

MA615final

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Airbnb property price and related factors

Background

Airbnb is a convenient website that we use to book lodging or primarily homestays. All of real estate listings are posted by property owners and these owners set unit room prices according to location, condition and many other seasonal influence factors. I plan to study elements that affect Airbnb room prices and try to find a model that could predict or provide a suggested price for Airbnb property. Then the model can be used by Airbnb hosts as a basic pricing tool.

Research question

Which factors could affect Airbnb room prices?

Data collection

I collect airbnb data of Boston in 2017. The dataset contains variables: room id, host id, room type, neighborhood, the number of reviews, the average rating, the number of guests a listing can accommodate, the number of bedrooms, the price for a night stay, latitude, longitude, the date and time that the values were read.

Read Data

Airbnb has 7 sheets of 2017 Boston dataset available online, and I just download and read them in RStudio first.

```
library(readr)
data1<-read_csv("~/Desktop/boston/tomslee_airbnb_boston_0779_2017-01-14.csv")
data2<-read_csv("~/Desktop/boston/tomslee_airbnb_boston_0858_2017-02-16.csv")
data3<-read_csv("~/Desktop/boston/tomslee_airbnb_boston_0931_2017-03-12.csv")
data4<-read_csv("~/Desktop/boston/tomslee_airbnb_boston_1043_2017-04-08.csv")
data5<-read_csv("~/Desktop/boston/tomslee_airbnb_boston_1187_2017-05-05.csv")
data6<-read_csv("~/Desktop/boston/tomslee_airbnb_boston_1309_2017-06-10.csv")
data7<-read_csv("~/Desktop/boston/tomslee_airbnb_boston_1429_2017-07-10.csv")
```

Data Cleaning

After viewing variables of each sheets, I find 4 sheets have 14 variables, while other 3 sheets have 20 variables. So, I decide to keep 14 variables.

```
length(colnames(data1))
```

```
## [1] 14
```

```
length(colnames(data2))
```

```
## [1] 14
```

```
length(colnames(data3))
```

```
## [1] 14
```

```
length(colnames(data4))
```

```
## [1] 14
```

```
length(colnames(data5))
```

```
## [1] 20
```

```
length(colnames(data6))
```

```
## [1] 20
```

```
length(colnames(data7))
```

```
## [1] 20
```

```
library(dplyr)
```

```
data5<-data5%>%select("room_id","host_id","room_type","borough","neighborhood","reviews","overall_satis
```

```
data6<-data6%>%select("room_id","host_id","room_type","borough","neighborhood","reviews","overall_satis
```

```
data7<-data7%>%select("room_id","host_id","room_type","borough","neighborhood","reviews","overall_satis
```

Data Organization

While combining these sheets, I find some properties have been updated and the whole sheet contains several observations with same room_id. So, I delete duplicates and only keep the most recent observation. After data analysis, I also delete 2 blank columns and rows containing missing values. Next, I generate a new csv file containing all data.

```
mydata <- rbind(data7,data6,data5,data4,data3,data2,data1)
sample<-mydata%>%filter(room_id=="12071820")
```

```
library(tidyverse)
mydata <- distinct(mydata, room_id, .keep_all = TRUE)
sample<-mydata%>%filter(room_id=="12071820")
```

```
mydata<-mydata%>%select("room_id","host_id","room_type","neighborhood","reviews","overall_satisfaction")
library(funModeling)
data_integrity(mydata)
```

```
## $vars_num_with_NA
## [1] variable q_na      p_na
## <0 rows> (or 0-length row.names)
##
## $vars_cat_with_NA
## [1] variable q_na      p_na
## <0 rows> (or 0-length row.names)
##
## $vars_cat_high_card
## [1] variable unique
## <0 rows> (or 0-length row.names)
##
## $MAX_UNIQUE
## [1] 35
##
## $vars_one_value
## character(0)
##
## $vars_cat
## [1] "room_type"      "neighborhood"
##
## $vars_num
## [1] "room_id"          "host_id"          "reviews"
## [4] "overall_satisfaction" "accommodates"      "bedrooms"
## [7] "price"            "latitude"          "longitude"
##
## $vars_char
## [1] "room_type"      "neighborhood"
##
## $vars_factor
## character(0)
##
## $vars_other
## [1] "last_modified"
```

```
mydata <- drop_na(mydata)
write.csv(mydata,"~/Desktop/boston/Boston2017.csv", row.names = FALSE)
```

