Airbnb Seattle Market, An Exploratory & Predictive Analysis

Market Assigned to the team : SEATTLE ”


```
library(stringr)
library(tidyr)
library(mice)
```

```
## Warning: package 'mice' was built under R version 3.6.3
```

```
##
## Attaching package: 'mice'
```

```
## The following objects are masked from 'package:base':
##
##     cbind, rbind
```

```
library(dplyr)
```

```
##
## Attaching package: 'dplyr'
```

```
## The following objects are masked from 'package:stats':
##
##     filter, lag
```

```
## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union

library(mice)
library(randomForest)

## Warning: package 'randomForest' was built under R version 3.6.3

## randomForest 4.6-14

## Type rfNews() to see new features/changes/bug fixes.

##
## Attaching package: 'randomForest'

## The following object is masked from 'package:dplyr':
##
##     combine

library(tidyverse)

## -- Attaching packages --------------------------------------- tidyverse 1.
3.0 --

## v ggplot2 3.2.1     v purrr   0.3.3
## v tibble  2.1.3     v forcats 0.4.0
## v readr   1.3.1

## -- Conflicts ------------------------------------------ tidyverse_conflict
s() --
## x randomForest::combine() masks dplyr::combine()
## x dplyr::filter()         masks stats::filter()
## x dplyr::lag()            masks stats::lag()
## x ggplot2::margin()       masks randomForest::margin()

library(tidymodels)

## Registered S3 method overwritten by 'xts':
##   method     from
##   as.zoo.xts zoo

## -- Attaching packages ---------------------------------- tidymodels 0.
0.3 --

## v broom     0.5.3     v recipes   0.1.9
## v dials     0.0.4     v rsample   0.0.5
## v infer     0.5.1     v yardstick 0.0.4
## v parsnip   0.0.5

## -- Conflicts ------------------------------------------ tidymodels_conflict
s() --
## x randomForest::combine() masks dplyr::combine()
```

```
## x scales::discard()       masks purrr::discard()
## x dplyr::filter()         masks stats::filter()
## x recipes::fixed()        masks stringr::fixed()
## x dplyr::lag()            masks stats::lag()
## x dials::margin()         masks ggplot2::margin(), randomForest::margin()
## x yardstick::spec()       masks readr::spec()
## x recipes::step()         masks stats::step()
## x recipes::yj_trans()     masks scales::yj_trans()
```

```
library(caret)
```

```
## Loading required package: lattice
```

```
##
## Attaching package: 'caret'
```

```
## The following objects are masked from 'package:yardstick':
##
##     precision, recall
```

```
## The following object is masked from 'package:purrr':
##
##     lift
```

```
library(skimr)
library(plotly)
```

```
##
## Attaching package: 'plotly'
```

```
## The following object is masked from 'package:ggplot2':
##
##     last_plot
```

```
## The following object is masked from 'package:stats':
##
##     filter
```

```
## The following object is masked from 'package:graphics':
##
##     layout
```

```
library(leaflet)
```

```
## Warning: package 'leaflet' was built under R version 3.6.3
```

```
library(widgetframe)
```

```
## Warning: package 'widgetframe' was built under R version 3.6.3
```

```
## Loading required package: htmlwidgets
```

```
library(bs4Dash)
```

```
## Warning: package 'bs4Dash' was built under R version 3.6.3

##
## Attaching package: 'bs4Dash'

## The following object is masked from 'package:graphics':
##
##     box

library(Imap)

##
## Attaching package: 'Imap'

## The following object is masked from 'package:purrr':
##
##     imap

library(tidytext)
library(wordcloud)

## Warning: package 'wordcloud' was built under R version 3.6.3

## Loading required package: RColorBrewer

library(lubridate)

##
## Attaching package: 'lubridate'

## The following object is masked from 'package:base':
##
##     date

library(tsibble)

## Warning: package 'tsibble' was built under R version 3.6.3

##
## Attaching package: 'tsibble'

## The following objects are masked from 'package:lubridate':
##
##     interval, new_interval

## The following object is masked from 'package:dplyr':
##
##     id

library(tmap)

## Warning: package 'tmap' was built under R version 3.6.3

library(tm)
```

```
## Warning: package 'tm' was built under R version 3.6.3

## Loading required package: NLP

##
## Attaching package: 'NLP'

## The following object is masked from 'package:ggplot2':
##
##     annotate

library(RColorBrewer)
```

Executive Summary

All of the research and analysis done for this project is with the aim of building a case to present to investors to make them understand most profitable locations to buy properties for Airbnb's in Seattle. We have done this by running various exploratory and predictive analysis models. For data exploration we have we have various visualizations like box plots, bar graphs, maps and tables to understand relations between different variables and high booking rate. For predictive analytics we have run kNN, Random Forest, XG Boost and Logistic regression with XG Boost giving us the best accuracy. Through our analysis, we figured out what factors attract the most number of customers to present to the investors.

Research Questions

What are the popular times to join Airbnb among the hosts? According to our research on the city and the dataset, there has been a steady increase in apartment construction due to rising rental demands since 2010. This has led to a large number of hosts joining the lucrative business since then. A trend can be seen from the dataset wherein maximum number of hosts (about 19%) have joined Airbnb in the months of August to December. Our analysis suggests that this time is ideal for an establishment to be set up and gain enough traction to cater to a huge crowd which prefer the months of June to August to visit the city. Events like the Seattle International Film Festival (May-June), Seattle Pride (June), Seattle International Beer Fest (July) and Seattle Art Fair (August) attract a large audience from all over the country. Chilly winds and a lot of rainy days make this city almost unvisitable. Despite this, the city has a lot to offer, which led us to believe that there has to be a popular time when the weather is pleasant, which will see a surge in the tourist numbers. Accordingly, the hosts should have a favourite time to enlist their establishment with the company.

What effects price of the establishment in the city? In order to find factors affecting the price of an establishment in the city we built a number of models and compared the Root Mean Square Error to choose the best one. Using our domain knowledge gained by the research we did on the city and its establishments, variables like bathrooms, bed type, bedrooms, host verification, superhost, host listings count, maximum nights, amenities count, host response time, instant bookable, number of beds were taken as important variables. Using these factors we built a linear regression model, a KNN model and a Random Forest model with the last one giving the best analysis for the chosen variables.

The model concluded that these variables were statistically significant in deciding the price of an establishment. It is all about the money! The price of an establishment will ultimately decide how much profit the establishment will make. Therefore, we took this to be an important factor in deciding whether to invest in an establishment. Given all other factors about an establishment are known, the predicted price can help an investor calculate the worth of the property in the future.

What are the best neighbourhoods in Seattle to invest in? Neighbourhood plays an important role in the value of any establishment. Though our analysis we found this to be true for this city as well. Certain neighbourhoods had a noticeably larger number of establishment with high booking rates. Further their availability for 30, 60, 90 and 365 days were very low. Combining both analysis led us to believe that these neighbourhoods including Capitol Hill, First Hill, Belltown, Queen Anne and Madison Valley are particularly popular among the tourists. Further Capitol Hill also have some of the most expensive rentals (about 13%) which have a high booking rate. Expanding on the first question, as the festivals are held in certain locations, we considered location to be a deciding factor for an establishment to perform well. Building on this notion we considered some of the most popular establishments with high rents and plotted a map of the popular areas. We reached to the conclusion that for Seattle, location of the property was an important factor to decide if it will be profitable.

Can COVID-19 be a factor in deciding how to keep a property profitable? Data about the highly infected areas in the city was fetched. This allowed us to compare the data against the establishments in the vicinity. These establishments can be used by authorities to be rented for providing quality accommodation to front line workers while keeping their businesses running. This would not only promote the property but also keep the property profitable in the times when businesses are taking huge hits. Economies of all the countries have been effected largely due to COVID-19. Many businesses have shut down and others are suffering gravely. In such harsh times, can we somehow take advantage of the situation? This motivated us to look for a viable solution to deal with the declining profits.

METHODOLOGY

The dataset provided to us was was not clean and we had to skim through the data. We had to go through each column and replace the NA values. In some cases we had to replace the missing values with the mean and in some cases with the median whereas in others we had to replace them with a 0 or FALSE, example host_is_superhost, cleaning_fee. (We performed EDA on various variables to see the relation with higher booking rate. We did a lot of research on the airbnb website as well as through external sources. We used the data dictionary to understand the variables and built our research on that. We used the skim and str function to understand our variables. We ran regression to see what variables that were significant for us. We then used those in our final model, xgboost, which gave us the highest accuracy. We also included some variables which we thought were important after our online research. (For determining whether a property will have a higher booking rate, we put ourselves in the shoes of the customer booking an airbnb property. We confirmed our thinking through online research. After running our model on the entire data on kaggle, we achieved an accuracy of 89% using random forest. We then decided to test the model

only on our Seattle data. We ran Knn, logistic, random forest and xgBoost for our Seattle dataset. The xgboost which used mostly numeric and logical variables, performed the best with an accuracy of 95%. We have used various text mining techniques and predictive models in our data. XGBoost offers several advanced features for model tuning, computing environments and algorithm enhancement. The algorithm efficiently reduces computing time and allocates an optimal usage of memory resources on the system. This model creates a strong model based on weak classifiers. This helps improve the accuracy. We optimized the parameters of this model to our dataset to achieve this.

```
dfAirbnbTrainSeattle<- read_csv("AirbnbSeattleTrain.csv")
```

```
## Parsed with column specification:
## cols(
##   .default = col_character(),
##   id = col_double(),
##   high_booking_rate = col_double(),
##   accommodates = col_double(),
##   availability_30 = col_double(),
##   availability_365 = col_double(),
##   availability_60 = col_double(),
##   availability_90 = col_double(),
##   bathrooms = col_double(),
##   bedrooms = col_double(),
##   beds = col_double(),
##   guests_included = col_double(),
##   host_has_profile_pic = col_logical(),
##   host_identity_verified = col_logical(),
##   host_is_superhost = col_logical(),
##   host_listings_count = col_double(),
##   host_since = col_date(format = ""),
##   instant_bookable = col_logical(),
##   is_business_travel_ready = col_logical(),
##   is_location_exact = col_logical(),
##   latitude = col_double()
##   # ... with 16 more columns
## )
```

```
## See spec(...) for full column specifications.
```

```
## Warning: 1 parsing failure.
##  row     col               expected actual                     file
## 4740 zipcode no trailing characters  -4417 'AirbnbSeattleTrain.csv'
```

```
dfAirbnbTestSeattle <- read_csv("AirbnbSeattleTest.csv")
```

```
## Parsed with column specification:
## cols(
##   .default = col_character(),
##   id = col_double(),
##   accommodates = col_double(),
```

```
##   availability_30 = col_double(),
##   availability_365 = col_double(),
##   availability_60 = col_double(),
##   availability_90 = col_double(),
##   bathrooms = col_double(),
##   bedrooms = col_double(),
##   beds = col_double(),
##   guests_included = col_double(),
##   host_has_profile_pic = col_logical(),
##   host_identity_verified = col_logical(),
##   host_is_superhost = col_logical(),
##   host_listings_count = col_double(),
##   host_since = col_date(format = ""),
##   instant_bookable = col_logical(),
##   is_business_travel_ready = col_logical(),
##   is_location_exact = col_logical(),
##   latitude = col_double(),
##   longitude = col_double()
##   # ... with 15 more columns
## )
## See spec(...) for full column specifications.

## Warning: 1 parsing failure.
##  row     col               expected actual                     file
## 1016 zipcode no trailing characters  -4417 'AirbnbSeattleTest.csv'

table(dfAirbnbTrainSeattle$market)

##
##           Los Angeles Other (International)               Seattle
##                     1                     1                  5399

skim(dfAirbnbTrainSeattle)
```

Data summary

Name	dfAirbnbTrainSeattle
Number of rows	5414
Number of columns	66

Column type frequency:

character	30
Date	1
logical	9
numeric	26

Group variables	None

Variable type: character

skim_variable	n_missing	complete_rate	min	max	empty	n_unique	whitespace
access	1927	0.64	1	1000	0	3059	0
amenities	0	1.00	2	1574	0	4701	0
bed_type	0	1.00	5	13	0	5	0
cancellation_policy	0	1.00	6	27	0	6	0
city	2	1.00	7	16	0	4	0
cleaning_fee	465	0.91	5	7	0	174	0
description	45	0.99	3	1000	0	4766	3
extra_people	0	1.00	5	7	0	45	0
host_about	1462	0.73	1	4134	0	2348	10
host_acceptance_rate	3	1.00	3	3	0	1	0
host_location	9	1.00	2	47	0	172	0
host_neighbourhood	523	0.90	4	25	0	123	0
host_response_rate	3	1.00	2	4	0	35	0
host_response_time	3	1.00	3	18	0	5	0
host_verifications	0	1.00	4	168	0	231	0
house_rules	1247	0.77	4	1000	0	3133	0
interaction	1407	0.74	1	1000	0	3131	0
market	13	1.00	7	21	0	3	0
monthly_price	4978	0.08	7	10	0	164	0
neighborhood_overview	1583	0.71	7	1000	0	3223	0
neighbourhood	1	1.00	4	25	0	79	0
notes	2312	0.57	1	1000	0	2484	0
price	0	1.00	5	9	0	349	0
property_type	0	1.00	4	18	0	27	0
room_type	0	1.00	10	15	0	4	0

security_deposit	926	0.83	5	9	0	62	0
space	1069	0.80	2	1000	0	3756	0
state	1	1.00	2	2	0	2	0
transit	1670	0.69	7	1000	0	3279	0
weekly_price	4828	0.11	7	9	0	212	0

Variable type: Date

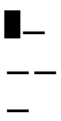
skim_variable	n_missing	complete_rate	min	max	median	n_unique
host_since	3	1	2008-03-03	2019-11-20	2015-04-17	1992

