security_deposit")+
  scale_fill_viridis_d(option = "viridis") +
 scale_color_viridis_d(option = "viridis") +
 theme_pander()

ggplot(aes(x = room_type, y = cleaning_fee,color=room_type,fill=room_type), data = list) +
  geom_boxplot() +
  geom_jitter(alpha = 0.1)+
  coord_cartesian(ylim=c(0,200))+
theme( axis.text.x  = element_text(angle=35, hjust=1, vjust=0.9))+
 xlab('Cleaning Fee') +
  labs(title = "Cleaning Fee")+
  scale_fill_viridis_d(option = "viridis") +
 scale_color_viridis_d(option = "viridis") +
 theme_pander()


#number of booking records based on room type
m<-ggplot(aes(x = price,fill=room_type,color=room_type), data = list) +
  geom_histogram()+
  facet_wrap(~room_type)+xlim(0, 500)+
  theme( axis.text.x  = element_text(angle=35, hjust=1, vjust=0.9))+
 labs(x = "Price", y = " Count") +
  ggtitle("Number of Booking Records among each Room Type")+
  scale_fill_viridis_d(option = "viridis") +
 scale_color_viridis_d(option = "viridis") +
 theme_pander()
m
#room type numbers in each category
library(dplyr)
list_roomtype<-list%>%group_by(list$room_type) %>% summarise(number =
n())%>%arrange(desc(number))
library(knitr)
kable(list_roomtype,format = "markdown")

library("RColorBrewer")
#pie chart
# Pie Chart with Percentages
slices <- c(28468, 14410, 1769, 406)
lbls <- c("Entire home/Apt", "Private Room", "Shared Room", "Hotel Room")
pct <- round(slices/sum(slices)*100)
lbls <- paste(lbls, pct) # add percents to labels
lbls <- paste(lbls,"%",sep="") # ad % to labels
coul <- brewer.pal(5, "BuPu")
pie(slices,labels = lbls, col=coul,
   main="Pie Chart of Room Type")

library(tidyverse)
library(tidytext)
library(knitr)
library(textdata)
library(magrittr)

summary<-data.frame(list$summary)
summary$list.summary<-as.character(summary$list.summary)
tidy_word <- summary %>%
  unnest_tokens(word,list.summary)

#find the most frequently used words in summary
library(wordcloud)
library(magrittr)
tidy_word %>%
  anti_join(stop_words) %>%
  count(word) %>%
  with(wordcloud(word, n, max.words = 20,colors = brewer.pal(7, 'Dark2'), random.order =
FALSE,rot.per=0.75))

review<-na.omit(review)
```

```
comment<-data.frame(review$comments)
comment$review.comments<-as.character(comment$review.comments)
tidy_word_com <- comment %>%
  unnest_tokens(word,review.comments)

tidy_word_com %>%
  anti_join(stop_words) %>%
  count(word) %>%
  with(wordcloud(word, n, max.words = 100,colors = brewer.pal(7, 'Dark2'), random.order =
FALSE,rot.per=0.35))

#get relevant columns in the dataset for regression
model_data<-list[,c(33:36,39:45,47,48)]
head(model_data)

#Find the corrleation among each variable
set.seed(200)
library(GGally)
ggpairs(model_data,cardinality_threshold = 100) +
  theme(text = element_text(size = 8)) +
  theme(axis.text.x = element_text(angle = 45, vjust = 1, hjust = 1, size = 4))

#correlation plot
pairs(model_data)

#Correlogram
library(corrgram)
library(PerformanceAnalytics)
corMat <- cor(model_data, use = "complete")
round(corMat, 3)
library(corrplot)
corrplot(cor(model_data), method = "circle")

#multiple regression
linear<-
lm(price~extra_people+maximum_nights+number_of_reviews+review_scores_rating+guests_in
cluded,data=model_data)
summary(linear)
#calculate AIC
AIC(linear)
plot(residuals(linear))
#residual plot
hist(linear$residuals)
#calcualte VIF
vif(linear)
```

```
#drop some observations(might be outlier)
model_data<-model_data[-c(5519,6209),]
adj.linear<-
lm(price~extra_people+maximum_nights+number_of_reviews+review_scores_rating+guests_included,data=model_data)
summary(adj.linear)
#model check( adjusted model)
plot(adj.linear)

#model check(old model)
plot(linear)

# F-statistic
summary(linear)$fstatistic
# confidence interval
confint(linear)
# visualize the confidence intervals
library(coefplot)
coefplot(linear, intercept = FALSE)

dwt(linear)
#make a scatter plot
ggplot(list)+aes(x=accommodates,y=price)+
  geom_point()+geom_smooth(method="lm",se=FALSE)

model2<-
lm(price~accommodates+bathrooms+bedrooms+beds+cleaning_fee+security_deposit,data=list)
summary(model2)
AIC(model2)


model1<-
lm(price~accommodates+bathrooms+bedrooms+beds+cleaning_fee+guests_included,data=list)
summary(model1)
hist(model1$residuals)

qqnorm(model1$residuals)
qqline(model1$residuals)

library(coefplot)
coefplot(model1)

plot(fitted(model1),model1$residuals)
abline(0,0,col="red")

library(tidyverse)
library(gridExtra)
library(car)
#Checking the assumption of independence
dwt(model1)
# VIF
vif(model1)