Review analysis

In order to visualize most frequent words shown in reviews, I use text mining to generate a graph.

```
library(gutenbergr)
library(tidytext)
library(knitr)
library(textdata)
library(magrittr)
library(tm)

booksource <- read.delim("~/Desktop/boston/reviews.txt", header=F, sep = "\n", stringsAsFactors = F)
booksource <- as.data.frame(booksource)
names(booksource)[1] <- "text"
booksource <- booksource %>% mutate(gutenberg_id = 2007)

book <- "Reviews"
as.character(book)

## [1] "Reviews"

original_book <- cbind(booksource, book)

library(janeaustenr)
tidy_book <- original_book %>%
  group_by(book) %>%
  mutate(linenumber = row_number(),
         chapter = cumsum(str_detect(text, regex("^chapter [\\divxlc]",
                                                ignore_case = TRUE)))) %>%
  ungroup()

tidy_book <- tidy_book %>%
  unnest_tokens(word, text)

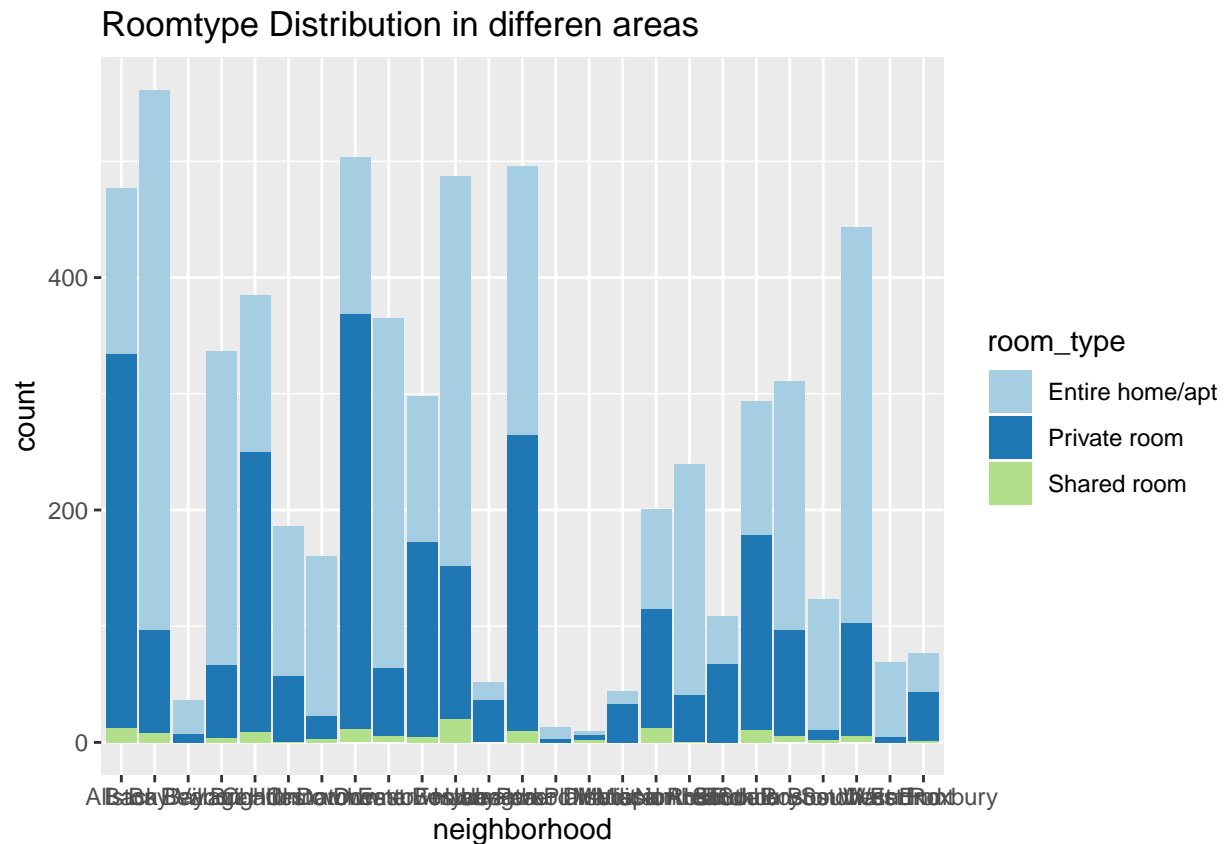
library(wordcloud)
tidy_book %>%
  anti_join(stop_words) %>%
  count(word) %>%
  with(wordcloud(word, n, max.words = 100))
```

apartment
perfect comfortable
experience location
minute check home
floor morning amenities parking local street time
coffee super time home
arrival shops subway absolutely access
fantastic bed cozy spacious close
family line warm transportation distance
amazing host bathroom airbnb 2 public located
awesome short boston 10 city stayed hosts safe station
friendly nice space easy provided
breakfast lovely stay welcoming minutes downtown
clean stay house
neighborhood accommodating

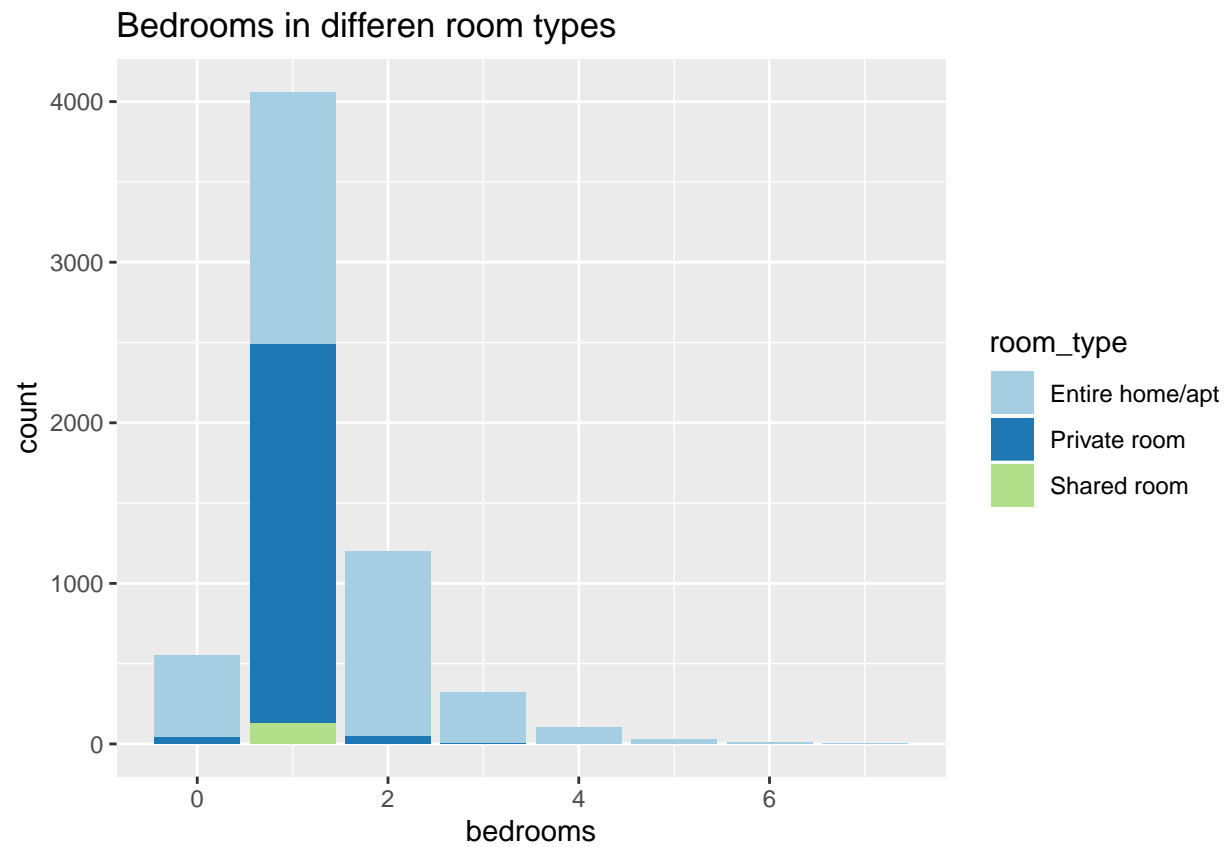
EDA

Data plots and table

```
library(ggplot2)
library(stringi)
ggplot(mydata, aes(x = neighborhood, fill = room_type)) +
  geom_bar() +
  ggtitle("Roomtype Distribution in differen areas") +
  scale_fill_brewer(palette = "Paired")
```

