# **KAGGLE REPORT**

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RMSE public: 55.98079 RMSE private: 57.43220

## Data exploration and visualizations

- I imported the AnalysisData file into R and ran an str() function on the file to see the various types of variables which were present in the file.
- The is.na() function helped me find the number of NA in each column and help me
  determine which columns should be dropped from the model. Square\_feet,
  weekly\_price and monthly\_price had almost no values and had 95% of their values
  missing. Hence the best option was to drop it.
- Initially I decided to run my models based on only numerical data since I was not sure of how to deal with the variables which contained text and long descriptions. I dropped all the variables which included text.
- After seeing the data, I realized there was not one type of NA but there was NA, N/A and "". I had to read the data again and needed to make sure that all types of NA were captured so that the model or predictions won't give error.
- I started plotting the numerical data to check its range and to give me an idea of the variable's average values. Doing this gave me some interesting insights.
- The variable "price" had some values with zero, which according to me would prove to worsen the dataset thus I removed these values.
- The variables maximum\_night, mimimum\_night, minimum\_maximum\_nights and minimum\_nights\_avg had a lot of outliers due to which predictions would be skewed. Thus, I capped them off at 6000 after plotting them and checking for outliers.

### Data Cleaning and Imputing

After checking for the NA values, I knew which variables had how many NA values. It
was essential for me to decide whether to fill the NA with zeros or with median/mode
values.

- Initially I filled the values with the average of the rest of the values. Then I realized that blank spaces might have meant zero cleaning fee or security deposit, thus I replaced them with zeroes. I replaced the host\_listing\_count and reviews\_per\_month with the mean values.
- I started running some basic linear regression models by now by adding all the variables which I had cleaned. By adding 2-3 variables to the model by RMSE started coming down. Due to this I got the wrong perception that more variables reflected lower RMSE.
- I started adding variables without checking if they were relevant or not after cleaning and eliminating the NA values.
- Neighbourhood\_cleansed and property\_type had some levels missing which were not in the Analysis data thus I added them from the scoring data.

# <u>Data Feature Engineering</u>

- At this point I realized that dropping the variables which had text was a mistake. I removed the function which was removing the text columns.
- By counting the number of commas in the Amenities, I could count the number of amenities which were existing in the house. Thus, I extracted the number into a new variable amenities\_nchar using the stringr library. This function had a function str\_count which counted the number of characters (commas in this case).
- I then converted the description, name, summary, space, notes, access and interaction into numerical data by counting the number of words in the string using the nchar () function. The logic behind this was that more the number the characters in a description, it would be a good review or the other way around too, i.e. long descriptions equal bad places which meant less price. Thus, number of characters would affect the pricing. Hence a lot of new variables with number of characters were formed to be added in the model.
- I was researching about how to use zip codes effectively in a model. I tried converting them to numeric type but the problem was the number was changing which affected the model. For example, the zip code "00071" converted to numeric was only 71 which was not a correct zip code for a place. After researching on the internet, there was something called geocoding. The package "zipcode" had all the place, state, longitude and latitude of the corresponding code. Running a simple SQL code which, I found online helped me add latitude and longitude to my dataset. The code was: merge(x = data, y = zipcode, by.x = "zipcode", by.y = "zip")
- I realized the word luxury, luxurious and Luxurious in the columns name, space, description, summary and neighbourhood\_overview indicated that the place was very good and highly priced. Thus, I extracted the word from the string and stored its count in a new variable. I added the count of all the luxury, Luxurious and luxurious into a new variable "luxury". This was another new variable in my model.

• I then found another new variable in a similar way. The number of transport ways available in a locality would help me determine if the area was in a good connected neighborhood or if it was poorly connected. A good connected area would have higher prices compared to a poorly connected area. Similar to luxury, I counted the words such as bus, buses, subways and trains and stored them in new variables. I totaled all of the counts and stored them in transit\_modes.