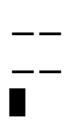
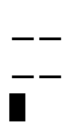
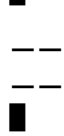
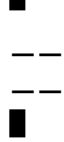
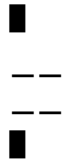
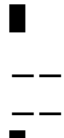
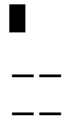
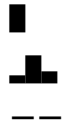
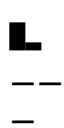
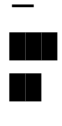
Variable type: logical

skim_variable	n_missing	complete_rate	mean	count
host_has_profile_pic	3	1	1.00	TRU: 5406, FAL: 5
host_identity_verified	3	1	0.56	TRU: 3010, FAL: 2401
host_is_superhost	3	1	0.42	FAL: 3135, TRU: 2276
instant_bookable	0	1	0.52	TRU: 2802, FAL: 2612
is_business_travel_ready	0	1	0.00	FAL: 5414
is_location_exact	0	1	0.83	TRU: 4479, FAL: 935
require_guest_phone_verification	0	1	0.07	FAL: 5058, TRU: 356
require_guest_profile_picture	0	1	0.06	FAL: 5081, TRU: 333
requires_license	0	1	1.00	TRU: 5401, FAL: 13

Variable type: numeric

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100	hist
id	0	1.00	11017785.41	583040.81	10000048.00	10512123.75	11022283.50	11523303.25	12020090.00	▆▆▁▁▆

high_booking_rate	0	1.00	0.39	0.49	0.00	0.00	0.00	1.00	1.00	
accommodates	0	1.00	3.65	2.28	1.00	2.00	3.00	4.00	28.00	
availability_30	0	1.00	12.47	11.21	0.00	0.00	12.00	23.00	30.00	
availability_365	0	1.00	141.19	133.89	0.00	9.00	90.00	278.00	365.00	
availability_60	0	1.00	26.94	21.99	0.00	0.00	28.00	47.00	60.00	
availability_90	0	1.00	43.72	33.93	0.00	0.00	49.00	76.00	90.00	
bathrooms	2	1.00	1.32	0.64	0.00	1.00	1.00	1.50	8.00	
bedrooms	4	1.00	1.38	1.01	0.00	1.00	1.00	2.00	8.00	
beds	3	1.00	1.89	1.47	0.00	1.00	1.00	2.00	17.00	
guests_included	0	1.00	2.03	1.67	1.00	1.00	1.00	2.00	16.00	
host_listings_count	3	1.00	151.10	436.83	0.00	1.00	2.00	10.00	1825.00	
latitude	0	1.00	47.63	0.05	47.50	47.61	47.62	47.66	47.73	
longitude	0	1.00	-122.33	0.03	-122.42	-122.35	-122.33	-122.31	-122.24	
maximum_nights	0	1.00	603.83	532.20	1.00	29.00	1124.00	1125.00	1125.00	