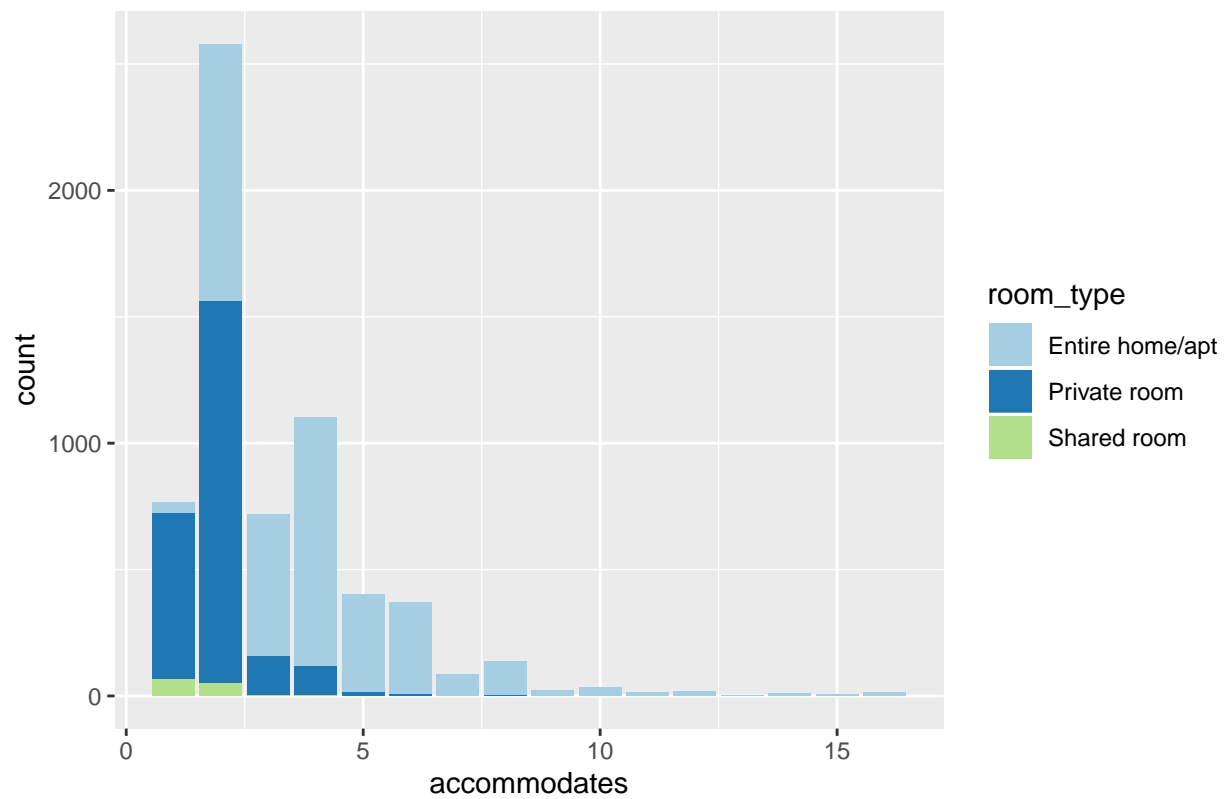


```
ggplot(mydata, aes(x = bedrooms, fill = room_type)) +  
  geom_bar() +  
  ggtitle("Bedrooms in differen room types") +  
  scale_fill_brewer(palette = "Paired")
```

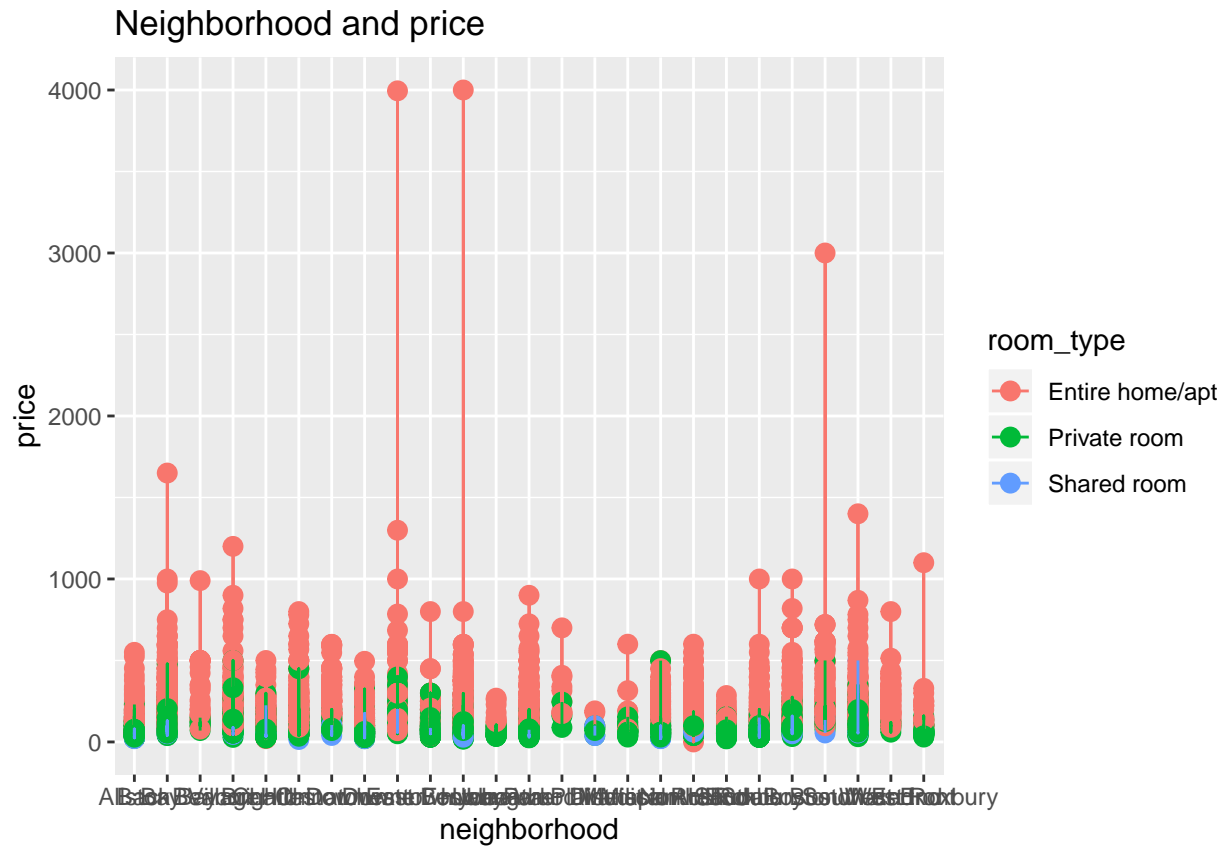


```
ggplot(mydata, aes(x = accommodates, fill = room_type)) +  
  geom_bar() +  
  ggtitle("Roomtype accommodation") +  
  scale_fill_brewer(palette = "Paired")
```