## Modelling - Finding the right model

- As stated earlier, I inserted all the variables in my linear regression model thinking more variables meant a better model and lower RMSE.
- After seeing the p-values of each variable, I realized my mistake that a lot variables were not relevant and influencing the model. They were just noise and actually making the model worse.
- I wanted to do feature selection using Lasso model but couldn't troubleshoot an error thus I reverted back to using Im() model to select my relevant variables.
- I added one variable at a time and observed the R square value increased or decreases and accordingly added or removed the variables. This was I was able to filter out a lot of variables which were just plain noise.
- Using the linear regression model helped me reach a score of RMSE -65. I was stuck at this point by using linear regression.
- I tried squaring the values for co-relations but the model had overfit my numerous variables. Thus, at this point I decided to move on to random forest.
- Random forest was useful in getting my score down to around RMSE-60. But there was a problem that I couldn't select variables which had more than 53 factors, hence I think I had to drop an important predictor neighbourhood cleansed.
- I initially put the number of trees to 100 and then increased to 150 and 200 but there was not much significant difference on the scores. It has to be noted that I had not engineered the zipcode and transit variables yet.
- Random forest took very long(about 1.5 hours) to run the model due to which I was not too excited to continue with it.
- I moved on to Gradient boosting model, which was notorious for overfitting but due to its shorter running speed I preferred this over the randomForest.
- Fine tuning this model proved quite a challenge. I started with 1000 trees and 1 interactions and shrinkage value of 0.01.
- I actually got an RMSE of 90 after this which was depressing!
- But after reading about gbm(), I increased the interactions to 8 and the shrinkage to 0.001 eventually. Because of the low shrinkage value, I had to drastically increase my trees to 30000! I did not reach to 30000 trees in one go but I reached there eventually since I could see improvements in my RMSE.

• I heard about Ranger model from a friend and tried but I couldn't use or had time to use it properly.

Thus, my final score of RMSE = **55.98079** on public leaderboard came from the **gbm()** model, which was on the final day of Kaggle.

I think I left it for too late but I have some ideas which I could have implemented and improved my score:

- Count the number of "NO" in the House Rules columns to see how many restrictions were present in the house which could affect the prize.
- Find ways of using the bag model and fine tuning it.
- Find out more about using categorical variables effectively and increase interactions.