minimum_nights	0	1.00	4.93	13.30	1.00	1.00	2.00	3.00	400.00	
review_scores_accuracy	786	0.85	9.72	0.74	2.00	10.00	10.00	10.00	10.00	
review_scores_checkin	787	0.85	9.80	0.68	2.00	10.00	10.00	10.00	10.00	
review_scores_cleanliness	786	0.85	9.64	0.76	2.00	9.00	10.00	10.00	10.00	
review_scores_communication	786	0.85	9.80	0.69	2.00	10.00	10.00	10.00	10.00	
review_scores_location	788	0.85	9.80	0.58	2.00	10.00	10.00	10.00	10.00	
review_scores_rating	784	0.86	95.08	7.57	20.00	94.00	97.00	99.00	100.00	
review_scores_value	787	0.85	9.51	0.82	2.00	9.00	10.00	10.00	10.00	
square_feet	5152	0.05	698.21	326.59	0.00	580.00	600.00	1000.00	2100.00	
zipcode	99	0.98	98116.34	17.48	98101.00	98104.00	98115.00	98122.00	98199.00	
{randomControl}	0	1.00	124497.35	289.13	124000.00	124244.25	124497.00	124750.00	124999.00	

```
#Availibility_365
#it's clean
dfAirbnbTrainSeattle$availability_365 <- as.numeric(dfAirbnbTrainSeattle$availability_365)
dfAirbnbTestSeattle$availability_365 <- as.numeric(dfAirbnbTestSeattle$availability_365)

#amenities_count
dfAirbnbTrainSeattle$amenities_count<-
  sapply(dfAirbnbTrainSeattle$amenities, function(x) length(unlist(strsplit(as.character(x), ','))))
```

```r
dfAirbnbTestSeattle$amenities_count<-
  sapply(dfAirbnbTestSeattle$amenities, function(x) length(unlist(strsplit(as
.character(x), ','))))

#host_verifications_count
dfAirbnbTrainSeattle$host_verification_count <-
  sapply(dfAirbnbTrainSeattle$host_verifications, function(x) length(unlist(s
trsplit(as.character(x), ','))))

dfAirbnbTestSeattle$host_verification_count <-
  sapply(dfAirbnbTestSeattle$host_verifications, function(x) length(unlist(st
rsplit(as.character(x), ','))))

#host_age
dfAirbnbTrainSeattle$host_since <- as.Date(dfAirbnbTrainSeattle$host_since)
dfAirbnbTrainSeattle$host_age <- as.integer(difftime(Sys.Date(), dfAirbnbTrai
nSeattle$host_since, units = 'weeks'))
summary(dfAirbnbTrainSeattle$host_age)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##    24.0   196.0   264.0   266.7   349.0   635.0       3

dfAirbnbTrainSeattle$host_age[is.na(dfAirbnbTrainSeattle$host_age)] <- 301.6


dfAirbnbTestSeattle$host_since <- as.Date(dfAirbnbTestSeattle$host_since)
dfAirbnbTestSeattle$host_age <- as.integer(difftime(Sys.Date(), dfAirbnbTestS
eattle$host_since, units = 'weeks'))
summary(dfAirbnbTestSeattle$host_age)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    25.0   194.0   258.0   264.8   349.0   599.0

dfAirbnbTestSeattle$host_age[is.na(dfAirbnbTestSeattle$host_age)] <- 301.6

#Bathrooms
dfAirbnbTrainSeattle$bathrooms <- as.numeric(dfAirbnbTrainSeattle$bathrooms)
dfAirbnbTestSeattle$bathrooms <- as.numeric(dfAirbnbTestSeattle$bathrooms)
summary(dfAirbnbTrainSeattle$bathrooms)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##   0.000   1.000   1.000   1.315   1.500   8.000       2

table(dfAirbnbTrainSeattle$bathrooms)

##
##    0  0.5    1  1.5    2  2.5    3  3.5    4  4.5    5    8
##    9   19 3988  290  617  218  131  118   12    7    1    2
```

```r
#Bed_Type

table(dfAirbnbTrainSeattle$bed_type)

##
##        Airbed         Couch         Futon Pull-out Sofa      Real Bed
##            10             4            27            19          5354

dfAirbnbTrainSeattle$bed_type <- as.character(dfAirbnbTrainSeattle$bed_type)
dfAirbnbTrainSeattle$bed_type[dfAirbnbTrainSeattle$bed_type == ''] <- 'Airbed
'
dfAirbnbTrainSeattle$bed_type[dfAirbnbTrainSeattle$bed_type == '100%'] <- 'Ai
rbed'
dfAirbnbTrainSeattle$bed_type[dfAirbnbTrainSeattle$bed_type == '81%'] <- 'Air
bed'
dfAirbnbTrainSeattle$bed_type <- as.factor(dfAirbnbTrainSeattle$bed_type)

dfAirbnbTestSeattle$bed_type <- as.character(dfAirbnbTestSeattle$bed_type)
dfAirbnbTestSeattle$bed_type[dfAirbnbTestSeattle$bed_type == ''] <- 'Airbed'
dfAirbnbTestSeattle$bed_type[dfAirbnbTestSeattle$bed_type == '100%'] <- 'Airb
ed'
dfAirbnbTestSeattle$bed_type[dfAirbnbTestSeattle$bed_type == '81%'] <- 'Airbe
d'
dfAirbnbTestSeattle$bed_type <- as.factor(dfAirbnbTestSeattle$bed_type)

#bedrooms
#Mean = 1.36
dfAirbnbTrainSeattle$bedrooms <- as.numeric(dfAirbnbTrainSeattle$bedrooms)
dfAirbnbTrainSeattle$bedrooms[is.na(dfAirbnbTrainSeattle$bedrooms)] <- 3.5
summary(dfAirbnbTrainSeattle$bedrooms)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.000   1.000   1.000   1.383   2.000   8.000

table(dfAirbnbTrainSeattle$bedrooms)

##
##    0    1    2    3  3.5    4    5    6    7    8
##  670 3000 1058  468    4  145   51    9    8    1

dfAirbnbTestSeattle$bedrooms <- as.numeric(dfAirbnbTestSeattle$bedrooms)
dfAirbnbTestSeattle$bedrooms[is.na(dfAirbnbTestSeattle$bedrooms)] <- 3.5

#beds

summary(dfAirbnbTrainSeattle$beds)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##   0.000   1.000   1.000   1.893   2.000  17.000       3

dfAirbnbTrainSeattle$beds <- as.numeric(dfAirbnbTrainSeattle$beds)
table(dfAirbnbTrainSeattle$beds)
```

```
##
##    0    1    2    3    4    5    6    7    8    9   10   11   12   13   14
15
##   97 2757 1375  659  263  117   65   27   13    2   10    3   18    1    2
1
##   17
##    1
```

```
dfAirbnbTestSeattle$beds <- as.numeric(dfAirbnbTestSeattle$beds)

#host_identity_Verified

table(dfAirbnbTrainSeattle$host_identity_verified)
```

```
##
## FALSE  TRUE
##  2401  3010
```

```
dfAirbnbTrainSeattle$host_identity_verified <- as.character(dfAirbnbTrainSeat
tle$host_identity_verified)
dfAirbnbTrainSeattle$host_identity_verified[dfAirbnbTrainSeattle$host_identit
y_verified == ''] <- 'TRUE'
dfAirbnbTrainSeattle$host_identity_verified[dfAirbnbTrainSeattle$host_identit
y_verified == '$2,960.00'] <- 'TRUE'
dfAirbnbTrainSeattle$host_identity_verified[dfAirbnbTrainSeattle$host_identit
y_verified == '$3,200.00'] <- 'TRUE'
dfAirbnbTrainSeattle$host_identity_verified[dfAirbnbTrainSeattle$host_identit
y_verified == '$8,500.00'] <- 'TRUE'

summary(dfAirbnbTrainSeattle$host_identity_verified)
```

```
##    Length     Class      Mode
##      5414 character character
```

```
dfAirbnbTrainSeattle$host_identity_verified <- as.factor(dfAirbnbTrainSeattle
$host_identity_verified)

levels(dfAirbnbTrainSeattle$host_identity_verified)
```

```
## [1] "FALSE" "TRUE"
```

```
dfAirbnbTestSeattle$host_identity_verified <- as.character(dfAirbnbTestSeattl
e$host_identity_verified)
dfAirbnbTestSeattle$host_identity_verified[dfAirbnbTestSeattle$host_identity_
verified == ''] <- 'TRUE'
dfAirbnbTestSeattle$host_identity_verified[dfAirbnbTestSeattle$host_identity_
verified == '$2,960.00'] <- 'TRUE'
dfAirbnbTestSeattle$host_identity_verified[dfAirbnbTestSeattle$host_identity_
verified == '$3,200.00'] <- 'TRUE'
dfAirbnbTestSeattle$host_identity_verified[dfAirbnbTestSeattle$host_identity_
verified == '$8,500.00'] <- 'TRUE'
```

```
dfAirbnbTestSeattle$host_identity_verified <- as.factor(dfAirbnbTestSeattle$h
ost_identity_verified)

#host_is_superhost

summary(dfAirbnbTrainSeattle$host_is_superhost)

##    Mode   FALSE    TRUE    NA's
## logical    3135    2276       3

dfAirbnbTrainSeattle$host_is_superhost <- as.character(dfAirbnbTrainSeattle$h
ost_is_superhost)
table(dfAirbnbTrainSeattle$host_is_superhost)

##
## FALSE  TRUE
##  3135  2276

dfAirbnbTrainSeattle$host_is_superhost <- ifelse(dfAirbnbTrainSeattle$host_is
_superhost == 'FALSE', 'FALSE', 'TRUE')
dfAirbnbTrainSeattle$host_is_superhost <- as.factor(dfAirbnbTrainSeattle$host
_is_superhost)


dfAirbnbTestSeattle$host_is_superhost <- as.character(dfAirbnbTestSeattle$hos
t_is_superhost)
table(dfAirbnbTestSeattle$host_is_superhost)

##
## FALSE  TRUE
##  1049   755

dfAirbnbTestSeattle$host_is_superhost <- ifelse(dfAirbnbTestSeattle$host_is_s
uperhost == 'FALSE', 'FALSE', 'TRUE')
dfAirbnbTestSeattle$host_is_superhost <- as.factor(dfAirbnbTestSeattle$host_i
s_superhost)

#host_listings_count

summary(dfAirbnbTrainSeattle$host_listings_count)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##     0.0     1.0     2.0   151.1    10.0  1825.0       3

dfAirbnbTrainSeattle$host_listings_count <- as.numeric(dfAirbnbTrainSeattle$h
ost_listings_count)
dfAirbnbTestSeattle$host_listings_count <- as.numeric(dfAirbnbTestSeattle$hos
t_listings_count)
```

```
#maximum_nights

summary(dfAirbnbTrainSeattle$maximum_nights)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##     1.0    29.0  1124.0   603.8  1125.0  1125.0

dfAirbnbTrainSeattle$maximum_nights <- as.numeric(dfAirbnbTrainSeattle$maximu
m_nights)
table(dfAirbnbTrainSeattle$maximum_nights)

##
##    1    2    3    4    5    6    7    8    9   10   11   12   13   14   15
16
##    6   17   35   37   56   29  221   39   14   85    5   47    7  228   46
9
##   17   18   20   21   23   24   25   26   27   28   29   30   31   32   33
35
##    3    4   42   76    1    2   22    5   17  225   90  347   78    9    3
15
##   36   37   40   42   44   45   48   50   55   59   60   61   62   63   65
66
##    1    1   13    3    1   24    1    2    5    3  126    1    5    1    2
1
##   70   72   78   79   80   85   88   89   90   91   92   93   95   96   99
100
##    3    1    1    1    2    1    2    7  171    2    2    1    9    1    1
26
##  120  125  140  150  160  170  180  181  185  186  190  200  210  215  220
240
##   63    1    1    8    1    3   81    1    1    1    2    8    4    1    1
3
##  250  270  300  325  330  360  364  365  366  500  555  600  720  730  740
800
##    1    1   11    1    1    5    4  218    3    2    1    1    1    3    1
1
## 1000 1095 1100 1118 1120 1123 1124 1125
##    9    1    1    1    1    8   60 2657

dfAirbnbTrainSeattle$maximum_nights[dfAirbnbTrainSeattle$maximum_nights > 112
5] <- 1125
dfAirbnbTrainSeattle$maximum_nights[is.na(dfAirbnbTrainSeattle$maximum_nights
)] <- 668


dfAirbnbTestSeattle$maximum_nights <- as.numeric(dfAirbnbTestSeattle$maximum_
nights)
table(dfAirbnbTestSeattle$maximum_nights)

##
##    1    2    3    4    5    6    7    8    9   10   12   13
```

```
14
##     8     6     9    11    13     9    81    10     3    28    14     2
69
##    15    16    17    18    19    20    21    22    24    25    26    27
28
##    21     5     4     1     1    13    22     3     4     4     1     3
83
##    29    30    31    32    33    35    40    45    47    50    55    58
59
##    30   120    33     1     3     7     2     6     1     1     1     1
1
##    60    61    62    65    70    71    75    80    82    89    90    95
100
##    41     1     1     1     1     1     1     1     1     1    56     2
11
##   120   125   150   153   155   160   175   180   198   200   240   246
260
##    20     2     5     1     1     1     1    26     1     4     2     1
1
##   300   330   356   360   365   369  1000  1095  1100  1120  1121  1123  1
124
##     2     1     1     4    82     1     5     1     1     2     2     2
15
##  1125 10000 1e+05
##   863     1     1
```

```
dfAirbnbTestSeattle$maximum_nights[dfAirbnbTestSeattle$maximum_nights > 1125]
<- 1125
dfAirbnbTestSeattle$maximum_nights[is.na(dfAirbnbTestSeattle$maximum_nights)]
<- 668

#minimum_nights
dfAirbnbTrainSeattle$minimum_nights<- as.numeric(dfAirbnbTrainSeattle$minimum
_nights)
summary(dfAirbnbTrainSeattle$minimum_nights)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.000   1.000   2.000   4.931   3.000 400.000
```

```
table(dfAirbnbTrainSeattle$minimum_nights)
```

```
##
##    1    2    3    4    5    6    7    8   10   13   14   15   17   19   20
21
## 1841 2081  625  137   99   30   89    4   14    2   18    2    1    1   10
9
##   23   25   28   29   30   31   32   40   45   55   60   80   81   90  120
150
##    1    3   13    2  397    7    1    1    1    1    5    1    1    6    5
1
```

```
##  180  210  345  365  400
##    1    1    1    1    1

dfAirbnbTrainSeattle$minimum_nights[is.na(dfAirbnbTrainSeattle$minimum_nights
)] <- 1
dfAirbnbTrainSeattle$minimum_nights[dfAirbnbTrainSeattle$minimum_nights == 0]
<- 1
dfAirbnbTrainSeattle$minimum_nights[dfAirbnbTrainSeattle$minimum_nights == 10
0000000] <- 1


dfAirbnbTestSeattle$minimum_nights<- as.numeric(dfAirbnbTestSeattle$minimum_n
ights)
summary(dfAirbnbTestSeattle$minimum_nights)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.000   1.000   2.000   5.216   3.000 365.000

table(dfAirbnbTestSeattle$minimum_nights)

##
##   1   2   3   4   5   6   7   8   9  10  13  14  15  18  20  21  28  30  3
1  55
## 617 710 206  39  41   7  14   1   1   7   1   7   2   1   1   4   2 128
4   2
##  70 108 180 330 365
##   1   1   5   1   1

dfAirbnbTestSeattle$minimum_nights[is.na(dfAirbnbTestSeattle$minimum_nights)]
<- 1
dfAirbnbTestSeattle$minimum_nights[dfAirbnbTestSeattle$minimum_nights == 0] <
- 1
dfAirbnbTestSeattle$minimum_nights[dfAirbnbTestSeattle$minimum_nights == 1000
00000] <- 1

#price


dfAirbnbTrainSeattle <- dfAirbnbTrainSeattle %>%
                      mutate(price = as.numeric(str_replace_all(dfAirbnbTrain
Seattle$price,"[$,]",'')))

meanPrice <- mean(dfAirbnbTrainSeattle$price, na.rm = TRUE)

dfAirbnbTrainSeattle <- dfAirbnbTrainSeattle %>%
                    mutate(price = replace_na(price, meanPrice))


dfAirbnbTestSeattle <- dfAirbnbTestSeattle %>%
                      mutate(price = as.numeric(str_replace_all(dfAirbnbTestS
```

```
eattle$price,"[$,]",'')))

meanPrice <- mean(dfAirbnbTestSeattle$price, na.rm = TRUE)

dfAirbnbTestSeattle <- dfAirbnbTestSeattle %>%
                    mutate(price = replace_na(price, meanPrice))

#dfAirbnbTrainSeattle$high_booking_rate <- dfAirbnbTrainSeattle_train_y$high_
booking_rate
dfAirbnbTrainSeattle$high_booking_rate <- as.factor(dfAirbnbTrainSeattle$high
_booking_rate)

# Final code for transformation of cleaning fee

dfAirbnbTrainSeattle <- dfAirbnbTrainSeattle %>%
                      mutate(cleaning_fee = as.numeric(str_replace_all(dfAirb
nbTrainSeattle$cleaning_fee,"[$,]",'')))

meanCleaningFee <- mean(dfAirbnbTrainSeattle$cleaning_fee, na.rm = TRUE)

dfAirbnbTrainSeattle <- dfAirbnbTrainSeattle %>%
                    mutate(cleaning_fee = replace_na(cleaning_fee, meanCleani
ngFee))


dfAirbnbTestSeattle <- dfAirbnbTestSeattle %>%
                      mutate(cleaning_fee = as.numeric(str_replace_all(dfAirb
nbTestSeattle$cleaning_fee,"[$,]",'')))

meanCleaningFee <- mean(dfAirbnbTestSeattle$cleaning_fee, na.rm = TRUE)

dfAirbnbTestSeattle <- dfAirbnbTestSeattle %>%
                    mutate(cleaning_fee = replace_na(cleaning_fee, meanCleani
ngFee))

# Final code for transformation of extra people
dfAirbnbTrainSeattle <- dfAirbnbTrainSeattle %>%
                      mutate(extra_people = as.numeric(str_replace_all(dfAirb
nbTrainSeattle$extra_people,"[$,]",'')))

dfAirbnbTestSeattle <- dfAirbnbTestSeattle %>%
                      mutate(extra_people = as.numeric(str_replace_all(dfAirb
nbTestSeattle$extra_people,"[$,]",'')))

#guests_included
dfAirbnbTrainSeattle <- dfAirbnbTrainSeattle %>%
  mutate(guests_included=as.numeric(str_replace_all(dfAirbnbTrainSeattle$gues
ts_included,"[,%]",'')))

dfAirbnbTrainSeattle <- dfAirbnbTrainSeattle %>%
```

```
  mutate(guests_included = ifelse(guests_included%in% c("17", "18", "19","20"
, "21", "22", "24", "25", "28", "30", "32", "34"), "Other", guests_included))

dfAirbnbTestSeattle <- dfAirbnbTestSeattle %>%
  mutate(guests_included=as.numeric(str_replace_all(dfAirbnbTestSeattle$guest
s_included,"[,%]",'')))

dfAirbnbTestSeattle <- dfAirbnbTestSeattle %>%
  mutate(guests_included = ifelse(guests_included%in% c("17", "18", "19","20"
, "21", "22", "24", "25", "28", "30", "32", "34"), "Other", guests_included))

#host_response_rate
dfAirbnbTrainSeattle <- dfAirbnbTrainSeattle %>%
                      mutate(host_response_rate = as.numeric(str_replace_all(
dfAirbnbTrainSeattle$host_response_rate,"[,%]",'')))

## Warning: NAs introduced by coercion

meanRespRate <- mean(dfAirbnbTrainSeattle$host_response_rate, na.rm = TRUE)

dfAirbnbTrainSeattle <- dfAirbnbTrainSeattle %>%
                    mutate(host_response_rate = replace_na(host_response_rate
, meanRespRate))

dfAirbnbTestSeattle <- dfAirbnbTestSeattle %>%
                      mutate(host_response_rate = as.numeric(str_replace_all(
dfAirbnbTestSeattle$host_response_rate,"[,%]",'')))

## Warning: NAs introduced by coercion

meanRespRate <- mean(dfAirbnbTestSeattle$host_response_rate, na.rm = TRUE)

dfAirbnbTestSeattle <- dfAirbnbTestSeattle %>%
                    mutate(host_response_rate = replace_na(host_response_rate
, meanRespRate))

dfAirbnbTrainSeattle <- dfAirbnbTrainSeattle %>%
  mutate(property_type = ifelse(property_type %in% c("Castle", "Igloo", "Tree
house", "Cave", "Dome house", "In-law", "Nature lodge", "Tipi", "Vacation hom
e", "Barn", "Campsite", "Chalet", "Dorm", "Houseboat", "Island", "Bus", "Casa
particular (Cuba)", "Earth house", "Hut", "Lighthouse", "Pension (South Korea
)", "Timeshare", "Train", "Yurt"), "Other", property_type))

dfAirbnbTestSeattle <- dfAirbnbTestSeattle %>%
  mutate(property_type = ifelse(property_type %in% c("Castle", "Igloo", "Mins
u (Taiwan)", "Treehouse", "Cave", "Dome house", "In-law", "Nature lodge", "Ti
pi", "Tent", "Vacation home", "Barn", "Campsite", "Chalet", "Dorm", "Houseboa
t", "Island", "Bus", "Casa particular (Cuba)", "Earth house", "Hut", "Lightho
use", "Pension (South Korea)", "Timeshare", "Train", "Yurt"), "Other", proper
ty_type))
```

```r
dfAirbnbTrainSeattle <- dfAirbnbTrainSeattle %>%
  mutate(cancellation_policy = ifelse(cancellation_policy %in% c("luxury_super_strict_125", "luxury_super_strict_95", "luxury_no_refund"), "Other", cancellation_policy))

dfAirbnbTestSeattle <- dfAirbnbTestSeattle %>%
  mutate(cancellation_policy = ifelse(cancellation_policy %in% c("luxury_super_strict_125", "luxury_moderate",  "luxury_super_strict_95", "luxury_no_refund"), "Other", cancellation_policy))

dfAirbnbTestSeattle$property_type <- as.factor(dfAirbnbTestSeattle$property_type)

# Final code for transformation of security deposit
dfAirbnbTrainSeattle <-  dfAirbnbTrainSeattle %>%
                      mutate(security_deposit = as.numeric(str_replace_all(dfAirbnbTrainSeattle$security_deposit,"[$,]",'')))

meanSecurtityDeposit <- mean(dfAirbnbTrainSeattle$security_deposit, na.rm = TRUE)

dfAirbnbTrainSeattle <-  dfAirbnbTrainSeattle %>%
                    mutate(security_deposit = replace_na(security_deposit, meanSecurtityDeposit))

dfAirbnbTrainSeattle$bed_type<-as.factor(dfAirbnbTrainSeattle$bed_type)
dfAirbnbTrainSeattle$host_identity_verified<-as.factor(dfAirbnbTrainSeattle$host_identity_verified)
dfAirbnbTrainSeattle$host_is_superhost<-as.factor(dfAirbnbTrainSeattle$host_is_superhost)
dfAirbnbTrainSeattle$market<-as.factor(dfAirbnbTrainSeattle$market)
dfAirbnbTrainSeattle$instant_bookable<-as.factor(dfAirbnbTrainSeattle$instant_bookable)
dfAirbnbTrainSeattle$is_location_exact<-as.factor(dfAirbnbTrainSeattle$is_location_exact)
dfAirbnbTrainSeattle$property_type<-as.factor(dfAirbnbTrainSeattle$property_type)
dfAirbnbTrainSeattle$requires_license<-as.factor(dfAirbnbTrainSeattle$requires_license)

dfAirbnbTrainSeattle$availability_365<- as.factor(dfAirbnbTrainSeattle$availability_365)
dfAirbnbTrainSeattle$bathrooms<-as.factor(dfAirbnbTrainSeattle$bathrooms)
dfAirbnbTrainSeattle$bed_type<-as.factor(dfAirbnbTrainSeattle$bed_type)
dfAirbnbTrainSeattle$host_identity_verified<-as.factor(dfAirbnbTrainSeattle$host_identity_verified)
dfAirbnbTrainSeattle$host_is_superhost<-as.factor(dfAirbnbTrainSeattle$host_is_superhost)
dfAirbnbTrainSeattle$host_listings_count<-as.factor(dfAirbnbTrainSeattle$host_listings_count)
```

```
dfAirbnbTrainSeattle$price<-as.factor(dfAirbnbTrainSeattle$price)
dfAirbnbTrainSeattle$cleaning_fee<-as.factor(dfAirbnbTrainSeattle$cleaning_fe
e)
dfAirbnbTrainSeattle$market<-as.factor(dfAirbnbTrainSeattle$market)
dfAirbnbTrainSeattle$guests_included<-as.factor(dfAirbnbTrainSeattle$guests_i
ncluded)
dfAirbnbTrainSeattle$minimum_nights<-as.factor(dfAirbnbTrainSeattle$minimum_n
ights)
dfAirbnbTrainSeattle$amenities_count<-as.factor(dfAirbnbTrainSeattle$amenitie
s_count)
# dfAirbnbTrainSeattle$host_verification_count<-as.factor(head(dfAirbnbTrainS
eattle)$host_verification_count)
dfAirbnbTrainSeattle$host_age<-as.factor(dfAirbnbTrainSeattle$host_age)
dfAirbnbTrainSeattle$host_response_rate<-as.factor(dfAirbnbTrainSeattle$host_
response_rate)
dfAirbnbTrainSeattle$instant_bookable<-as.factor(dfAirbnbTrainSeattle$instant
_bookable)
dfAirbnbTrainSeattle$is_location_exact<-as.factor(dfAirbnbTrainSeattle$is_loc
ation_exact)
dfAirbnbTrainSeattle$market<-as.factor(dfAirbnbTrainSeattle$market)
dfAirbnbTrainSeattle$property_type<-as.factor(dfAirbnbTrainSeattle$property_t
ype)
dfAirbnbTrainSeattle$requires_license<-as.factor(dfAirbnbTrainSeattle$require
s_license)

# Final code for transformation of monthly price

dfAirbnbTrainSeattle <- dfAirbnbTrainSeattle %>%
                      mutate(monthly_price = as.numeric(str_replace_all(dfAir
bnbTrainSeattle$monthly_price,"[$,]",'')))

meanMonthly_price <- mean(dfAirbnbTrainSeattle$monthly_price, na.rm = TRUE)


dfAirbnbTrainSeattle <- dfAirbnbTrainSeattle %>%
                    mutate(monthly_price = replace_na(monthly_price, meanMont
hly_price))

# Final code for transformation of monthly price

dfAirbnbTestSeattle <- dfAirbnbTestSeattle %>%
                      mutate(monthly_price = as.numeric(str_replace_all(dfAir
bnbTestSeattle$monthly_price,"[$,]",'')))

meanMonthly_price <- mean(dfAirbnbTestSeattle$cleaning_fee, na.rm = TRUE)


dfAirbnbTestSeattle <- dfAirbnbTestSeattle %>%
                    mutate(monthly_price = replace_na(monthly_price, meanMont
hly_price))
```

```
dfAirbnbTrainSeattle %>%
                      leaflet() %>%
                      addProviderTiles(provider = "CartoDB.Positron") %>%
                      addCircleMarkers(color = "cyan", radius = 0.5, weight =
0.1) %>%
                      setView(zoom = 12, lat = 47.615258, lng = -122.335892)

## Assuming "longitude" and "latitude" are longitude and latitude, respective
ly
```