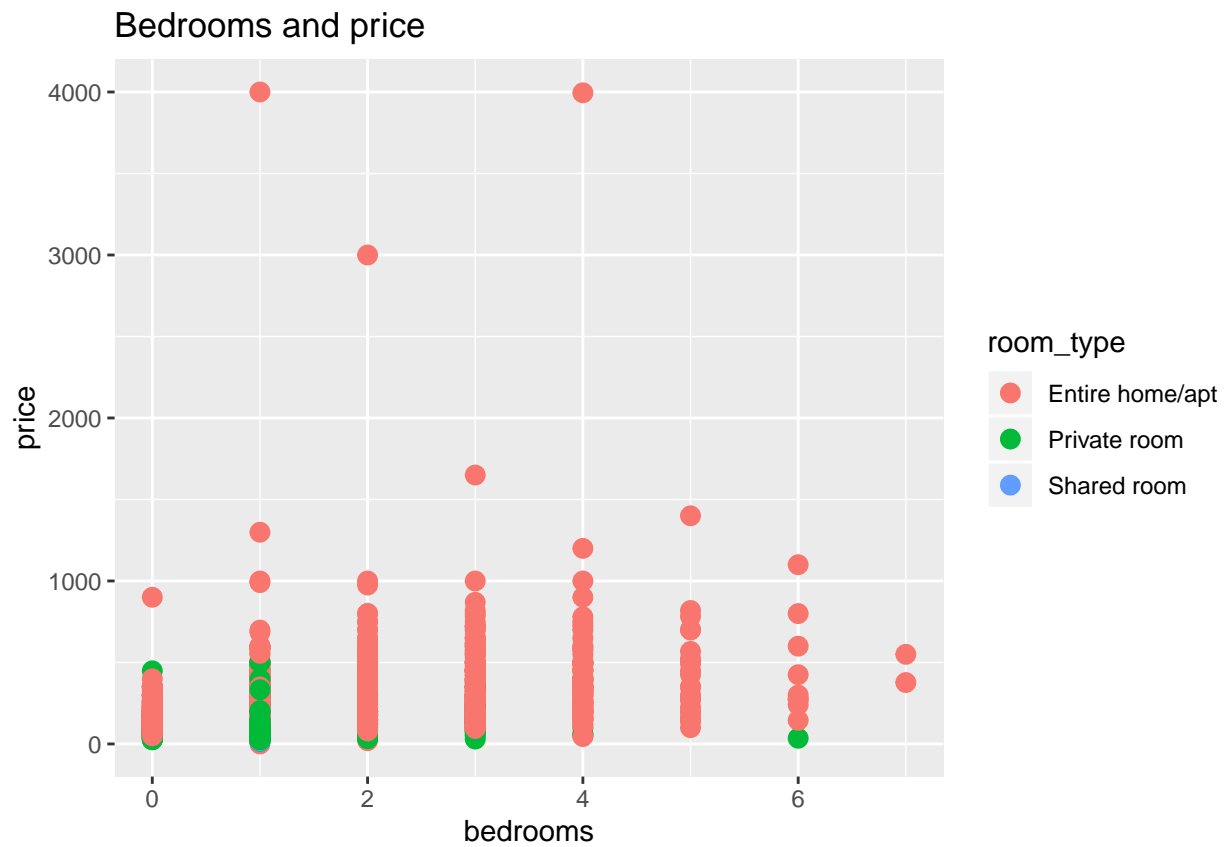
Roomtype accommodation



```
ggplot(data = mydata, aes(x = neighborhood, y = price, color = room_type)) +  
  geom_point(size = 3) +  
  geom_line() +  
  ggtitle("Neighborhood and price")
```

```
ggplot(data = mydata, aes(x = bedrooms, y = price, color = room_type)) +
  geom_point(size = 3) +
  ggtitle("Bedrooms and price")
```



```
ggplot(data = mydata, aes(x = accommodates, y = price, color = room_type)) +  
  geom_point(size = 3) +  
  ggtitle("Accommodates and price")
```



```

library(kableExtra)
df1 <- mydata[,c("neighborhood","accommodates","price")]
df2 <- aggregate(df1[,2:3],by=list(df1$neighborhood),mean)
kable(df2, digits = 2,      ## call kable to make the table
      col.names = c("Location", "Average Rating", "Price"),
      caption = "Location and price by average rating",align = 'c') %>%
kable_styling(latex_options = 'hold_position',font_size = 12,full_width = F,position = "center")%>%
column_spec(1,bold = T)

```

Table 1: Location and price by average rating

Location	Average Rating	Price
Allston	2.53	89.40
Back Bay	3.13	218.80
Bay Village	3.67	270.31
Beacon Hill	3.02	194.54
Brighton	2.74	93.73
Charlestown	3.53	201.94
Chinatown	4.10	232.96
Dorchester	2.87	91.88
Downtown	3.67	230.74
East Boston	3.02	111.36
Fenway	2.93	184.14
Hyde Park	2.75	81.75
Jamaica Plain	3.21	132.41
Leather District	3.38	278.77
Longwood Medical Area	2.20	98.70
Mattapan	3.00	98.36
Mission Hill	2.73	124.71
North End	3.58	172.13
Roslindale	3.13	87.96
Roxbury	3.22	119.08
South Boston	3.99	188.60
South Boston Waterfront	3.81	306.25
South End	2.93	192.68
West End	3.68	241.94
West Roxbury	3.23	114.34

The data has 25 subregions in the neighborhood variable and plots compare unit room prices in different locations. The table also show summary of price and accomodates regardless of room types.