#### **APPENDIX**

```
getwd()
rm(list = ls())
setwd('/Users/shashank/Desktop/Frameworks/Kaggle competition')
data = read.csv('analysisData.csv', na.strings = c("NA","N/A"," "))
#analysing the data
colnames(data)
str(data)
sapply(data, class)
#counting na values in each column
colSums(is.na(data))
#converting character to numneric
data$host listings count = as.numeric(data$host listings count)
data$host total listings count = as.numeric(data$host total listings count)
data$beds = as.numeric(data$beds)
#converting date to days from today
data$first review day = as.Date(Sys.Date())-as.Date(data$first review)
data$last review day = as.Date(Sys.Date())-as.Date(data$last review)
data$host since day = as.Date(Sys.Date())-as.Date(data$host since)
#counting characters
data$name nchar<-nchar(as.character(data$name), type = 'chars')</pre>
data$description nchar<-nchar(as.character(data$description), type = 'chars')
data$neighborhood overview nchar<-nchar(as.character(data$neighborhood overview), type
= 'chars')
data$summary nchar<-nchar(as.character(data$summary), type = 'chars')
data$space nchar<-nchar(as.character(data$space), type = 'chars')</pre>
data$notes nchar<-nchar(as.character(data$notes), type = 'chars')</pre>
data$access nchar<-nchar(as.character(data$access), type = 'chars')</pre>
data$interaction nchar<-nchar(as.character(data$interaction), type = 'chars')
#number of amenities
library(stringr)
data$amenities nchar = str count(data$amenities, ',')
#replacing NA with mean or mode
```

```
data$cleaning fee[which(is.na(data$cleaning fee))] = 0
data$security deposit[which(is.na(data$security deposit))] = 0
data$beds[which(is.na(data$beds))] = 0
data$host_total_listings_count[which(is.na(data$host_total_listings_count))] =
mean(data$host total listings count, na.rm = TRUE)
data$host listings count[which(is.na(data$host listings count))] =
mean(data$host listings count, na.rm = TRUE)
data$reviews per month[which(is.na(data$reviews per month))] =
mean(data$reviews per month, na.rm = TRUE)
data$host since day[is.na(data$host since day)] =
mean(data$host since day[!is.na(data$host since day)])
data$description nchar[is.na(data$description nchar)] = 0
data$summary nchar[is.na(data$summary nchar)] = 0
data$notes nchar[is.na(data$notes nchar)] = 0
data$access nchar[is.na(data$access nchar)] = 0
data$interaction nchar[is.na(data$interaction nchar)] = 0
colSums(is.na(data))
str(data)
# OUTLIERS
# MAXIMUM NIGHTS
mask maximum nights outlier = (data$maximum nights>6000)
data[mask maximum nights outlier, 'maximum nights'] =
median(data$maximum nights,na.rm = T)
summary(data$maximum nights)
#plot(data$maximum nights)
# MINIMUM MAXIMUM NIGHTS
mask minimum maximum nights outlier = (data$minimum maximum nights>6000)
data[mask minimum maximum nights outlier, 'minimum maximum nights'] =
median(data$minimum maximum nights,na.rm = T)
summary(data$minimum maximum nights)
#plot(data$minimum maximum nights)
# MAXIMUM MAXIMUM NIGHTS
mask maximum maximum nights outlier = (data$maximum maximum nights>6000)
data[mask maximum maximum nights outlier, 'maximum maximum nights'] =
median(data$maximum maximum nights,na.rm = T)
summary(data$maximum maximum nights)
#plot(data$maximum maximum nights)
```

```
# MAXIMUM MAXIMUM NIGHTS
mask maximum nights avg ntm outlier = (data$maximum nights avg ntm>6000)
data[mask_maximum_nights_avg_ntm_outlier, 'maximum_nights_avg_ntm'] =
median(data$maximum_nights_avg_ntm,na.rm = T)
summary(data$maximum nights avg ntm)
#plot(data$maximum nights avg ntm)
#library(ggplot2)
ggplot(data=data, aes(x=price)) +
 geom histogram(fill="blue", binwidth = 10)
table(data$price)
                   # 15 rows have Price = 0, which is not good data
# Remove Rows which have Price = 0, these are not good values
data = data[!data$price==0,]
table(data$price)
#add levels to factors
levels(data$neighbourhood cleansed) <- c(levels(data$neighbourhood cleansed), "Howland
Hook", "New Dorp", "New Dorp Beach")
levels(data$property type) <- c(levels(data$property type), "Casa particular (Cuba)", "Castle",
"Farm stay")
# Read scoring data and apply model to generate predictions
scoringData = read.csv('scoringData.csv', na.strings = c("NA","N/A"," "))
#setting levels to analysis data
scoringData$property type = factor(scoringData$property type, levels =
levels(data$property type))
scoringData$neighbourhood cleansed = factor(scoringData$neighbourhood cleansed, levels =
levels(data$neighbourhood cleansed))
#counting na values in each column
colSums(is.na(scoringData))
#converting cahracter to numneric
scoringData$host listings count = as.numeric(scoringData$host listings count)
scoringData$host_total_listings_count = as.numeric(scoringData$host_total_listings_count)
```

```
#converting date to days from today
scoringData$first review day = as.Date(Sys.Date())-as.Date(scoringData$first review)
scoringData$last review day = as.Date(Sys.Date())-as.Date(scoringData$last review)
scoringData$host_since_day = as.Date(Sys.Date())-as.Date(scoringData$host_since)
#counting characters
scoringData$name nchar = nchar(as.character(scoringData$name), type = 'chars')
scoringData$description nchar = nchar(as.character(scoringData$description), type = 'chars')
scoringData$neighborhood overview nchar =
nchar(as.character(scoringData$neighborhood overview), type = 'chars')
scoringData$summary nchar = nchar(as.character(scoringData$summary), type = 'chars')
scoringData$space nchar = nchar(as.character(scoringData$space), type = 'chars')
scoringData$notes nchar = nchar(as.character(scoringData$notes), type = 'chars')
scoringData$access nchar = nchar(as.character(scoringData$access), type = 'chars')
scoringData$interaction_nchar = nchar(as.character(scoringData$interaction), type = 'chars')
#number of amenities
library(stringr)
scoringData$amenities nchar = str count(scoringData$amenities, ',')
#replacing NA with mean or mode
scoringData$cleaning fee[which(is.na(scoringData$cleaning fee))] = 0
scoringData$security deposit[which(is.na(scoringData$security deposit))] = 0
scoringData$beds[which(is.na(scoringData$beds))] = 0
scoringData$host total listings count[which(is.na(scoringData$host total listings count))] =
mean(scoringData$host total listings count, na.rm = TRUE)
scoringData$host listings count[which(is.na(scoringData$host listings count))] =
mean(scoringData$host listings count, na.rm = TRUE)
scoringData$reviews_per_month[which(is.na(scoringData$reviews_per_month))] =
mean(scoringData$reviews per month, na.rm = TRUE)
scoringData$host since day[is.na(scoringData$host since day)] =
mean(scoringData$host since day[!is.na(scoringData$host since day)])
scoringData$description nchar[is.na(scoringData$description nchar)] = 0
scoringData$summary nchar[is.na(scoringData$summary nchar)] = 0
scoringData$notes_nchar[is.na(scoringData$notes_nchar)] = 0
scoringData$access nchar[is.na(scoringData$access nchar)] = 0
scoringData$interaction nchar[is.na(scoringData$interaction nchar)] = 0
#scoringData$property type[is.na(scoringData$property type)] = "Apartment"
#scoringData$neighbourhood cleansed[is.na(scoringData$neighbourhood cleansed)] =
"Williamsburg"
```