###The map shows the location of listings in Seattle.As can be seen most of the listings are from central seattle.

```
dfAirbnbTrainSeattle %>%
                      group_by(neighbourhood) %>%
                      leaflet() %>%
                      addTiles() %>%
                      addCircleMarkers(clusterOptions = markerClusterOptions(
), label = ~price) %>%
                      setView(zoom = 12, lat = 47.615258, lng = -122.335892)

## Assuming "longitude" and "latitude" are longitude and latitude, respective
ly
```

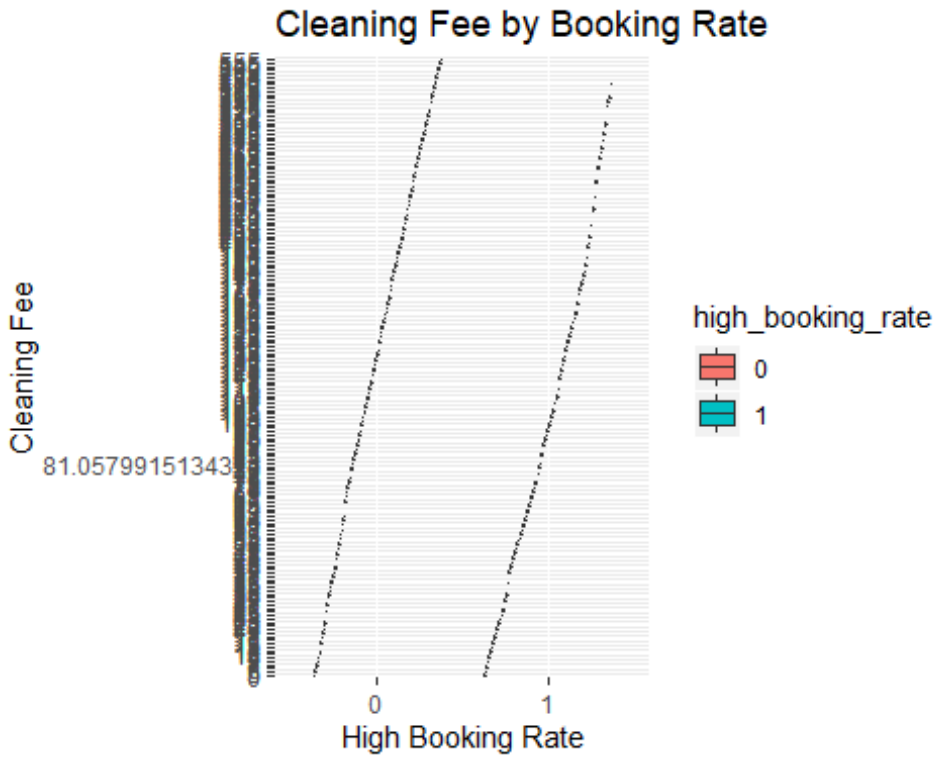
###The map here shows number of listings in the respective neighborhood, and we found the top neighborhoods in terms of proerties listed.

```
dfBestNeighbourhood <- dfAirbnbTrainSeattle %>%
  filter(neighbourhood %in% c("Wallingford", "South Lake Union", "Queen Anne"
, "Minor","Pike Place Market","First Hill", "Central Business District","Capi
tol Hill", "Belltown", "Ballard"))

dfBestNeighbourhood <-
    dfBestNeighbourhood %>%
      mutate(minimum_nights = as.double(minimum_nights),
             weekly_price = as.double(weekly_price),
             availability_365 = as.double(availability_365))

## Warning: NAs introduced by coercion

dfBestNSummary <- dfBestNeighbourhood %>%
  group_by(neighbourhood) %>%
  mutate(meanMonthlyPrice = mean(monthly_price), meanAvailability_30 = mean(a
vailability_30), meanAvailability_60 = mean(availability_60), meanAvailabilit
y_90 = mean(availability_90), meanAvailability_365 = mean(availability_365),
meanMinimum_nights = mean(minimum_nights),
         meanBeds = mean(beds),
         meanSquareFeet = mean(square_feet),
         meanExtraPeople = mean(extra_people))
```

```r
dfBestNSummary %>%
  group_by(neighbourhood,meanAvailability_30) %>%
  select(neighbourhood,meanAvailability_30)
```

```
## # A tibble: 2,539 x 2
## # Groups:   neighbourhood, meanAvailability_30 [10]
##    neighbourhood             meanAvailability_30
##    <chr>                                   <dbl>
##  1 First Hill                               16.8
##  2 Wallingford                               9.86
##  3 Wallingford                               9.86
##  4 Capitol Hill                             10.3
##  5 Belltown                                 13.4
##  6 Central Business District                17.6
##  7 Belltown                                 13.4
##  8 First Hill                               16.8
##  9 Belltown                                 13.4
## 10 Belltown                                 13.4
## # ... with 2,529 more rows
```

```r
# Cleaning Fee vs Booking Rate
plot <- dfAirbnbTrainSeattle %>%
  ggplot(aes(high_booking_rate, cleaning_fee, fill = high_booking_rate)) + ge
om_boxplot() + labs(x = "High Booking Rate", y = "Cleaning Fee", title = "Cle
aning Fee by Booking Rate")
plot
```



###It can be seen that as the cleaning fee charges increase which contribute to increase in the rent of the property, the booking rate decreases.

```
#Amenities Frequency
dfAirbnbTrainSeattle <- dfAirbnbTrainSeattle %>%
  mutate(amenities = gsub("[{}\"]", "", amenities))

tokens <- str_split(as.character(dfAirbnbTrainSeattle$amenities), ',')

amenitiesCountdf <- as.data.frame(table(unlist(tokens))) %>% arrange(desc(Fre
q))
amenitiesCountdf
```

```
##                                          Var1 Freq
## 1                                        Wifi 5296
## 2                                  Essentials 5294
## 3                                     Heating 5233
## 4                               Smoke detector 5214
## 5                                     Shampoo 4940
## 6                                     Kitchen 4783
## 7                                     Hangers 4763
## 8                                  Hair dryer 4670
## 9                   Carbon monoxide detector 4666
## 10                 Laptop friendly workspace 4383
## 11                                       Iron 4348
## 12                                         TV 4283
## 13                                     Washer 4219
```

```
## 14                                        Dryer 4207
## 15                              Fire extinguisher 3588
## 16                                      Hot water 3488
## 17                                   Refrigerator 3115
## 18                          Dishes and silverware 3029
## 19                                  Self check-in 3017
## 20                                      Microwave 2950
## 21                                   Coffee maker 2871
## 22                                   First aid kit 2700
## 23                                          Stove 2538
## 24                                Cooking basics 2486
## 25                                           Oven 2459
## 26                                     Bed linens 2451
## 27                                Private entrance 2416
## 28                            Free street parking 2352
## 29                          Free parking on premises 2212
## 30                               Family/kid friendly 2154
## 31                       Extra pillows and blankets 2034
## 32                                     Dishwasher 1903
## 33                                       Internet 1848
## 34                          Long term stays allowed 1630
## 35                                      Cable TV 1562
## 36                            Lock on bedroom door 1556
## 37                     No stairs or steps to enter 1530
## 38                                         Keypad 1497
## 39                                Patio or balcony 1483
## 40                          Luggage dropoff allowed 1414
## 41                                Air conditioning 1360
## 42                                        Elevator 1227
## 43                             Garden or backyard 1208
## 44                               Indoor fireplace 1081
## 45                                        Lockbox 1015
## 46                                   Safety card  982
## 47                                           Gym  898
## 48                                       Bathtub  890
## 49                               24-hour check-in  864
## 50                                   Pets allowed  854
## 51                                      BBQ grill  830
## 52                             Private living room  793
## 53                       Pack ’n Play/travel crib  681
## 54  translation missing: en.hosting_amenity_50  676
## 55                                     Smart lock  605
## 56                      Well-lit path to entrance  559
## 57  translation missing: en.hosting_amenity_49  544
## 58                     Pets live on this property  532
## 59                               Single level home  451
## 60                                     Breakfast  447
## 61                      Children’s books and toys  445
## 62                      Paid parking off premises  393
## 63                          Room-darkening shades  382
```

```
## 64                                    Other  335
## 65                Wide entrance for guests  321
## 66                         Host greets you  310
## 67                                 Hot tub  307
## 68                              High chair  302
## 69                                  Dog(s)  300
## 70                    Ethernet connection  298
## 71                          Wide hallways  282
## 72                            Lake access  275
## 73               Paid parking on premises  272
## 74                 Extra space around bed  247
## 75           Flat path to guest entrance  247
## 76                                   Pool  229
## 77                          Wide entrance  223
## 78                                  Cat(s)  217
## 79                Children’s dinnerware  215
## 80                          Wide entryway  215
## 81                     Wireless intercom  209
## 82                           Full kitchen  207
## 83                   Bathroom essentials  186
## 84                      Bedroom comforts  186
## 85                Accessible-height bed  179
## 86                           Bath towel  178
## 87                            Body soap  178
## 88                          Toilet paper  178
## 89               Buzzer/wireless intercom  176
## 90                   Handheld shower head  172
## 91                    Suitable for events  165
## 92                         Building staff  163
## 93            Babysitter recommendations  159
## 94              Accessible-height toilet  150
## 95              Cleaning before checkout  147
## 96                 Wheelchair accessible  130
## 97                          Outlet covers  126
## 98                                   Crib  124
## 99              Central air conditioning  123
## 100       Wide doorway to guest bathroom  121
## 101                        Game console  116
## 102                             Doorman  115
## 103                          Stair gates   95
## 104                     Smoking allowed   86
## 105                    Beach essentials   76
## 106                    Fireplace guards   73
## 107                     Outdoor seating   72
## 108                              toilet   70
## 109              Wide clearance to shower   70
## 110                             Netflix   69
## 111                           Smart TV   66
## 112                    Hot water kettle   64
## 113                           Baby bath   63
```

```
## 114                      Disabled parking spot   62
## 115                                 Waterfront   62
## 116                           Breakfast table   54
## 117                               Pocket wifi   54
## 118                 Fixed grab bars for shower   53
## 119                                EV charger   52
## 120                            Changing table   44
## 121                                  Gas oven   43
## 122                            Walk-in shower   41
## 123                              Baby monitor   39
## 124                     Memory foam mattress   39
## 125                        En suite bathroom   35
## 126                                Beachfront   33
## 127                                   Balcony   32
## 128                              Other pet(s)   32
## 129                        Step-free shower   30
## 130                       Formal dining area   29
## 131                            Window guards   29
## 132                              Kitchenette   28
## 133                            Heated floors   27
## 134                                   HBO GO   25
## 135                              Ceiling fan   24
## 136                          Espresso machine   24
## 137                              Sound system   24
## 138                                   Terrace   24
## 139                     Pillow-top mattress   23
## 140                                Rain shower   22
## 141                           Outdoor parking   21
## 142                                DVD player   20
## 143                              Mountain view   20
## 144                           Convection oven   19
## 145                                  Fire pit   19
## 146                              Soaking tub   18
## 147                              Mini fridge   17
## 148                              Amazon Echo   16
## 149                       Exercise equipment   14
## 150                 Fixed grab bars for toilet   14
## 151                                  Day bed   13
## 152                              Shower chair   11
## 153                              Sun loungers   11
## 154                     Table corner guards   11
## 155                  Electric profiling bed   10
## 156                 Bathtub with bath chair    8
## 157                              Shared gym    8
## 158                                            7
## 159                           Firm mattress    7
## 160                              Heat lamps    7
## 161                                 Printer    7
## 162                           Private bathroom    7
## 163                                Beach view    6
```

```
## 164                              Shared hot tub    6
## 165                                 Shared pool    6
## 166                               Warming drawer    6
## 167                        Ground floor access    5
## 168                                  Jetted tub    4
## 169                                     Mudroom    4
## 170                           Private hot tub    4
## 171                               Wine cooler    4
## 172                                   Hammock    3
## 173                                Private gym    3
## 174                              Standing valet    3
## 175          High-resolution computer monitor    2
## 176                                Murphy bed    2
## 177                      Pool with pool hoist    2
## 178                      Projector and screen    2
## 179                                     Sauna    2
## 180                Stand alone steam shower    2
## 181                                 Steam oven    2
## 182                               Air purifier    1
## 183                                Double oven    1
## 184                           Heated towel rack    1
## 185                              Ski-in/Ski-out    1
## 186                                Tennis court    1
```