Concerns

Zero values in “the number of reviews” and “the average rating” may lead to potential problems. Usually, living spots with unattractive appearance or location probably have few or no reviews. But new posted houses also have zero review since no one has stayed before. If I keep these zero values in the fitted model, the model will predict relatively low prices for those new lodgings. In addition, the plot shows 3 outliers with pretty high price above \$3000, which might make regression less reliable. In this way, I remove these observations.

```
mydata$reviews[mydata$reviews=="0"] <- NA
mydata <- drop_na(mydata)
mydata <- mydata[!(mydata$price==max(mydata$price)),]
mydata <- mydata[!(mydata$price==max(mydata$price)),]
mydata <- mydata[!(mydata$price==max(mydata$price)),]
```

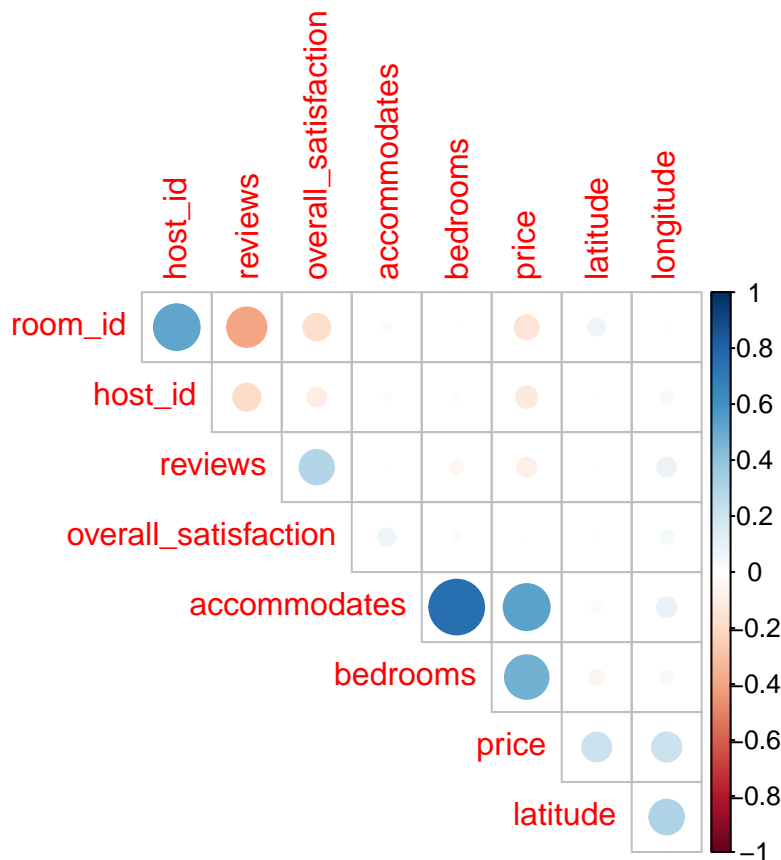
Methods

Correlation

```
mydata$reviews<-as.numeric(mydata$reviews)
mydata$overall_satisfaction<-as.numeric(mydata$overall_satisfaction)
mydata$latitude<-as.numeric(mydata$latitude)
mydata$longitude<-as.numeric(mydata$longitude)
sapply(mydata, is.numeric)
```

```
##          room_id          host_id          room_type
##          TRUE          TRUE          FALSE
##    neighborhood          reviews overall_satisfaction
##          FALSE          TRUE          TRUE
##    accommodates          bedrooms          price
##          TRUE          TRUE          TRUE
##    latitude          longitude          last_modified
##          TRUE          TRUE          FALSE
```

```
cordata <- mydata[, sapply(mydata, is.numeric)]
cor.ma <- cor(cordata, method = "pearson")
corrplot::corrplot(cor.ma, method = "circle", type = "upper", diag = F)
```



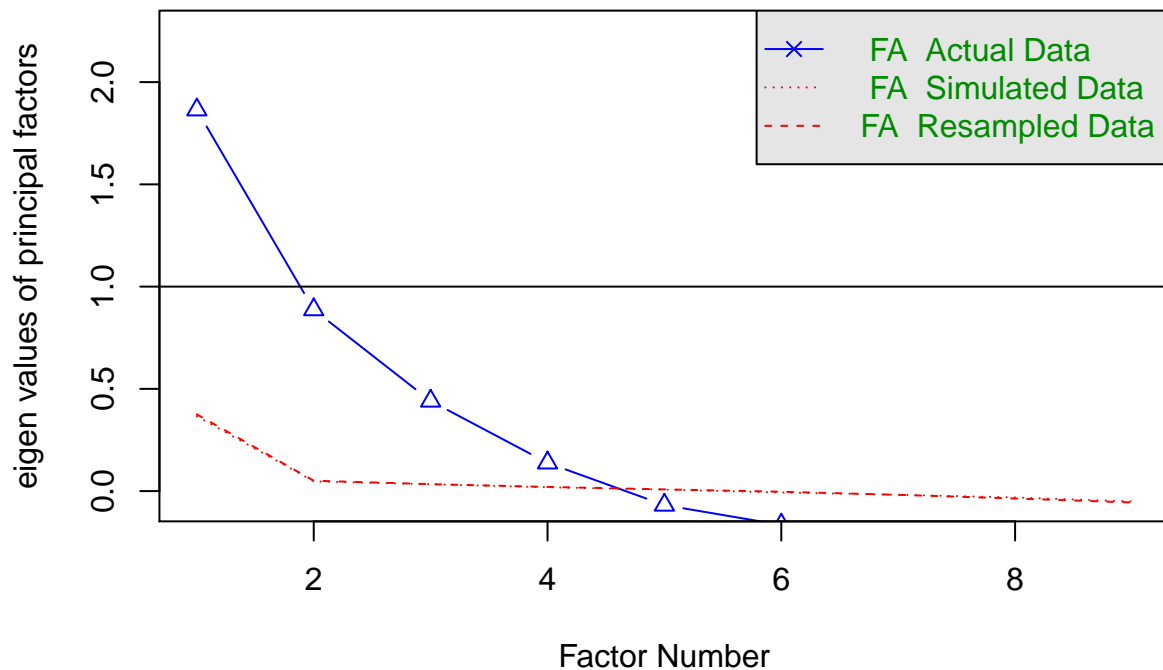
Some variables like accomodates and bedrooms have high correlations, so I need to consider only use part of them in models.