# # MAXIMUM NIGHTS mask maximum nights outlier1 = (scoringData\$maximum nights>6000) scoringData[mask\_maximum\_nights\_outlier1, 'maximum\_nights'] = median(scoringData\$maximum nights,na.rm = T) summary(data\$maximum nights) # MINIMUM MAXIMUM NIGHTS mask minimum maximum nights outlier1 = (scoringData\$maximum nights>6000) scoringData[mask\_minimum\_maximum\_nights\_outlier1, 'minimum\_maximum\_nights'] = median(scoringData\$minimum maximum nights,na.rm = T) # MAXIMUM MAXIMUM NIGHTS mask maximum maximum nights outlier1 = (scoringData\$maximum maximum nights>6000) scoringData[mask maximum maximum nights outlier1, 'maximum maximum nights'] = median(scoringData\$maximum\_maximum\_nights,na.rm = T) # MAXIMUM MAXIMUM NIGHTS mask maximum nights avg ntm outlier1 = (scoringData\$maximum nights avg ntm>6000) scoringData[mask maximum nights avg ntm outlier1, 'maximum nights avg ntm'] = median(scoringData\$maximum\_nights\_avg\_ntm,na.rm = T) #Zipcoding data\$zipcode[data\$zipcode == ""] <- "10002" scoringData\$zipcode[scoringData\$zipcode == ""] <- "10002" data\$zipcode[data\$zipcode == "11249\n11249"] <- "11249"

scoringData\$zipcode[scoringData\$zipcode == "11249\n11249"] <- "11249"

scoringData\$zipcode[scoringData\$zipcode == "11385-2308"] <- "11385"

scoringData\$zipcode[scoringData\$zipcode == "11413-3220"] <- "11413"