###The top 10 amenties provided at the rentals listed with Airbnb, Wifi is provided by the almost all the hosts and luxury amaenties likeski-in/ski-out and Tennis court only provied by one host.

```
#Amenities Word Cloud
dfAirbnbTrainSeattle <- dfAirbnbTrainSeattle %>%
  mutate(amenities = gsub("[{}\"]", "", amenities))
tokens <- str_split(as.character(dfAirbnbTrainSeattle$amenities), ',')
amenitiesCountdf <- as.data.frame(table(unlist(tokens))) %>% arrange(desc(Fre
q))

set.seed(123)
wordcloud(words = amenitiesCountdf$Var1, freq = amenitiesCountdf$Freq, min.fr
eq = 1, max.words=75, random.order=FALSE, rot.per=0.35, colors=brewer.pal(8,
"Dark2"))
```

```
## Warning in wordcloud(words = amenitiesCountdf$Var1, freq =
## amenitiesCountdf$Freq, : Smoke detector could not be fit on page. It will
not be
## plotted.

## Warning in wordcloud(words = amenitiesCountdf$Var1, freq =
## amenitiesCountdf$Freq, : Hair dryer could not be fit on page. It will not
be
## plotted.
```

```
## Warning in wordcloud(words = amenitiesCountdf$Var1, freq =
## amenitiesCountdf$Freq, : Carbon monoxide detector could not be fit on page
. It
## will not be plotted.

## Warning in wordcloud(words = amenitiesCountdf$Var1, freq =
## amenitiesCountdf$Freq, : Laptop friendly workspace could not be fit on pag
e. It
## will not be plotted.

## Warning in wordcloud(words = amenitiesCountdf$Var1, freq =
## amenitiesCountdf$Freq, : Washer could not be fit on page. It will not be
## plotted.

## Warning in wordcloud(words = amenitiesCountdf$Var1, freq =
## amenitiesCountdf$Freq, : Dryer could not be fit on page. It will not be pl
otted.

## Warning in wordcloud(words = amenitiesCountdf$Var1, freq =
## amenitiesCountdf$Freq, : Fire extinguisher could not be fit on page. It wi
ll not
## be plotted.

## Warning in wordcloud(words = amenitiesCountdf$Var1, freq =
## amenitiesCountdf$Freq, : Hot water could not be fit on page. It will not b
e
## plotted.

## Warning in wordcloud(words = amenitiesCountdf$Var1, freq =
## amenitiesCountdf$Freq, : Refrigerator could not be fit on page. It will no
t be
## plotted.

## Warning in wordcloud(words = amenitiesCountdf$Var1, freq =
## amenitiesCountdf$Freq, : Dishes and silverware could not be fit on page. I
t will
## not be plotted.

## Warning in wordcloud(words = amenitiesCountdf$Var1, freq =
## amenitiesCountdf$Freq, : Self check-in could not be fit on page. It will n
ot be
## plotted.

## Warning in wordcloud(words = amenitiesCountdf$Var1, freq =
## amenitiesCountdf$Freq, : Coffee maker could not be fit on page. It will no
t be
## plotted.

## Warning in wordcloud(words = amenitiesCountdf$Var1, freq =
## amenitiesCountdf$Freq, : First aid kit could not be fit on page. It will n
ot be
## plotted.
```

```
## Warning in wordcloud(words = amenitiesCountdf$Var1, freq =
## amenitiesCountdf$Freq, : Cooking basics could not be fit on page. It will
not be
## plotted.

## Warning in wordcloud(words = amenitiesCountdf$Var1, freq =
## amenitiesCountdf$Freq, : Bed linens could not be fit on page. It will not
be
## plotted.

## Warning in wordcloud(words = amenitiesCountdf$Var1, freq =
## amenitiesCountdf$Freq, : Private entrance could not be fit on page. It wil
l not
## be plotted.

## Warning in wordcloud(words = amenitiesCountdf$Var1, freq =
## amenitiesCountdf$Freq, : Free street parking could not be fit on page. It
will
## not be plotted.

## Warning in wordcloud(words = amenitiesCountdf$Var1, freq =
## amenitiesCountdf$Freq, : Free parking on premises could not be fit on page
. It
## will not be plotted.

## Warning in wordcloud(words = amenitiesCountdf$Var1, freq =
## amenitiesCountdf$Freq, : Family/kid friendly could not be fit on page. It
will
## not be plotted.

## Warning in wordcloud(words = amenitiesCountdf$Var1, freq =
## amenitiesCountdf$Freq, : Extra pillows and blankets could not be fit on pa
ge. It
## will not be plotted.

## Warning in wordcloud(words = amenitiesCountdf$Var1, freq =
## amenitiesCountdf$Freq, : Long term stays allowed could not be fit on page.
It
## will not be plotted.

## Warning in wordcloud(words = amenitiesCountdf$Var1, freq =
## amenitiesCountdf$Freq, : Lock on bedroom door could not be fit on page. It
will
## not be plotted.

## Warning in wordcloud(words = amenitiesCountdf$Var1, freq =
## amenitiesCountdf$Freq, : No stairs or steps to enter could not be fit on p
age.
## It will not be plotted.

## Warning in wordcloud(words = amenitiesCountdf$Var1, freq =
## amenitiesCountdf$Freq, : Patio or balcony could not be fit on page. It wil
```

```
l not
## be plotted.

## Warning in wordcloud(words = amenitiesCountdf$Var1, freq =
## amenitiesCountdf$Freq, : Luggage dropoff allowed could not be fit on page.
It
## will not be plotted.

## Warning in wordcloud(words = amenitiesCountdf$Var1, freq =
## amenitiesCountdf$Freq, : Air conditioning could not be fit on page. It wil
l not
## be plotted.

## Warning in wordcloud(words = amenitiesCountdf$Var1, freq =
## amenitiesCountdf$Freq, : Garden or backyard could not be fit on page. It w
ill
## not be plotted.

## Warning in wordcloud(words = amenitiesCountdf$Var1, freq =
## amenitiesCountdf$Freq, : Indoor fireplace could not be fit on page. It wil
l not
## be plotted.

## Warning in wordcloud(words = amenitiesCountdf$Var1, freq =
## amenitiesCountdf$Freq, : Safety card could not be fit on page. It will not
be
## plotted.

## Warning in wordcloud(words = amenitiesCountdf$Var1, freq =
## amenitiesCountdf$Freq, : 24-hour check-in could not be fit on page. It wil
l not
## be plotted.

## Warning in wordcloud(words = amenitiesCountdf$Var1, freq =
## amenitiesCountdf$Freq, : Private living room could not be fit on page. It
will
## not be plotted.

## Warning in wordcloud(words = amenitiesCountdf$Var1, freq =
## amenitiesCountdf$Freq, : Pack ’n Play/travel crib could not be fit on page
. It
## will not be plotted.

## Warning in wordcloud(words = amenitiesCountdf$Var1, freq =
## amenitiesCountdf$Freq, : translation missing: en.hosting_amenity_50 could
not be
## fit on page. It will not be plotted.

## Warning in wordcloud(words = amenitiesCountdf$Var1, freq =
## amenitiesCountdf$Freq, : Well-lit path to entrance could not be fit on pag
e. It
## will not be plotted.
```

```
## Warning in wordcloud(words = amenitiesCountdf$Var1, freq =
## amenitiesCountdf$Freq, : translation missing: en.hosting_amenity_49 could
not be
## fit on page. It will not be plotted.

## Warning in wordcloud(words = amenitiesCountdf$Var1, freq =
## amenitiesCountdf$Freq, : Pets live on this property could not be fit on pa
ge. It
## will not be plotted.

## Warning in wordcloud(words = amenitiesCountdf$Var1, freq =
## amenitiesCountdf$Freq, : Single level home could not be fit on page. It wi
ll not
## be plotted.

## Warning in wordcloud(words = amenitiesCountdf$Var1, freq =
## amenitiesCountdf$Freq, : Children’s books and toys could not be fit on pag
e. It
## will not be plotted.

## Warning in wordcloud(words = amenitiesCountdf$Var1, freq =
## amenitiesCountdf$Freq, : Paid parking off premises could not be fit on pag
e. It
## will not be plotted.

## Warning in wordcloud(words = amenitiesCountdf$Var1, freq =
## amenitiesCountdf$Freq, : Room-darkening shades could not be fit on page. I
t will
## not be plotted.

## Warning in wordcloud(words = amenitiesCountdf$Var1, freq =
## amenitiesCountdf$Freq, : Wide entrance for guests could not be fit on page
. It
## will not be plotted.

## Warning in wordcloud(words = amenitiesCountdf$Var1, freq =
## amenitiesCountdf$Freq, : Paid parking on premises could not be fit on page
. It
## will not be plotted.

## Warning in wordcloud(words = amenitiesCountdf$Var1, freq =
## amenitiesCountdf$Freq, : Extra space around bed could not be fit on page.
It
## will not be plotted.

## Warning in wordcloud(words = amenitiesCountdf$Var1, freq =
## amenitiesCountdf$Freq, : Flat path to guest entrance could not be fit on p
age.
## It will not be plotted.
```