EFA

Dataset has 12 variables and I want to find out the number of factors that will be selected for later analysis.

```
library(psych)
library(GPArotation)
parallel <- fa.parallel(cordata, fm = 'minres', fa = 'fa') # parallel analysis
```

Parallel Analysis Scree Plots

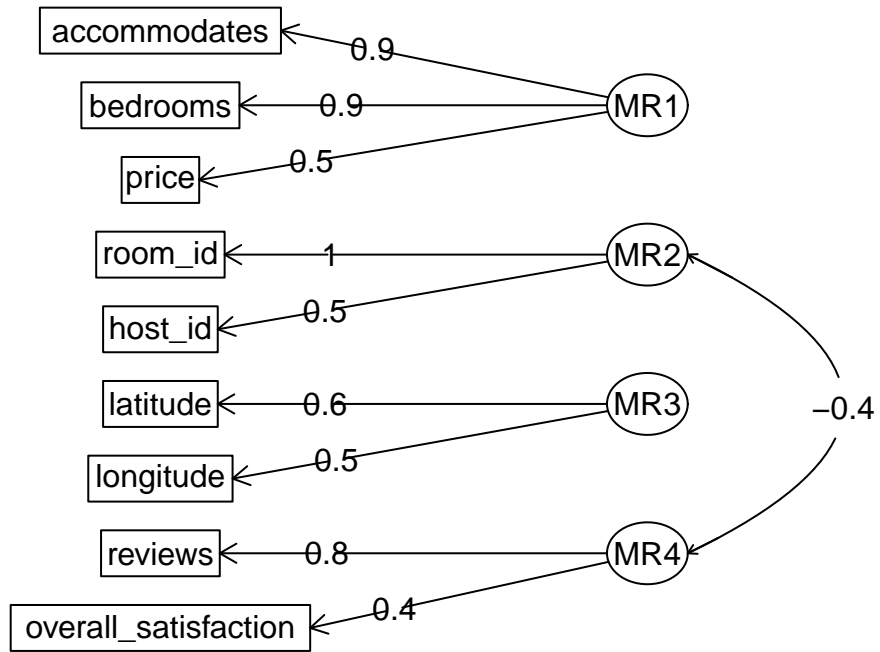


```
## Parallel analysis suggests that the number of factors = 4 and the number of components = NA
```

The blue line shows eigenvalues of actual data and the two red lines (placed on top of each other) show simulated and resampled data. Here we look at the large drops in the actual data and spot the point where it levels off to the right. Also we locate the point of inflection – the point where the gap between simulated data and actual data tends to be minimum.

```
fourfactor <- fa(cordata,nfactors = 4,rotate = "oblimin",fm="minres") # 4 factor analysis
fa.diagram(fourfactor)
```