# tolerance
1/vif(model1)
# mean VIF
mean(vif(model1))

plot(model1)
# F-statistic
summary(model1)$fstatistic
# confidence interval
confint(model1)
# visualize the confidence intervals
library(coefplot)
coefplot(model1, intercept = FALSE)

library(MASS)
#Shapiro-Wilk Normality Test
## Distribution of studentized residuals
student_residuals <- studres(model1)
shapiro.test(sample(student_residuals, size = 5000))
#p-value is less than 0.05, reject the null hypothesis that residuals are normally distributed.


#change price into binary outcome
library(magrittr)
library(tidyverse)
log_list<-list
log_list$price<-as.factor(ifelse(log_list$price>400,1,0))
#get confusion matrix
(table(log_list$price))
6759/(6759+421)
library(caTools)
#Splitting Training & Testing Data
# Randomly split data
set.seed(6888)
split = sample.split(log_list$price, SplitRatio = 0.94)
# Create training and testing sets
priceTrain = subset(log_list, split == TRUE)
priceTrain<-data.frame(priceTrain)
priceTest = subset(log_list, split == FALSE)
```

```
priceTest<-data.frame(priceTest)
nrow(priceTrain)
nrow(priceTest)

#logistic regression
logistic.model1=glm(price~accommodates+bathrooms+bedrooms+beds+cleaning_fee+security_deposit,data=priceTrain , family=binomial )
summary(logistic.model1)
#model check
library(car)
marginalModelPlots(logistic.model1)
#binned residual plot
library(arm)
binnedplot(fitted(logistic.model1),residuals(logistic.model1,type="response"))

#use model to get prediction
predictTrain = predict(logistic.model1, type="response")
summary(predictTrain)

tapply(predictTrain, priceTrain$price, mean)

#Confusion matrix for threshold of 0.5
table(priceTrain$price, predictTrain > 0.5)

#sensitivity
82/(339+82)

#Iload ROCR package
library(ROCR)
ROCRpred = prediction(predictTrain, priceTrain$price)
# Performance function
ROCRperf = performance(ROCRpred, "tpr", "fpr")
# Add threshold labels
plot(ROCRperf, colorize=TRUE, print.cutoffs.at=seq(0,1,by=0.1), text.adj=c(-0.2,1.7))

predictTest = predict(logistic.model1, type = "response", newdata = priceTest)
table(priceTest$price,predictTest >= 0.3)
# Accuracy
(400+9)/(409+22)

#multi-level regression
data<-read.csv("list.csv")
neigh<-data$neighbourhood
data<-data[,c(40:55)]
#data$neigh<-neigh
data$host_since<-NULL
```

```
data$calendar_updated<-NULL
data$cancellation_policy<-as.factor(data$cancellation_policy)
data$require_guest_phone_verification<-as.factor(data$require_guest_phone_verification)
data$require_guest_profile_picture<-as.factor(data$require_guest_profile_picture)
index<-sample(7180,7180/2,replace = F)
variable<-data[index,]
modelset<-data[-index,]
# function for leave-one-out cv
looCv<- function(model){
mean(residuals(model)^2/(1-hatvalues(model))^2)
}

# random forest
mod1<-randomForest(price~.,data = variable,importance=T,ntree=500)
mod2<-randomForest(price~.,data = variable,importance=T,ntree=1000)

varImpPlot(mod1)
varImpPlot(mod2)
# select top 6
finaldata<-data[,c(1,2,3,4,5)]
finaldata$neigh<-neigh
finaldata$cancelPolicy<-data$cancellation_policy
finaldata$instant_bookable<-data$instant_bookable


#find relationship between price and each variable
p1<-ggplot(finaldata, aes(x=security_deposit, y=price)) +
  geom_smooth()
p2<-ggplot(finaldata, aes(x=cleaning_fee, y=price)) +
  geom_smooth()
p3<-ggplot(finaldata, aes(x=guests_included, y=price)) +
  geom_smooth()
p4<-ggplot(finaldata, aes(x=extra_people, y=price)) +
  geom_smooth()
grid.arrange(p1,p2,p3,p4,nrow=2)

# random intercept
finaldata<-na.omit(finaldata)
mod1<-lmer(price^0.1~security_deposit+cleaning_fee+guests_included+(-
extra_people^2)+cancelPolicy+instant_bookable+(1|neigh),data = finaldata)
# normality of residual
qqnorm(residuals(mod1))
qqline(residuals(mod1))
summary(mod1)