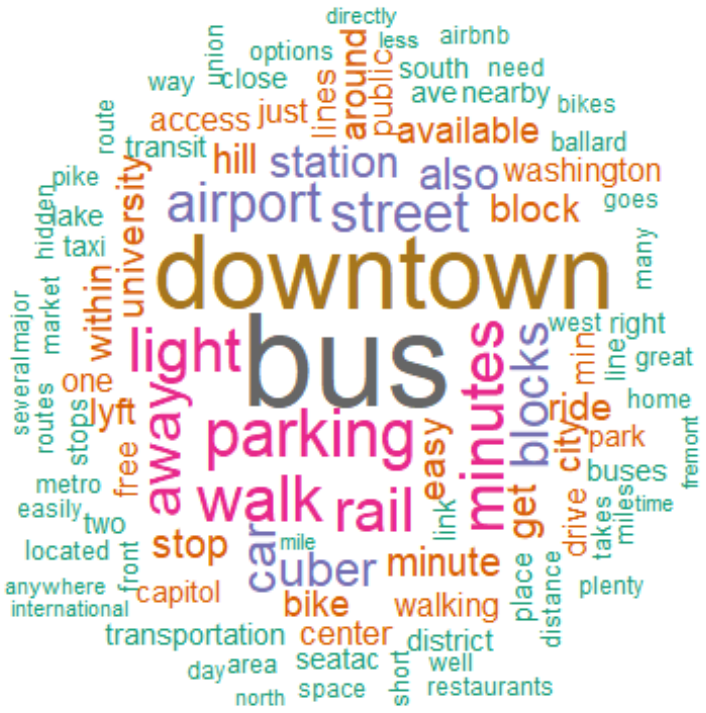

```
# install.packages("corpus")

library(corpus)

## Warning: package 'corpus' was built under R version 3.6.3

# Neighborhood Overview Word Cloud
corpus <- Corpus(VectorSource(dfAirbnbTrainSeattle$neighborhood_overview))
corpus = tm_map(corpus, PlainTextDocument)

## Warning in tm_map.SimpleCorpus(corpus, PlainTextDocument): transformation
drops
## documents

corpus = tm_map(corpus, tolower)

## Warning in tm_map.SimpleCorpus(corpus, tolower): transformation drops docu
ments

corpus = tm_map(corpus, removePunctuation)

## Warning in tm_map.SimpleCorpus(corpus, removePunctuation): transformation
drops
## documents

corpus = tm_map(corpus, removeWords, c("seattle", "please", "will", "use", "'
re one", "guests", "house", "allowed", "keep", "can", "take", "like", "per",
"make", "neighborhood", stopwords("english")))
```

```
## Warning in tm_map.SimpleCorpus(corpus, removeWords, c("seattle", "please",
:
## transformation drops documents

corpus = tm_map(corpus, stripWhitespace)

## Warning in tm_map.SimpleCorpus(corpus, stripWhitespace): transformation dr
ops
## documents

dtm <- TermDocumentMatrix(corpus)
matrix <- as.matrix(dtm)
words <- sort(rowSums(matrix), decreasing=TRUE)
wordCountdf <- data.frame(word = names(words), freq = words)
set.seed(123)
wordcloud(words = wordCountdf$word, freq = wordCountdf$freq, min.freq = 1, ma
x.words=49, rot.per=0.35, random.order=FALSE, colors=brewer.pal(8, "Dark2"))

## Warning in wordcloud(words = wordCountdf$word, freq = wordCountdf$freq, :
## washington could not be fit on page. It will not be plotted.

## Warning in wordcloud(words = wordCountdf$word, freq = wordCountdf$freq, :
many
## could not be fit on page. It will not be plotted.

## Warning in wordcloud(words = wordCountdf$word, freq = wordCountdf$freq, :
## grocery could not be fit on page. It will not be plotted.

## Warning in wordcloud(words = wordCountdf$word, freq = wordCountdf$freq, :
## capitol could not be fit on page. It will not be plotted.

## Warning in wordcloud(words = wordCountdf$word, freq = wordCountdf$freq, :
## university could not be fit on page. It will not be plotted.

## Warning in wordcloud(words = wordCountdf$word, freq = wordCountdf$freq, :
home
## could not be fit on page. It will not be plotted.

## Warning in wordcloud(words = wordCountdf$word, freq = wordCountdf$freq, :
short
## could not be fit on page. It will not be plotted.

## Warning in wordcloud(words = wordCountdf$word, freq = wordCountdf$freq, :
nearby
## could not be fit on page. It will not be plotted.

## Warning in wordcloud(words = wordCountdf$word, freq = wordCountdf$freq, :
## district could not be fit on page. It will not be plotted.

## Warning in wordcloud(words = wordCountdf$word, freq = wordCountdf$freq, :
easy
## could not be fit on page. It will not be plotted.
```

```
## Warning in wordcloud(words = wordCountdf$word, freq = wordCountdf$freq, :
parks
## could not be fit on page. It will not be plotted.
```


```
# Transit Word Cloud
corpus <- Corpus(VectorSource(dfAirbnbTrainSeattle$transit))
corpus = tm_map(corpus, PlainTextDocument)

## Warning in tm_map.SimpleCorpus(corpus, PlainTextDocument): transformation
drops
## documents

corpus = tm_map(corpus, tolower)

## Warning in tm_map.SimpleCorpus(corpus, tolower): transformation drops docu
ments

corpus = tm_map(corpus, removePunctuation)

## Warning in tm_map.SimpleCorpus(corpus, removePunctuation): transformation
drops
## documents

corpus = tm_map(corpus, removeWords, c("seattle", "please", "will", "use", "'
re one", "guests", "house", "allowed", "keep", "can", "take", "like", "per",
"make", "neighborhood", stopwords("english")))
```

```
## Warning in tm_map.SimpleCorpus(corpus, removeWords, c("seattle", "please",
:
## transformation drops documents

corpus = tm_map(corpus, stripWhitespace)

## Warning in tm_map.SimpleCorpus(corpus, stripWhitespace): transformation dr
ops
## documents

dtm <- TermDocumentMatrix(corpus)
matrix <- as.matrix(dtm)
words <- sort(rowSums(matrix), decreasing=TRUE)
wordCountdf <- data.frame(word = names(words), freq = words)
set.seed(123)
wordcloud(words = wordCountdf$word, freq = wordCountdf$freq, min.freq = 1, ma
x.words=100, rot.per=0.35, random.order=FALSE, colors=brewer.pal(8, "Dark2"))
```




```
#Cancellation Policy

dfAirbnbTrainSeattleCancellationPolicy<- dfAirbnbTrainSeattle %>% select(pric
e, cancellation_policy)

text_cancellation_policy <- tibble(text =dfAirbnbTrainSeattleCancellationPoli
cy$cancellation_policy, price=dfAirbnbTrainSeattleCancellationPolicy$price)

word_cancellation_policy <- text_cancellation_policy %>%
```

```
  unnest_tokens(word, text)

data(stop_words)
word_cancellation_policy <- word_cancellation_policy %>%
  anti_join(stop_words)

## Joining, by = "word"

count_cancellation_policy <- word_cancellation_policy %>% count(word, sort=TR
UE)
count_cancellation_policy

## # A tibble: 6 x 2
##   word                           n
##   <chr>                      <int>
## 1 strict_14_with_grace_period  2104
## 2 moderate                     1905
## 3 flexible                     1192
## 4 strict                        149
## 5 super_strict_30                42
## 6 super_strict_60                22

#to split host_since into year, month and day

dfAirbnbSeattleTrain1 <-dfAirbnbTrainSeattle
any(is.na(dfAirbnbSeattleTrain1$host_since))

## [1] TRUE

sum(is.na(dfAirbnbSeattleTrain1$host_since))

## [1] 3

nrow(dfAirbnbSeattleTrain1)

## [1] 5414

na<-which(!complete.cases( dfAirbnbSeattleTrain1 $host_since))
dfAirbnbSeattleTrain1 <-  dfAirbnbSeattleTrain1 [-na,]
any(is.na( dfAirbnbSeattleTrain1 $host_since))

## [1] FALSE

str( dfAirbnbSeattleTrain1 $host_since)

##  Date[1:5411], format: "2014-09-06" "2012-08-15" "2018-12-04" "2014-04-16"
"2014-11-26" ...

library(data.table)

##
## Attaching package: 'data.table'
```

```
## The following object is masked from 'package:tsibble':
##
##     key

## The following objects are masked from 'package:lubridate':
##
##     hour, isoweek, mday, minute, month, quarter, second, wday, week,
##     yday, year

## The following object is masked from 'package:purrr':
##
##     transpose

## The following objects are masked from 'package:dplyr':
##
##     between, first, last
```

```
setDT(dfAirbnbSeattleTrain1)[, Month_Year := format(as.Date(host_since), "%Y-
%m")]
dfAirbnbSeattleTrain1<-dfAirbnbSeattleTrain1 %>%
  dplyr::mutate(year = lubridate::year(host_since),
                month = lubridate::month(host_since),
                day = lubridate::day(host_since))
library(tsibble)
dfAirbnbSeattleTrain1$Month_Year2 <- yearmonth(dfAirbnbSeattleTrain1$host_sin
ce)
#str(dfAirbnbSeattleTrain1)

#In which year maximum number of people joined Airbnb
 dfAirbnbSeattleTrain1 %>%
  group_by(year) %>%
  tally() %>%
  mutate(pct = 100*n/sum(n)) %>%
  arrange(desc(pct))
```

```
## # A tibble: 12 x 3
##     year     n    pct
##    <dbl> <int>  <dbl>
##  1  2015  1042 19.3
##  2  2013   817 15.1
##  3  2014   792 14.6
##  4  2016   737 13.6
##  5  2017   479  8.85
##  6  2012   429  7.93
##  7  2018   368  6.80
##  8  2019   330  6.10
##  9  2011   278  5.14
## 10  2010    97  1.79
## 11  2009    35  0.647
## 12  2008     7  0.129
```

Most of the hosts joined Airbnb in the year 2015 which decreased to 6.09% by the year2019. This could be attributed to strong in-migration and low inventory of reasonably priced housing available for sale contributed to rising rental demand since 2010(~1.79%).As lenders became more and more confident in the economic recovery builders responded by significantly increasing apartment construction.

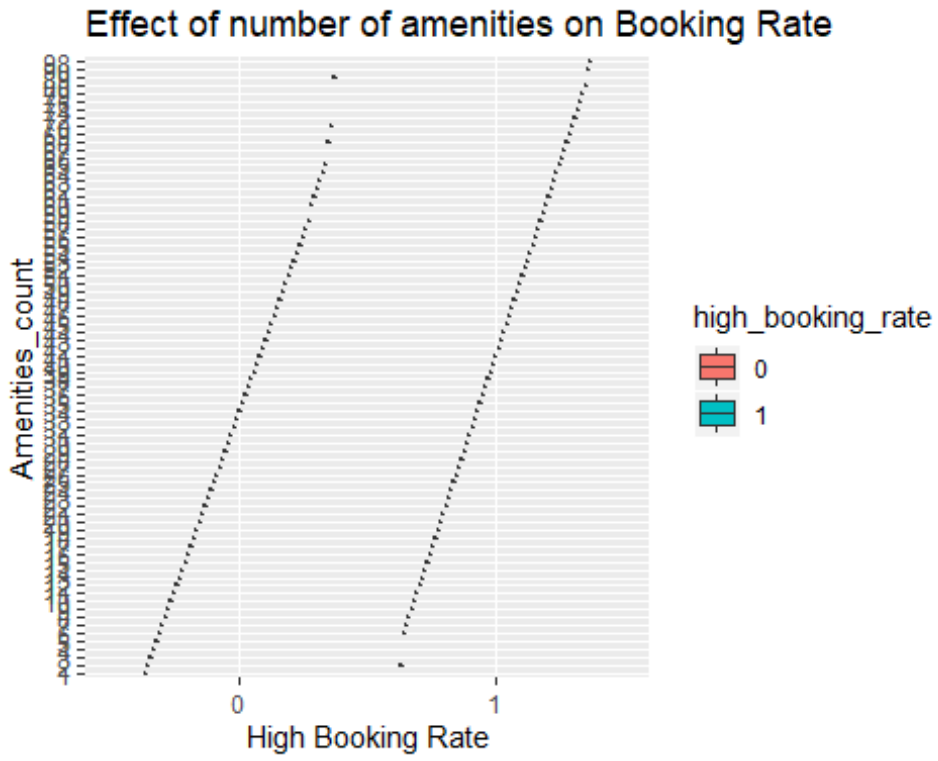
###In 2015, permitting increased by 33 percent, followed by 14,700 multifamily units permitted in 2016. Of the estimated 20,800 unit under construction, ~ 40% were in the Downtown/ Capitol Hill/Queen Anne market area, which includes the neighborhoods encompassing Amazon.com campuses. ###These then prevailing conditions must have motivated to invest in available business options.

```
#during which particular months of the year did hosts preferred joining
 dfAirbnbSeattleTrain1 %>%
  group_by(Month_Year2) %>%
  tally() %>%
  mutate(pct = 100*n/sum(n)) %>%
  arrange(desc(pct))
```

```
## # A tibble: 129 x 3
##    Month_Year2     n   pct
##          <mth> <int> <dbl>
##  1    2013 Aug   279  5.16
##  2    2015 Nov   198  3.66
##  3    2015 Dec   149  2.75
##  4    2016 Jul   147  2.72
##  5    2016 Jan   111  2.05
##  6    2014 Aug   100  1.85
##  7    2017 Feb    98  1.81
##  8    2014 Jul    97  1.79
##  9    2017 Jul    92  1.70
## 10    2015 Jul    84  1.55
## # ... with 119 more rows
```

A large number of people joined Airbnb as host in August 2013. In 2013 Forbes,ranked Seattle No. 9 on its list of the Best Places for Business and Careers.Seattle was economically the fastest growing city in 2013. These then prevailing economically sound conditions must have encouraged the property owners to leverage them.

```
#amenities_count  on booking rate

plot5<- dfAirbnbTrainSeattle%>%
  ggplot(aes(y= amenities_count, x= as.factor(high_booking_rate),fill = high_
booking_rate) )+ geom_boxplot()+ labs(x = "High Booking Rate", y = "Amenities
_count", title = "Effect of number of amenities on Booking Rate")
plot5
```



For properties listed on Airbnb as the number of amenities offered increases the booking rate also increase.

###The effect of Security deposit on high booking rate

```
#security deposit on booking rate
 dfAirbnbTrainSeattle %>%
  group_by(security_deposit) %>%
  filter(high_booking_rate==1)%>%
  tally()%>%
  mutate(pct = 100*n/sum(n)) %>%
  arrange(desc(pct))
```

```
## # A tibble: 47 x 3
##    security_deposit     n   pct
##               <dbl> <int> <dbl>
##  1                0   623 29.2
##  2              252.  272 12.8
##  3              100   217 10.2
##  4              200   204  9.58
##  5              250   179  8.40
##  6              500   177  8.31
##  7              300   161  7.56
##  8              150    98  4.60
##  9             1000    50  2.35
## 10              400    28  1.31
## # ... with 37 more rows
```

```
plot4<- dfAirbnbTrainSeattle%>%
  ggplot(aes(y= security_deposit, x= as.factor(high_booking_rate),fill = high
_booking_rate) )+ geom_boxplot()+ labs(x = "High Booking Rate", y = "Security
Deposit", title = "Security Deposit by Booking Rate")
plot4
```

As the secutity deposit for a property increase the booking rate decreases.But the impact is not significantly distingusable on high booking rate as it is almost comparable.

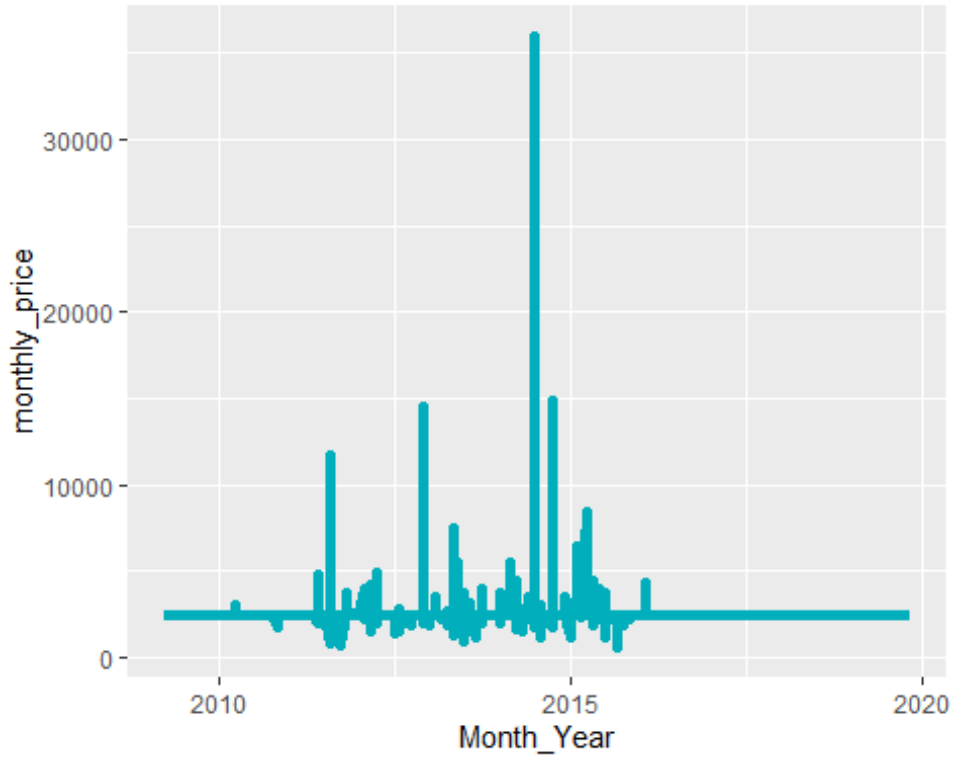
```
# determine range of monthly price distribution across neighborhoods
 dfAirbnbTrainSeattle %>%
  group_by(neighbourhood) %>%
  filter(monthly_price >5000)%>%
  tally()%>%
  mutate(pct = 100*n/sum(n)) %>%
  arrange(desc(pct))
```

```
## # A tibble: 18 x 3
##    neighbourhood        n   pct
##    <chr>            <int> <dbl>
##  1 Capitol Hill         3 13.0
##  2 Bryant               2  8.70
##  3 Magnolia             2  8.70
##  4 Queen Anne           2  8.70
##  5 Alki                 1  4.35
##  6 Ballard              1  4.35
```

```
##  7 Belltown             1  4.35
##  8 Dunlap               1  4.35
##  9 Eastlake             1  4.35
## 10 Genesee              1  4.35
## 11 Green Lake           1  4.35
## 12 Leschi               1  4.35
## 13 Licton Springs       1  4.35
## 14 Maple Leaf           1  4.35
## 15 Mathews Beach        1  4.35
## 16 Minor                1  4.35
## 17 South Lake Union     1  4.35
## 18 Stevens              1  4.35
```

According to the given dataset 13% of the most Expensive rentals(monthly_price>5000) are located in Capitol hill as well. The maximum rent for a property listed is 36000 dollars in Ballard.

```
# monthly_price of top neighborhood listings across years(after joining)
dfBestNeighbourhood1 <- dfBestNeighbourhood
dfBestNeighbourhood1$Month_Year <- yearmonth(dfBestNeighbourhood1$host_since)
plot3<- dfBestNeighbourhood1%>%

  ggplot(aes(x= Month_Year, y= monthly_price))+ geom_line(color=  "#00AFBB",
size = 2)
plot3
```



no significant observations.