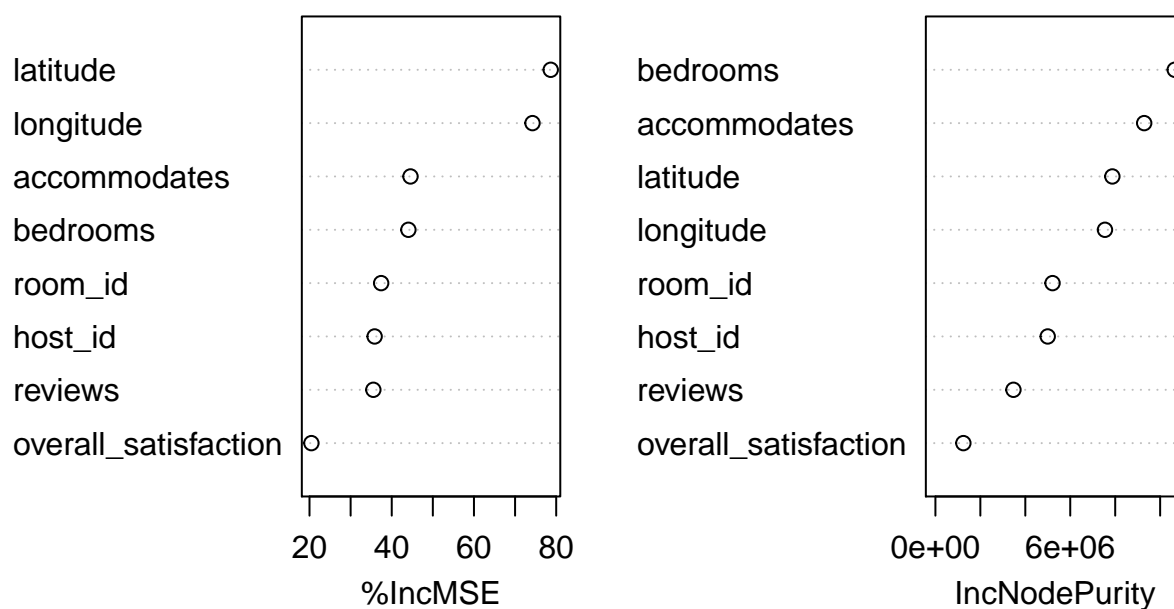
Factor Analysis



Random Forest

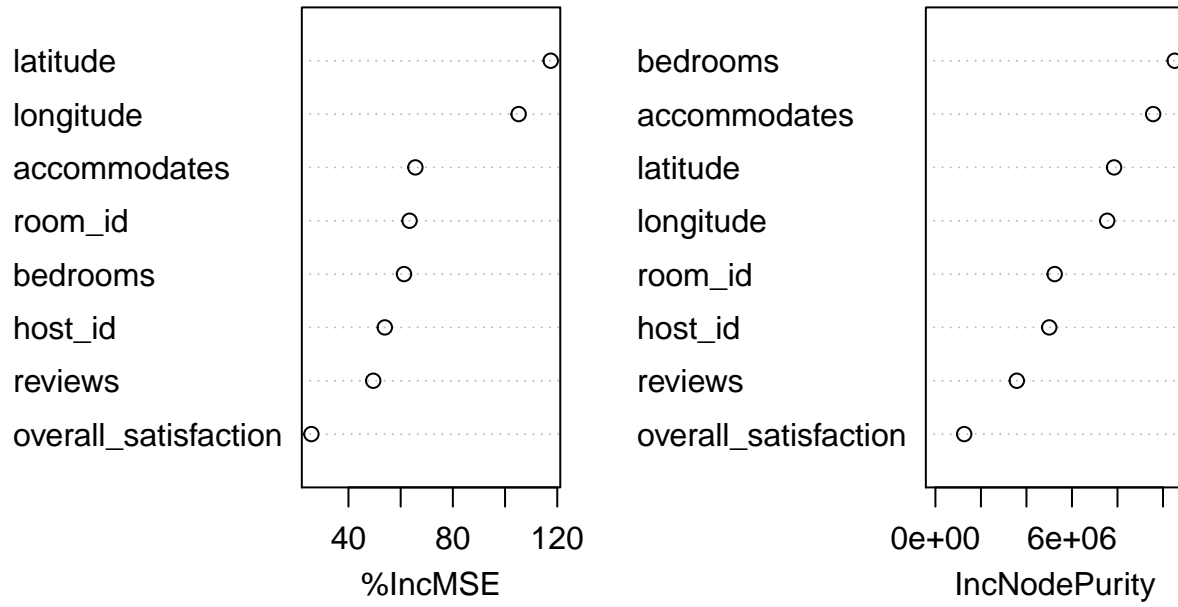
```
library(randomForest)
model1 <- randomForest(price~., data=cordata, importance=T, ntree=500)
model2 <- randomForest(price~., data=cordata, importance=T, ntree=1000)
varImpPlot(model1)
```