#head(coef(mod1))
```

```
library(arm)
display(mod1)
# normality of parameters
para<-data.frame(ranef(mod1))
qqnorm(para[,4])
qqline(para[,4])
# independentce of residual
plot(residuals(mod1))
# constant variable
plot(residuals(mod1))
# check multicollinearity
vif(mod1)

#calculate MSE after cross validation for model 1
mse1<-looCv(mod1)
mse1
# random slope
mod2<-
lmer(price^0.1~security_deposit+cleaning_fee+guests_included+cancelPolicy+instant_bookable
+(0+cleaning_fee|neigh),data = finaldata)
# normality of residual
qqnorm(residuals(mod2))
qqline(residuals(mod2))
# normality of parameters
para<-data.frame(ranef(mod2))
qqnorm(para[,4])
qqline(para[,4])
# independentce of residual
plot(residuals(mod2))
# constant variance
plot(residuals(mod2))
# check multicollinearity
vif(mod2)
summary(mod2)

#coef(mod2)
display(mod2)

#calculate MSE after cross validation for model 2
mse2<-looCv(mod2)
mse2

# random intercept and slope
```

```
mod3<-
lmer(price^0.1~security_deposit+cleaning_fee+guests_included+extra_people+cancelPolicy+ins
tant_bookable+(1+security_deposit+cleaning_fee|neigh),data = finaldata)
# normality of residual
qqnorm(residuals(mod3))
qqline(residuals(mod3))

# normality of parameters
para<-data.frame(ranef(mod3))
qqnorm(para[,4])
qqline(para[,4])
# independentce of residual
plot(residuals(mod3))
# constant variable
plot(residuals(mod3))
# check multicollinearity
vif(mod3)

#graph relationship between price and each variable grouped by different category of
instant_bookable
p1<-ggplot(finaldata, aes(x=security_deposit, y=price,color=instant_bookable)) +
geom_smooth()
p2<-ggplot(finaldata, aes(x=cleaning_fee, y=price,color=instant_bookable)) +
  geom_smooth()
p3<-ggplot(finaldata, aes(x=guests_included, y=price,color=instant_bookable)) +
  geom_smooth()
p4<-ggplot(finaldata, aes(x=extra_people, y=price,color=instant_bookable)) +
  geom_smooth()
grid.arrange(p1,p2,p3,p4,nrow=2)

#calculate MSE after cross validation for model 3
mse3<-looCv(mod3)
mse3

compare <- cbind(mse1,mse2,mse3)%>%as.data.frame()
knitr::kable(compare)%>%kableExtra::kable_styling(bootstrap_options = c("striped", "hover"))

# random intercept
finaldata<-na.omit(finaldata)
mod4<-lmer(price^0.1~security_deposit+cleaning_fee+guests_included+(-
extra_people^2)+cancelPolicy+(1|instant_bookable),data = finaldata)
display(mod4)
# normality of residual
qqnorm(residuals(mod4))
qqline(residuals(mod4))
```

```
# normality of parameters
para<-data.frame(ranef(mod4))
qqnorm(para[,4])
qqline(para[,4])
# independentce of residual
plot(residuals(mod4))

# constant variable

plot(residuals(mod4))

# check multicollinearity
vif(mod4)


mse4<-looCv(mod4)
mse4
glmerControl(optimizer="bobyqa", optCtrl = list(maxfun = 10000000))
mod5<-
lmer(price~security_deposit+cleaning_fee+guests_included+cancelPolicy+(0+security_deposit+
cleaning_fee+guests_included|instant_bookable),data = finaldata)
# normality of residual
qqnorm(residuals(mod5))
qqline(residuals(mod5))

# normality of parameters
para<-data.frame(ranef(mod5))
qqnorm(para[,4])
qqline(para[,4])
# independentce of residual
plot(residuals(mod5))

# constant variance
plot(residuals(mod5))
# check multicollinearity
vif(mod5)
mse5<-looCv(mod5)
mse5
# random intercept and slope
mod6<-
lmer(price^0.1~security_deposit+cleaning_fee+guests_included+cancelPolicy+(1+security_depo
sit+cleaning_fee+guests_included|instant_bookable),data = finaldata)
# normality of residual
qqnorm(residuals(mod6))
qqline(residuals(mod6))
```

```
# normality of parameters
para<-data.frame(ranef(mod6))
qqnorm(para[,4])
qqline(para[,4])
# independentce of residual
plot(residuals(mod6))
# constant variable
plot(residuals(mod6))
# check multicollinearity
vif(mod6)
mse6<-looCv(mod6)
mse6
compare_new <- cbind(mse4,mse5,mse6)%>%as.data.frame()
knitr::kable(compare_new)%>%kableExtra::kable_styling(bootstrap_options = c("striped",
"hover"))
```