scoringData\$zipcode[scoringData\$zipcode == "11103-3233"] <- "11103"

scoringData\$zipcode[scoringData\$zipcode == "111211"] <- "11221"

data\$zipcode[data\$zipcode == "11385-2308"] <- "11385"

data\$zipcode[data\$zipcode == "11413-3220"] <- "11413"

data\$zipcode[data\$zipcode == "11103-3233"] <- "11103"

data\$zipcode[data\$zipcode == "111211"] <- "11221"

```
data$zipcode[data$zipcode == "1m"] <- "10002"
scoringData$zipcode[scoringData$zipcode == "1m"] <- "10002"
#install.packages("zipcode")
library(zipcode)
data("zipcode")
data <- merge(x = data, y = zipcode, by.x = "zipcode", by.y = "zip")
scoringData <- merge(x = scoringData, y = zipcode, by.x = "zipcode", by.y = "zip")
colSums(is.na(scoringData))
str(scoringData)
#Find Keyword
library(dplyr)
#install.packages("sqldf")
library(sqldf)
library(data.table)
# luxury
data$luxury1 = data$name %like% "luxury"
scoringData$luxury1 = scoringData$name %like% "luxury"
data$luxury1 = as.numeric(as.logical(data$luxury1))
scoringData$luxury1 = as.numeric(as.logical(scoringData$luxury1))
data$luxury2 = data$summary %like% "luxury"
scoringData$luxury2 = scoringData$summary %like% "luxury"
data$luxury2 = as.numeric(as.logical(data$luxury2))
scoringData$luxury2 = as.numeric(as.logical(scoringData$luxury2))
data$luxury3 = data$space %like% "luxury"
scoringData$luxury3 = scoringData$space %like% "luxury"
data$luxury3 = as.numeric(as.logical(data$luxury3))
scoringData$luxury3 = as.numeric(as.logical(scoringData$luxury3))
data$luxury4 = data$description %like% "luxury"
scoringData$luxury4 = scoringData$description %like% "luxury"
data$luxury4 = as.numeric(as.logical(data$luxury4))
scoringData$luxury4 = as.numeric(as.logical(scoringData$luxury4))
data$luxury5 = data$neighborhood overview %like% "luxury"
scoringData$luxury5 = scoringData$neighborhood overview %like% "luxury"
```

```
data$luxury5 = as.numeric(as.logical(data$luxury5))
scoringData$luxury5 = as.numeric(as.logical(scoringData$luxury5))
# Luxury
data$luxury6 = data$name %like% "Luxury"
scoringData$luxury6 = scoringData$name %like% "Luxury"
data$luxury6 = as.numeric(as.logical(data$luxury6))
scoringData$luxury6 = as.numeric(as.logical(scoringData$luxury6))
data$luxury7 = data$summary %like% "Luxury"
scoringData$luxury7 = scoringData$summary %like% "Luxury"
data$luxury7 = as.numeric(as.logical(data$luxury7))
scoringData$luxury7 = as.numeric(as.logical(scoringData$luxury7))
data$luxury8 = data$space %like% "Luxury"
scoringData$luxury8 = scoringData$space %like% "Luxury"
data$luxury8 = as.numeric(as.logical(data$luxury8))
scoringData$luxury8 = as.numeric(as.logical(scoringData$luxury8))
data$luxury9 = data$description %like% "Luxury"
scoringData$luxury9 = scoringData$description %like% "Luxury"
data$luxury9 = as.numeric(as.logical(data$luxury9))
scoringData$luxury9 = as.numeric(as.logical(scoringData$luxury9))
data$luxury10 = data$neighborhood overview %like% "Luxury"
scoringData$luxury10 = scoringData$neighborhood overview %like% "Luxury"
data$luxury10 = as.numeric(as.logical(data$luxury10))
scoringData$luxury10 = as.numeric(as.logical(scoringData$luxury10))
# luxurious
data$luxury11 = data$name %like% "luxurious"
scoringData$luxury11 = scoringData$name %like% "luxurious"
data$luxury11 = as.numeric(as.logical(data$luxury11))
scoringData$luxury11 = as.numeric(as.logical(scoringData$luxury11))
data$luxury12 = data$summary %like% "luxurious"
scoringData$luxury12 = scoringData$summary %like% "luxurious"
data$luxury12 = as.numeric(as.logical(data$luxury12))
scoringData$luxury12 = as.numeric(as.logical(scoringData$luxury12))
data$luxury13 = data$space %like% "luxurious"
scoringData$luxury13 = scoringData$space %like% "luxurious"
data$luxury13 = as.numeric(as.logical(data$luxury13))
scoringData$luxury13 = as.numeric(as.logical(scoringData$luxury13))
```

```
data$luxury14 = data$description %like% "luxurious"