model1



```
varImpPlot(model2)
```

model2



Try to fit models using top factors

Models

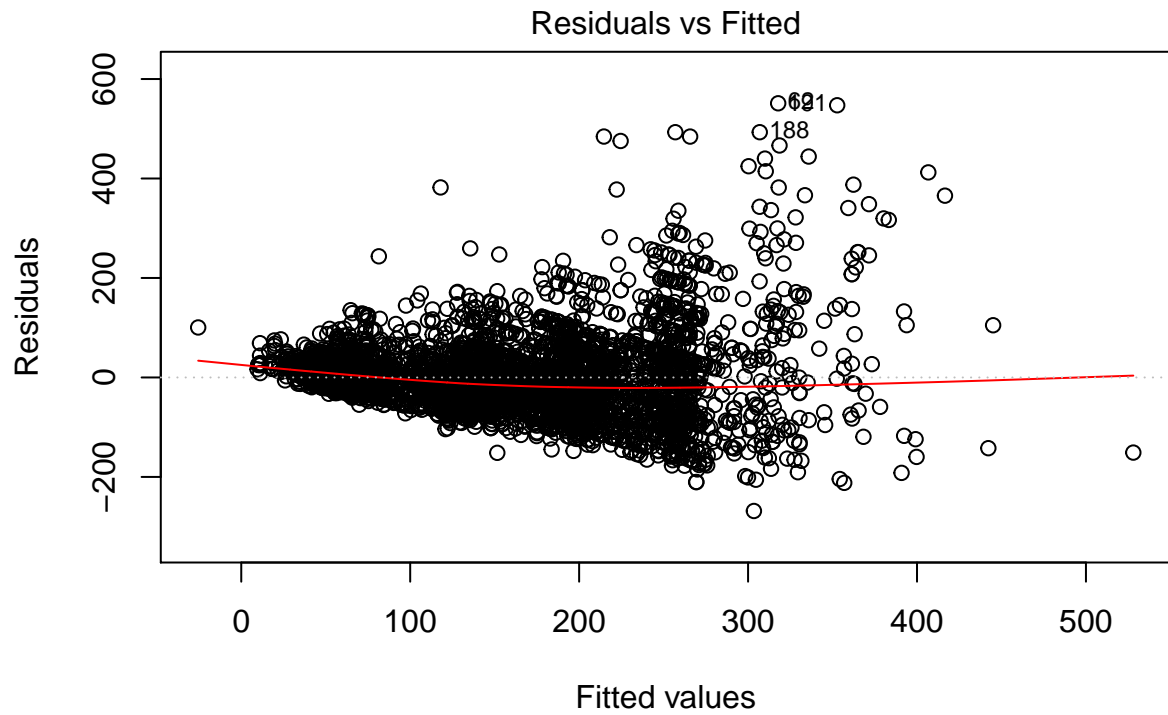
```
fit1 <- lm(price~log(accommodates)+bedrooms+reviews*overall_satisfaction+as.factor(neighborhood)+as.factor(room_type),
summary(fit1)
```

```
##
## Call:
## lm(formula = price ~ log(accommodates) + bedrooms + reviews *
##     overall_satisfaction + as.factor(neighborhood) + as.factor(room_type),
##     data = mydata)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -268.45  -36.80   -4.81   25.88  551.18
##
## Coefficients:
##                                     Estimate Std. Error
## (Intercept)                       66.72498     5.53226
## log(accommodates)                  21.84811     3.07796
## bedrooms                          46.82777     1.79909
## reviews                          -1.07118     0.31741
## overall_satisfaction               -1.50798     0.59976
## as.factor(neighborhood)Back Bay    82.71440     5.43277
## as.factor(neighborhood)Bay Village 86.36800    13.41012
## as.factor(neighborhood)Beacon Hill 71.28623     6.01118
## as.factor(neighborhood)Brighton   -7.41221     5.85838
## as.factor(neighborhood)Charlestown 50.47330     7.37905
## as.factor(neighborhood)Chinatown   65.34073     8.43886
## as.factor(neighborhood)Dorchester  -8.04243     5.30369
## as.factor(neighborhood)Downtown    67.03606     6.14315
## as.factor(neighborhood)East Boston  0.81827     6.05857
## as.factor(neighborhood)Fenway       57.15089     5.63847
## as.factor(neighborhood)Hyde Park   -20.16416    12.52559
## as.factor(neighborhood)Jamaica Plain 10.29973     5.35887
## as.factor(neighborhood)Leather District 138.44788    22.18337
## as.factor(neighborhood)Longwood Medical Area 45.86323    29.94530
## as.factor(neighborhood)Mattapan   -10.12923    12.51801
## as.factor(neighborhood)Mission Hill 13.91584     7.72606
## as.factor(neighborhood)North End    30.54092     6.57196
## as.factor(neighborhood)Roslindale  -21.91381     8.53485
## as.factor(neighborhood)Roxbury      8.99643     6.14965
## as.factor(neighborhood)South Boston 41.61851     6.08265
## as.factor(neighborhood)South Boston Waterfront 122.90569     8.83656
## as.factor(neighborhood)South End    73.92047     5.55521
## as.factor(neighborhood)West End     62.26874    12.74232
## as.factor(neighborhood)West Roxbury -18.35354    10.35129
## as.factor(room_type)Private room   -56.01553     2.98953
## as.factor(room_type)Shared room    -86.59251     8.33934
## reviews:overall_satisfaction       0.20649     0.06761
##                                     t value Pr(>|t|)
## (Intercept)                       12.061 < 2e-16 ***
## log(accommodates)                   7.098 1.45e-12 ***
## bedrooms                           26.029 < 2e-16 ***
## reviews                           -3.375 0.000745 ***
```

```

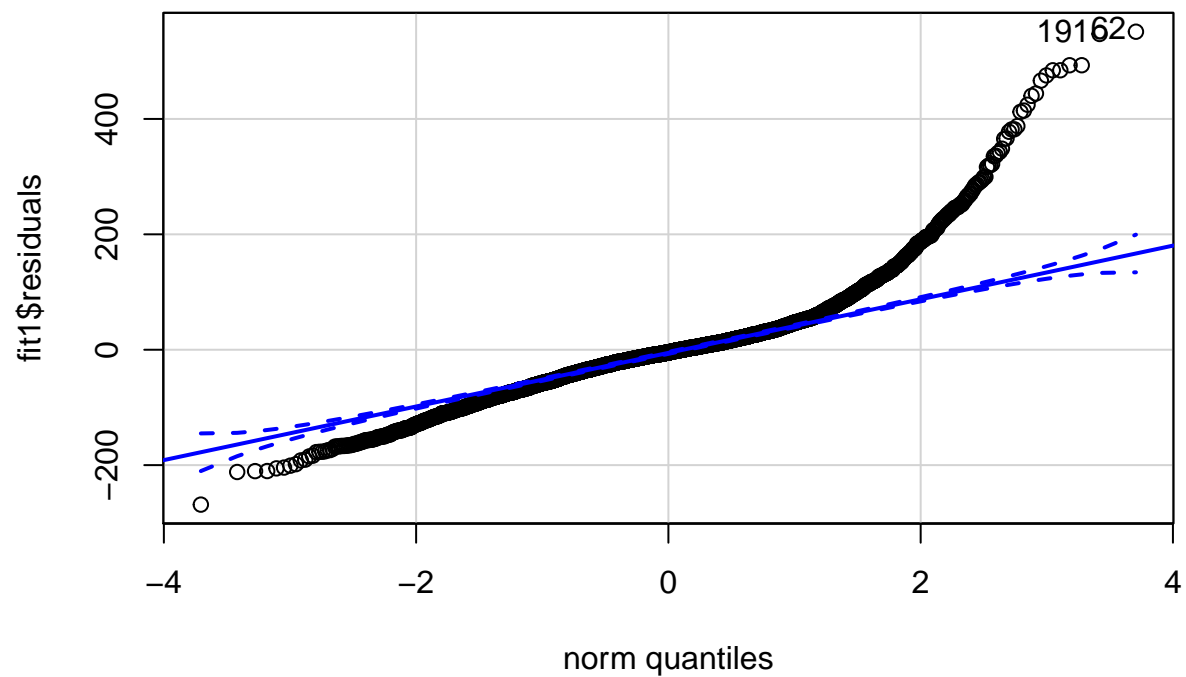
## overall_satisfaction -2.514 0.011959 *
## as.factor(neighborhood)Back Bay 15.225 < 2e-16 ***
## as.factor(neighborhood)Bay Village 6.441 1.31e-10 ***
## as.factor(neighborhood)Beacon Hill 11.859 < 2e-16 ***
## as.factor(neighborhood)Brighton -1.265 0.205850
## as.factor(neighborhood)Charlestown 6.840 8.92e-12 ***
## as.factor(neighborhood)Chinatown 7.743 1.18e-14 ***
## as.factor(neighborhood)Dorchester -1.516 0.129489
## as.factor(neighborhood)Downtown 10.912 < 2e-16 ***
## as.factor(neighborhood)East Boston 0.135 0.892570
## as.factor(neighborhood)Fenway 10.136 < 2e-16 ***
## as.factor(neighborhood)Hyde Park -1.610 0.107500
## as.factor(neighborhood)Jamaica Plain 1.922 0.054666 .
## as.factor(neighborhood)Leather District 6.241 4.73e-10 ***
## as.factor(neighborhood)Longwood Medical Area 1.532 0.125696
## as.factor(neighborhood)Mattapan -0.809 0.418457
## as.factor(neighborhood)Mission Hill 1.801 0.071742 .
## as.factor(neighborhood)North End 4.647 3.46e-06 ***
## as.factor(neighborhood)Roslindale -2.568 0.010272 *
## as.factor(neighborhood)Roxbury 1.463 0.143557
## as.factor(neighborhood)South Boston 6.842 8.79e-12 ***
## as.factor(neighborhood)South Boston Waterfront 13.909 < 2e-16 ***
## as.factor(neighborhood)South End 13.307 < 2e-16 ***
## as.factor(neighborhood)West End 4.887 1.06e-06 ***
## as.factor(neighborhood)West Roxbury -1.773 0.076282 .
## as.factor(room_type)Private room -18.737 < 2e-16 ***
## as.factor(room_type)Shared room -10.384 < 2e-16 ***
## reviews:overall_satisfaction 3.054 0.002270 **
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 72.31 on 4733 degrees of freedom
## Multiple R-squared: 0.5433, Adjusted R-squared: 0.5403
## F-statistic: 181.6 on 31 and 4733 DF, p-value: < 2.2e-16
plot(fit1,which=1)

```



$\text{lm}(\text{price} \sim \log(\text{accommodates}) + \text{bedrooms} + \text{reviews} * \text{overall_satisfaction} + \dots)$

```
car::qqPlot(fit1$residuals)
```



```
## [1] 62 191
```

Citation

<http://tomslee.net/airbnb-data-collection-get-the-data>

<http://insideairbnb.com/get-the-data.html>