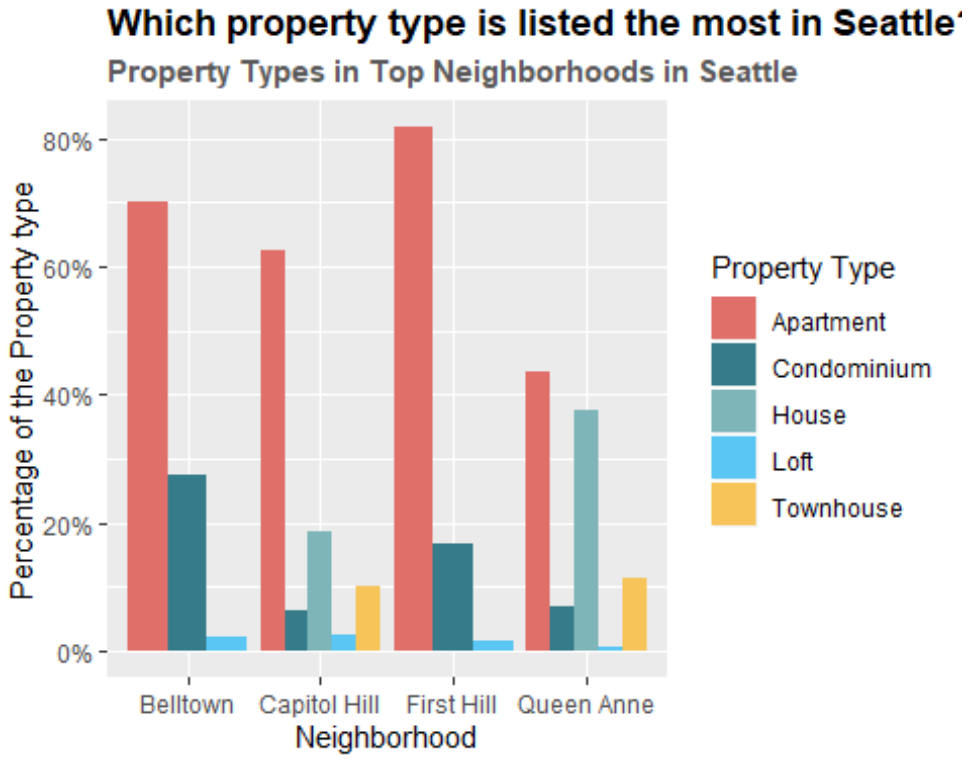
```
 dfAirbnbTrainSeattle %>%
  group_by(neighbourhood) %>%
  filter(high_booking_rate==1)%>%
  tally()%>%
  mutate(pct = 100*n/sum(n)) %>%
  arrange(desc(pct))
```

```
## # A tibble: 77 x 3
##    neighbourhood         n   pct
##    <chr>             <int> <dbl>
##  1 Capitol Hill        187  8.78
##  2 Queen Anne          150  7.04
##  3 Minor               141  6.62
##  4 Ballard             128  6.01
##  5 Belltown            124  5.82
##  6 North Beacon Hill    95  4.46
##  7 Wallingford          87  4.08
##  8 Fremont              78  3.66
##  9 First Hill           62  2.91
## 10 Columbia City        56  2.63
## # ... with 67 more rows
```

Listings in Capitol Hill contributes maximum to the properties with high booking rate.

```
#"Property Types in Top Neighborhoods in Seattle
dfAirbnbSeattlePrpTyp <- dfAirbnbTrainSeattle %>% group_by(neighbourhood,prop
erty_type) %>% summarize(Freq = n())
dfAirbnbSeattlePrpTyp <- dfAirbnbSeattlePrpTyp %>% filter(property_type %in%
c("Apartment","House","Condominium","Townhouse", "Loft"))
dfAirbnbSeattlePrpTyp <- dfAirbnbSeattlePrpTyp %>% filter (neighbourhood %in%
c("Capitol Hill","Queen Anne","Belltown","First Hill"))
dfAirbnbSeattleSpcPrp<-  dfAirbnbTrainSeattle %>% filter(property_type %in% c
("Apartment","House","Condominium","Townhouse", "Loft"))%>% group_by(neighbou
rhood) %>% summarize(sum = n())
propertyratio <- merge(dfAirbnbSeattlePrpTyp, dfAirbnbSeattleSpcPrp, by="neig
hbourhood")
propertyratio <- propertyratio %>% mutate(ratio = Freq/sum)
ggplot(propertyratio, aes(x=neighbourhood, y=ratio, fill = property_type)) +
  geom_bar(position = "dodge",stat="identity") +
  scale_fill_discrete(name = "Property Type") +
  scale_y_continuous(labels = scales::percent) +
  ggtitle("Which property type is listed the most in Seattle?",
          subtitle = "Property Types in Top Neighborhoods in Seattle ") +
          theme(plot.title = element_text(face = "bold")) +
          theme(plot.subtitle = element_text(face = "bold", color = "grey35")
) +
          theme(plot.caption = element_text(color = "grey68"))+scale_color_gr
adient(low="#d3cbcb", high="#852eaa")+
```

```
          scale_fill_manual("Property Type", values=c("#e06f69","#357b8a", "#
7db5b8", "#59c6f3", "#f6c458")) +
          xlab("Neighborhood") + ylab("Percentage of the Property type")

## Scale for 'fill' is already present. Adding another scale for 'fill', whic
h
## will replace the existing scale.
```



In top neighborhoods the property type which are listed the most are Apartments and Houses.In capitol Hill which has a variety of property types to be rented ~65 %of the listed properties are Apartments.

```
# what is the contribution of proerty_type on high booking rate
 dfAirbnbTrainSeattle %>%
  group_by(property_type) %>%
  filter(high_booking_rate==1)%>%
  tally()%>%
  mutate(pct = 100*n/sum(n)) %>%
  arrange(desc(pct))

## # A tibble: 20 x 3
##    property_type          n     pct
##    <fct>              <int>   <dbl>
##  1 House                619 29.1
##  2 Apartment            615 28.9
##  3 Guest suite          361 16.9
##  4 Townhouse            181  8.50
```

```
##  5 Guesthouse           106  4.98
##  6 Condominium          104  4.88
##  7 Loft                  40  1.88
##  8 Bungalow              33  1.55
##  9 Cottage               17  0.798
## 10 Serviced apartment    13  0.610
## 11 Other                 10  0.469
## 12 Tiny house             8  0.376
## 13 Cabin                  5  0.235
## 14 Bed and breakfast      4  0.188
## 15 Camper/RV              4  0.188
## 16 Boat                   3  0.141
## 17 Boutique hotel         2  0.0939
## 18 Hostel                 2  0.0939
## 19 Villa                  2  0.0939
## 20 Tent                   1  0.0469
```

Apartments and Houses contribute ~60 % to high booking rate, wheres condos only contribute ~4%.It confirms with our research for initial acquisition of homes For Property type if one want to run an Airbnb "hotel" it is advisable to buy a house or apartments since almost all condo buildings in Seattle prohibit this type of rental.The advantage of single-family homes is that they generally charge much more in rent and the tenants may stay for multiple years.

RESULTS AND FINDINGS:

It's a great time to invest in the Seattle housing market based on our research as real estate properties are selling at the market price which is a good sign for Seattle real estate investors. Home prices in Seattle will fall.The city is shifting toward the "neutral" territory.

Seattle is also a bustling city for business,the surrounding suburbs house eight Fortune 500 companies including Amazon, Nordstrom, Microsoft, and Starbucks. Other large companies include MSNBC, Costco, Capital One Investing, and T-Mobile.Amazon HQ2 has effected the Seattle Housing Market,the median home price in the Seattle housing market shot up.Home prices in the metro area went up 47% which is nearly twice as high as the national increase of 24%. After Washington State outlawed rent control,the Market is friendly for Landlords as the rents can be raised to keep up with inflation and demand. We would $recommend$ according to our findings to invest in or near Capitol Hill and $UniversityDistrict$ for steady income. To invest in Apartment or House. And Finally, to list the property with airbnb during Nov or December[as also obtained in analysis] to leverage the popular times of Jan_apr and most

importantly Jun-September when most of the tourists visit Settle for varoius festivals and events like Seattle International Film Festival (May-June),Capitol Hill Block Party (July),Bumbershoot (September). Most of the tourist return year round and therefore Airbnb platform can be used during these periods for network effects and to create a loyal customer base.

PREDICTIVE ANALYSIS:

Running xGBoost model. Makking a copy of the dataset since we need to change data types of some variables.

```
##

airbnbSeattleTrain<- dfAirbnbTrainSeattle

## Parsed with column specification:
## cols(
##   .default = col_character(),
##   id = col_double(),
##   high_booking_rate = col_double(),
##   accommodates = col_double(),
##   availability_30 = col_double(),
##   availability_365 = col_double(),
##   availability_60 = col_double(),
##   availability_90 = col_double(),
##   bathrooms = col_double(),
##   bedrooms = col_double(),
##   beds = col_double(),
##   guests_included = col_double(),
##   host_has_profile_pic = col_logical(),
##   host_identity_verified = col_logical(),
##   host_is_superhost = col_logical(),
##   host_listings_count = col_double(),
##   host_since = col_date(format = ""),
##   instant_bookable = col_logical(),
##   is_business_travel_ready = col_logical(),
##   is_location_exact = col_logical(),
##   latitude = col_double()
##   # ... with 16 more columns
## )

## See spec(...) for full column specifications.

## Warning: 1 parsing failure.
##  row     col               expected actual                      file
## 4740 zipcode no trailing characters  -4417 'AirbnbSeattleTrain.csv'

airbnbSeattleTest <- dfAirbnbTestSeattle
```

```
## Parsed with column specification:
## cols(
##   .default = col_character(),
##   id = col_double(),
##   accommodates = col_double(),
##   availability_30 = col_double(),
##   availability_365 = col_double(),
##   availability_60 = col_double(),
##   availability_90 = col_double(),
##   bathrooms = col_double(),
##   bedrooms = col_double(),
##   beds = col_double(),
##   guests_included = col_double(),
##   host_has_profile_pic = col_logical(),
##   host_identity_verified = col_logical(),
##   host_is_superhost = col_logical(),
##   host_listings_count = col_double(),
##   host_since = col_date(format = ""),
##   instant_bookable = col_logical(),
##   is_business_travel_ready = col_logical(),
##   is_location_exact = col_logical(),
##   latitude = col_double(),
##   longitude = col_double()
##   # ... with 15 more columns
## )
## See spec(...) for full column specifications.

## Warning: 1 parsing failure.
##  row     col               expected actual                    file
## 1016 zipcode no trailing characters  -4417 'AirbnbSeattleTest.csv'

dropCols <- c("weekly_price","id","zipcode","host_acceptance_rate","host_has_
profile_pic","square_feet","latitude","longitude","require_guest_phone_verifi
cation","require_guest_profile_picture","space","state","transit","monthly_pr
ice","access","city","description","interaction","neighborhood_overview","hos
t_about","host_location","host_neighbourhood","host_response_rate","host_resp
onse_time","host_since","host_verifications","house_rules","notes","is_locati
on_exact","market","requires_license", "review_scores_accuracy","review_score
s_checkin","review_scores_cleanliness","review_scores_communication","review_
scores_location","review_scores_rating","review_scores_value","host_listings_
count", "is_business_travel_ready","availability_30","availability_60","avail
ability_90","amenities","neighbourhood")


airbnbSeattleTrain <- airbnbSeattleTrain %>% select(- (dropCols))
airbnbSeattleTest <- airbnbSeattleTest %>% select(-(dropCols))
```