scoringData$luxury14 = scoringData$description %like% "luxurious"
data$luxury14 = as.numeric(as.logical(data$luxury14))
scoringData$luxury14 = as.numeric(as.logical(scoringData$luxury14))
data$luxury15 = data$neighborhood overview %like% "luxurious"
scoringData$luxury15 = scoringData$neighborhood overview %like% "luxurious"
data$luxury15 = as.numeric(as.logical(data$luxury15))
scoringData$luxury15 = as.numeric(as.logical(scoringData$luxury15))
# Luxurious
data$luxury16 = data$name %like% "Luxurious"
scoringData$luxury16 = scoringData$name %like% "Luxurious"
data$luxury16 = as.numeric(as.logical(data$luxury16))
scoringData$luxury16 = as.numeric(as.logical(scoringData$luxury16))
data$luxury17 = data$summary %like% "Luxurious"
scoringData$luxury17 = scoringData$summary %like% "Luxurious"
data$luxury17 = as.numeric(as.logical(data$luxury17))
scoringData$luxury17 = as.numeric(as.logical(scoringData$luxury17))
data$luxury18 = data$space %like% "Luxurious"
scoringData$luxury18 = scoringData$space %like% "Luxurious"
data$luxury18 = as.numeric(as.logical(data$luxury18))
scoringData$luxury18 = as.numeric(as.logical(scoringData$luxury18))
data$luxury19 = data$description %like% "Luxurious"
scoringData$luxury19 = scoringData$description %like% "Luxurious"
data$luxury19 = as.numeric(as.logical(data$luxury19))
scoringData$luxury19 = as.numeric(as.logical(scoringData$luxury19))
data$luxury20 = data$neighborhood overview %like% "Luxurious"
scoringData$luxury20 = scoringData$neighborhood overview %like% "Luxurious"
data$luxury20 = as.numeric(as.logical(data$luxury20))
scoringData$luxury20 = as.numeric(as.logical(scoringData$luxury20))
data$luxury = (data$luxury1 + data$luxury2 + data$luxury3 + data$luxury4 + data$luxury5 +
data$luxury6 + data$luxury7 + data$luxury8 + data$luxury9 + data$luxury10
        + data$luxury11 + data$luxury12 + data$luxury13 + data$luxury14 + data$luxury15 +
data$luxury16 + data$luxury17 + data$luxury18 + data$luxury19
       + data$luxury20)
```

```
scoringData$luxury = (scoringData$luxury1 + scoringData$luxury2 + scoringData$luxury3 +
scoringData$luxury4 + scoringData$luxury5 + scoringData$luxury6
            + scoringData$luxury7 + scoringData$luxury8 + scoringData$luxury9 +
scoringData$luxury10 + scoringData$luxury11 + scoringData$luxury12
           + scoringData$luxury13 + scoringData$luxury14 + scoringData$luxury15 +
scoringData$luxury16 + scoringData$luxury17 + scoringData$luxury18
           + scoringData$luxury19 + scoringData$luxury20)
#transit
data$transit bus = data$transit %like% "bus"
scoringData$transit bus = scoringData$name %like% "bus"
data$transit bus = as.numeric(as.logical(data$transit bus))
scoringData$transit bus = as.numeric(as.logical(scoringData$transit bus))
data$transit bus1 = data$transit %like% "buses"
scoringData$transit bus1 = scoringData$name %like% "bus"
data$transit bus1 = as.numeric(as.logical(data$transit bus1))
scoringData$transit bus1 = as.numeric(as.logical(scoringData$transit bus1))
data$transit_train = data$transit %like% "train"
scoringData$transit train = scoringData$name %like% "train"
data$transit train = as.numeric(as.logical(data$transit train))
scoringData$transit train = as.numeric(as.logical(scoringData$transit train))
data$transit subway = data$transit %like% "subway"
scoringData$transit subway = scoringData$name %like% "subway"
data$transit subway = as.numeric(as.logical(data$transit subway))
scoringData$transit subway = as.numeric(as.logical(scoringData$transit subway))
data$transit modes = data$transit bus + data$transit subway + data$transit train
scoringData$transit modes = scoringData$transit bus + scoringData$transit subway +
scoringData$transit train
#Linear model
model1 = lm(price~
       host total listings count
      + host is superhost
      + host has profile pic
       + host identity verified
#
      + is location exact
```

- + property\_type
- + neighbourhood group cleansed
- + room\_type
- + accommodates
- + security deposit
- + cleaning\_fee
- + guests\_included
- + extra people
- + minimum\_nights
- + maximum maximum nights
- + minimum\_maximum\_nights
- + maximum\_nights
- + review\_scores\_rating
- + bathrooms
- + bedrooms
- + beds
- + bed type
- + availability\_30
- + availability 60
- + availability\_90
- + availability 365
- + neighbourhood cleansed
- + number of reviews
- + number\_of\_reviews\_ltm
- + review scores accuracy
- + review scores cleanliness
- + review scores checkin
- # + review scores communication
- # + review scores location
  - + review scores value
- # + reviews per month
- # + instant bookable
  - + cancellation\_policy
- # + require guest profile picture
- # + require\_guest\_phone\_verification
  - + calculated host listings count
  - + calculated\_host\_listings\_count\_entire\_homes
  - + calculated host listings count private rooms
  - + name\_nchar
- # + description\_nchar
- # +neighborhood overview nchar
  - + summary\_nchar
  - + space nchar
- # + notes nchar

```
#
       + access_nchar
#
      + interaction_nchar
      + amenities_nchar
      + first_review_day
      + last review day
      + latitude
      + longitude
      + luxury
      + transit_modes
      + host_since_day
#
,data)
summary(model1)
levels(data$property_type)
levels(data$neighbourhood_cleansed)
levels(scoringData$neighbourhood cleansed)
#Random forest model
library(randomForest)
set.seed(617)
model2 = randomForest(price~ host total listings count
           + host_is_superhost
           + host has profile pic
                   + host_identity_verified
           + is location exact
           + property type
           + neighbourhood group cleansed
           + room type
           + accommodates
           + security deposit
           + cleaning_fee
           + guests included
           + extra_people
           + minimum nights
           + maximum_nights
           + review_scores_rating
           + bathrooms
           + bedrooms
           + beds
           + bed_type
           + availability 30
           + availability 60
```

```
+ availability 365
           # + neighbourhood_cleansed
           + number_of_reviews
           + number of reviews Itm
           + review scores accuracy
           + review scores cleanliness
           + review scores checkin
           #
                  + review_scores_communication
                  + review scores location
           + review_scores value
                  + reviews_per_month
                  + instant bookable
          # + cancellation policy
                   + require_guest_profile_picture
                   + require guest phone verification
          + calculated host listings count
          + calculated_host_listings_count_entire_homes
          + calculated_host_listings_count_private_rooms
          + name nchar
          #
                 + description nchar
          #
                 +neighborhood_overview_nchar
          + summary_nchar
          + space_nchar
                 + notes nchar
          #
                 + access nchar
                 + interaction nchar
          + amenities nchar
          + first review day
          + last review day
                  + host since day
           +latitude
          +longitude
          + maximum maximum nights
          + minimum maximum nights
          + luxury
          + transit modes
            ,data=data,ntree = 150, na.action=na.exclude)
pred = predict(model2,newdata=scoringData)
rmseForest = sqrt(mean((pred-data$price)^2)); rmseForest
table(is.na(pred))
```