#Changing datatype to numeric to run xgBoost for Train

```
airbnbSeattleTrain$extra_people <- as.numeric(gsub('\\$|,', '', airbnbSeattle
Train$extra_people))
```

```
airbnbSeattleTrain$price <- as.numeric(gsub('\\$|,', '', airbnbSeattleTrain$p
rice))
airbnbSeattleTrain$security_deposit <- as.numeric(gsub('\\$|,', '', airbnbSea
ttleTrain$security_deposit))
airbnbSeattleTrain$cleaning_fee <- as.numeric(gsub('\\$|,', '', airbnbSeattle
Train$cleaning_fee))

airbnbSeattleTest$extra_people <- as.numeric(gsub('\\$|,', '', airbnbSeattleT
est$extra_people))
airbnbSeattleTest$price <- as.numeric(gsub('\\$|,', '', airbnbSeattleTest$pri
ce))
airbnbSeattleTest$security_deposit <- as.numeric(gsub('\\$|,', '', airbnbSeat
tleTest$security_deposit))
airbnbSeattleTest$cleaning_fee <- as.numeric(gsub('\\$|,', '', airbnbSeattleT
est$cleaning_fee))

airbnbSeattleTrain <- airbnbSeattleTrain %>%
                      mutate(cleaning_fee = as.numeric(str_replace_all(airbnb
SeattleTrain$cleaning_fee,"[$,]",'')))

meanCleaningFee <- mean(airbnbSeattleTrain$cleaning_fee, na.rm = TRUE)

airbnbSeattleTrain <- airbnbSeattleTrain %>%
                     mutate(cleaning_fee = replace_na(cleaning_fee, meanCleani
ngFee))


airbnbSeattleTest <- airbnbSeattleTest %>%
                      mutate(cleaning_fee = as.numeric(str_replace_all(airbnb
SeattleTest$cleaning_fee,"[$,]",'')))

meanCleaningFee <- mean(airbnbSeattleTest$cleaning_fee, na.rm = TRUE)

airbnbSeattleTest <- airbnbSeattleTest %>%
                     mutate(cleaning_fee = replace_na(cleaning_fee, meanCleani
ngFee))

airbnbSeattleTrain <- airbnbSeattleTrain %>%
                      mutate(extra_people = as.numeric(str_replace_all(airbnb
SeattleTrain$extra_people,"[$,]",'')))

airbnbSeattleTest <- airbnbSeattleTest %>%
                      mutate(extra_people = as.numeric(str_replace_all(airbnb
SeattleTest$extra_people,"[$,]",'')))

airbnbSeattleTrain <- airbnbSeattleTrain %>%
                      mutate(price = as.numeric(str_replace_all(airbnbSeattle
Train$price,"[$,]",'')))

meanPrice <- mean(airbnbSeattleTrain$price, na.rm = TRUE)
```

```r
airbnbSeattleTrain <- airbnbSeattleTrain %>%
                    mutate(price = replace_na(price, meanPrice))


airbnbSeattleTest <- airbnbSeattleTest %>%
                     mutate(price = as.numeric(str_replace_all(airbnbSeattle
Test$price,"[$,]",'')))

meanPrice <- mean(airbnbSeattleTest$price, na.rm = TRUE)

airbnbSeattleTest <- airbnbSeattleTest %>%
                    mutate(price = replace_na(price, meanPrice))

airbnbSeattleTrain$security_deposit <- ifelse(is.na(airbnbSeattleTrain$securi
ty_deposit),0,airbnbSeattleTrain$security_deposit)
airbnbSeattleTest$security_deposit <- ifelse(is.na(airbnbSeattleTest$security
_deposit),0,airbnbSeattleTest$security_deposit)

#Mean = 1.36
airbnbSeattleTrain$bedrooms <- as.numeric(airbnbSeattleTrain$bedrooms)
airbnbSeattleTrain$bedrooms[is.na(airbnbSeattleTrain$bedrooms)] <- 3.5
summary(airbnbSeattleTrain$bedrooms)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.000   1.000   1.000   1.383   2.000   8.000

table(airbnbSeattleTrain$bedrooms)

##
##    0    1    2    3  3.5    4    5    6    7    8
##  670 3000 1058  468    4  145   51    9    8    1

airbnbSeattleTest$bedrooms <- as.numeric(airbnbSeattleTest$bedrooms)
airbnbSeattleTest$bedrooms[is.na(airbnbSeattleTest$bedrooms)] <- 3.5

airbnbSeattleTrain$beds = ifelse(is.na(airbnbSeattleTrain$beds), ave(airbnbSe
attleTrain$beds, FUN = function(x) median(x, na.rm = TRUE)), airbnbSeattleTra
in$beds)

airbnbSeattleTest$beds = ifelse(is.na(airbnbSeattleTest$beds), ave(airbnbSeat
tleTest$beds, FUN = function(x) median(x, na.rm = TRUE)), airbnbSeattleTest$b
eds)

airbnbSeattleTrain$bathrooms = ifelse(is.na(airbnbSeattleTrain$bathrooms), av
e(airbnbSeattleTrain$bathrooms, FUN = function(x) median(x, na.rm = TRUE)), a
irbnbSeattleTrain$bathrooms)

airbnbSeattleTest$bathrooms = ifelse(is.na(airbnbSeattleTest$bathrooms), ave(
airbnbSeattleTest$bathrooms, FUN = function(x) median(x, na.rm = TRUE)), airb
nbSeattleTest$bathrooms)
```

```
airbnbSeattleTrain$host_identity_verified = ifelse(is.na(airbnbSeattleTrain$h
ost_identity_verified),FALSE, airbnbSeattleTrain$host_identity_verified)

airbnbSeattleTest$host_identity_verified = ifelse(is.na(airbnbSeattleTest$hos
t_identity_verified),FALSE, airbnbSeattleTest$host_identity_verified)

airbnbSeattleTrain$host_is_superhost = ifelse(is.na(airbnbSeattleTrain$host_i
s_superhost),FALSE, airbnbSeattleTrain$host_is_superhost)

airbnbSeattleTest$host_is_superhost = ifelse(is.na(airbnbSeattleTest$host_is_
superhost),FALSE, airbnbSeattleTest$host_is_superhost)

airbnbSeattleTrain$high_booking_rate <- as.factor(airbnbSeattleTrain$high_boo
king_rate)
airbnbSeattleTrain$cancellation_policy <- as.numeric(airbnbSeattleTrain$cance
llation_policy)

## Warning: NAs introduced by coercion

airbnbSeattleTest$cancellation_policy <- as.numeric(airbnbSeattleTest$cancell
ation_policy)

## Warning: NAs introduced by coercion

airbnbSeattleTrain$room_type <- as.numeric(airbnbSeattleTrain$room_type)

## Warning: NAs introduced by coercion

airbnbSeattleTest$room_type <- as.numeric(airbnbSeattleTest$room_type)

## Warning: NAs introduced by coercion

airbnbSeattleTrain$bed_type <- as.numeric(airbnbSeattleTrain$bed_type)

## Warning: NAs introduced by coercion

airbnbSeattleTest$bed_type <- as.numeric(airbnbSeattleTest$bed_type)

## Warning: NAs introduced by coercion

airbnbSeattleTrain$property_type <- as.numeric(airbnbSeattleTrain$property_ty
pe)

## Warning: NAs introduced by coercion

airbnbSeattleTest$property_type <- as.numeric(airbnbSeattleTest$property_type
)

## Warning: NAs introduced by coercion

airbnbSeattleTrain$instant_bookable <- as.numeric(airbnbSeattleTrain$instant_
bookable)
airbnbSeattleTest$instant_bookable <- as.numeric(airbnbSeattleTest$instant_bo
okable)
```

```
airbnbSeattleTrain$host_identity_verified <- as.numeric(airbnbSeattleTrain$ho
st_identity_verified)
airbnbSeattleTest$host_identity_verified <- as.numeric(airbnbSeattleTest$host
_identity_verified)
airbnbSeattleTrain$host_is_superhost <- as.numeric(airbnbSeattleTrain$host_is
_superhost)
airbnbSeattleTest$host_is_superhost <- as.numeric(airbnbSeattleTest$host_is_s
uperhost)
```

#running the xgBoost model

```
dfTrain <- airbnbSeattleTrain %>% sample_frac(.80)
dfValid <- setdiff(airbnbSeattleTrain, dfTrain)

library("xgboost")

##
## Attaching package: 'xgboost'

## The following object is masked from 'package:plotly':
##
##     slice

## The following object is masked from 'package:dplyr':
##
##     slice

set.seed(123)
X_train = xgb.DMatrix(as.matrix(dfTrain %>% select(-(high_booking_rate))))
Y_train = dfTrain$high_booking_rate

set.seed(123)

X_test = xgb.DMatrix(as.matrix(dfValid %>% select(-high_booking_rate)))
Y_test = dfValid$high_booking_rate

xgb_trcontrol = trainControl(
  method = "cv",
  number = 10,
  allowParallel = TRUE,
  verboseIter = FALSE,
  returnData = FALSE
)

xgbGrid <- expand.grid(nrounds = c(100,200),
                       max_depth = c(10, 15, 20, 25),
                       colsample_bytree = seq(0.5, 0.9, length.out = 5),
                       eta = 0.1,
                       gamma=0,
                       min_child_weight = 1,
                       subsample = 1
                      )
```

```
xgb_model = train(
  X_train, Y_train,
  trControl = xgb_trcontrol,
  tuneGrid = xgbGrid,
  method = "xgbTree"
)

resultsXg <-
  xgb_model %>%
    predict(X_test, type= 'prob') %>%
  bind_cols(dfValid,predictedClass=.)
resultsXg
```

```
## # A tibble: 5,414 x 23
##    high_booking_ra… accommodates availability_365 bathrooms bed_type bedro
oms
##    <fct>                   <dbl>            <dbl>     <dbl>    <dbl>    <d
bl>
##  1 1                           3               16         1       NA
0
##  2 1                           4                0         1       NA
1
##  3 0                           2               90         1       NA
1
##  4 0                           1                0         1       NA
1
##  5 0                           6              160         1       NA
2
##  6 0                           4              358         2       NA
2
##  7 1                           2              137         1       NA
1
##  8 0                           4                0         1       NA
0
##  9 0                           2               66         1       NA
1
## 10 0                           3              273         1       NA
1
## # … with 5,404 more rows, and 17 more variables: beds <dbl>,
## #   cancellation_policy <dbl>, cleaning_fee <dbl>, extra_people <dbl>,
## #   guests_included <dbl>, host_identity_verified <dbl>,
## #   host_is_superhost <dbl>, instant_bookable <dbl>, maximum_nights <dbl>,
## #   minimum_nights <dbl>, price <dbl>, property_type <dbl>, room_type <dbl
>,
## #   security_deposit <dbl>, `{randomControl}` <dbl>, `0` <dbl>, `1` <dbl>
```

```
names(resultsXg)[23] <- "predictedClass"

#resultsXg$predictedClass<- as.numeric(resultsXg$predictedClass)
```

```
resultsXg = resultsXg %>% mutate(predictedHbr = as.factor(ifelse(predictedCla
ss > 0.6, 1, 0)))

resultsXg
```

```
## # A tibble: 5,414 x 24
##    high_booking_ra… accommodates availability_365 bathrooms bed_type bedro
oms
##    <fct>                  <dbl>            <dbl>     <dbl>    <dbl>    <d
bl>
##  1 1                          3               16         1       NA
0
##  2 1                          4                0         1       NA
1
##  3 0                          2               90         1       NA
1
##  4 0                          1                0         1       NA
1
##  5 0                          6              160         1       NA
2
##  6 0                          4              358         2       NA
2
##  7 1                          2              137         1       NA
1
##  8 0                          4                0         1       NA
0
##  9 0                          2               66         1       NA
1
## 10 0                          3              273         1       NA
1
## # … with 5,404 more rows, and 18 more variables: beds <dbl>,
## #   cancellation_policy <dbl>, cleaning_fee <dbl>, extra_people <dbl>,
## #   guests_included <dbl>, host_identity_verified <dbl>,
## #   host_is_superhost <dbl>, instant_bookable <dbl>, maximum_nights <dbl>,
## #   minimum_nights <dbl>, price <dbl>, property_type <dbl>, room_type <dbl
>,
## #   security_deposit <dbl>, `{randomControl}` <dbl>, `0` <dbl>,
## #   predictedClass <dbl>, predictedHbr <fct>
```

```
resultsXg %>%
  xtabs(~predictedHbr+high_booking_rate, .) %>%
  confusionMatrix(positive='1')
```

```
## Confusion Matrix and Statistics
##
##              high_booking_rate
## predictedHbr    0    1
##            0 3201  156
##            1   83 1974
##
```

```
##                Accuracy : 0.9559
##                  95% CI : (0.95, 0.9612)
##     No Information Rate : 0.6066
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.9069
##
##  Mcnemar's Test P-Value : 3.204e-06
##
##             Sensitivity : 0.9268
##             Specificity : 0.9747
##          Pos Pred Value : 0.9596
##          Neg Pred Value : 0.9535
##              Prevalence : 0.3934
##          Detection Rate : 0.3646
##    Detection Prevalence : 0.3799
##       Balanced Accuracy : 0.9507
##
##        'Positive' Class : 1
##
```

We see the specificity and sensitivity are high. We have a good model here to predict high booking rate. Investor can use this model and see if their listings will have a good booking rate or not.

CONCLUSION AND DISCUSSION

Findings

1. **Belltown was the neighbourhood with the highest listings.**
2. **Capitol Hill was the neighbourhood which had the most expensive as well as the least expensive properties.**
3. **Apartments were the most common property type in Seattle.**
4. **The spread of properties was almost consistant across the whole state. There is a little higher concentration in central Seattle compared to the rest of the state.**
5. **Restaurants were the most common attraction in a neihbourhood.**
6. **Bus was the most popular type of transit.**
7. **Wifi, Shampoo, Essentials and Kitchens were the most common amenities.**

Future Research

1. **If the data that is gathered and has less NA values, we can give more accurate recommendations with the help of the models we run.**
2. **If seasonality can be added to the data, it will help us greatly in future predictions.**
3. **If we have a column for the periods of time the properties are accupied, it can help do better EDA to present to the investors.**
4. **If we have some additional parameters we can calculate the time required to break-even on the investment. This will help build a strong case for investors.**

Limitations

1. The data scraped for this research was not clean and there were a lot of missing values due to which we had to remove all the NA values which led to the analysis being skewed.
2. We had difficulties in merging with other data sets to do a more in-depth analysis.
3. We were unable to get reviews of the users. The reviews provided by the owners would be biased in their favor and could not give us the correct picture.

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