+ availability 90

```
#boosting
library(gbm)
set.seed(617)
model3 = gbm(price~ host_total_listings_count
      + host is superhost
      + host has profile pic
      + host identity verified
      + is location exact
      + property type
      + neighbourhood group cleansed
      + room type
      + accommodates
      + security deposit
      + cleaning fee
      + guests included
      + extra people
      + minimum_nights
      + maximum nights
      + review scores rating
      + bathrooms
      + bedrooms
      + beds
      + bed type
      + availability 30
      + availability 60
      + availability 90
      + availability 365
       + neighbourhood cleansed
      + number of reviews
      + number of reviews Itm
      + review scores accuracy
      + review scores cleanliness
      + review_scores_checkin
      #
             + review scores communication
      #
              + review_scores_location
      + review scores value
             + reviews_per_month
      #
              + instant bookable
       + cancellation_policy
            + require guest profile picture
              + require_guest_phone_verification
      + calculated_host_listings_count
       + calculated host listings count entire homes
       + calculated host listings count private rooms
```

```
+ name_nchar
              + description nchar
      #
              +neighborhood overview nchar
      + summary_nchar
      + space nchar
      #
             + notes nchar
            + access nchar
              + interaction nchar
      + amenities nchar
      # + first review day
      # + last review day
      #
              + host since day
      +latitude
      +longitude
      + luxury
      + transit modes
      , data=data, distribution="gaussian", n.trees = 30000,interaction.depth = 8,shrinkage =
0.001)
predBoostTrain = predict(model3,n.trees = 30000)
rmseBoostTrain = sqrt(mean((predBoostTrain-data$price)^2)); rmseBoostTrain
pred = predict(model3,newdata=scoringData, n.trees = 30000)
rmseBoostTest = sqrt(mean((pred-data$price)^2)); rmseBoostTest
table(is.na(pred))
#ranger
install.packages("ranger")
library(ranger)
ranger rf = ranger(formula = price~host total listings count
          + host_is_superhost
          + host has profile pic
          + host_identity_verified
          + is location exact
          + property_type
          + neighbourhood group cleansed
          + room_type
          + accommodates
          + security deposit
          + cleaning_fee
          + guests included
          + extra people
```

```
+ minimum nights
+ maximum nights
+ review_scores_rating
+ bathrooms
+ bedrooms
+ beds
+ bed type
+ availability_30
+ availability 60
+ availability 90
+ availability 365
+ neighbourhood cleansed
+ number of reviews
+ number of reviews Itm
+ review scores accuracy
+ review scores cleanliness
+ review scores checkin
      + review_scores_communication
#
       + review scores location
+ review_scores_value
+ reviews_per_month
#
       + instant bookable
+ cancellation policy
+ require_guest_profile_picture
       + require guest phone verification
+ calculated_host_listings_count
+ calculated host listings count entire homes
+ calculated host listings count private rooms
+ name nchar
#
       + description nchar
       +neighborhood overview nchar
+ summary nchar
+ space_nchar
#
      + notes nchar
+ access nchar
      + interaction nchar
+ amenities nchar
# + first review day
# + last_review_day
      + host since daye,
data = data,num.trees = 500,write.forest = TRUE)
```

# Construct submission from predictions submissionFile = data.frame(id = scoringData\$id, price = pred) write.csv(submissionFile, 'boost\_submission.csv',row.names = F)

str(data)