Istanbul_airbnb_factor_analysis

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

library(data.table)

## Warning: package 'data.table' was built under R version 3.6.2

library(fpp)

## Loading required package: forecast

## Warning: package 'forecast' was built under R version 3.6.2

## Registered S3 method overwritten by 'quantmod':
##   method            from
##   as.zoo.data.frame zoo

## Loading required package: fma

## Warning: package 'fma' was built under R version 3.6.2

## Loading required package: expsmooth

## Loading required package: lmtest

## Loading required package: zoo

## Warning: package 'zoo' was built under R version 3.6.2

##
## Attaching package: 'zoo'

## The following objects are masked from 'package:base':
##
##     as.Date, as.Date.numeric

## Loading required package: tseries

library(fpp2)

## Loading required package: ggplot2

##
## Attaching package: 'fpp2'

## The following objects are masked from 'package:fpp':
##
##     ausair, ausbeer, austa, austourists, debitcards, departures,
##     elecequip, euretail, guinearice, oil, sunspotarea, usmelec

library(cowplot)
```

```
## Warning: package 'cowplot' was built under R version 3.6.2

##
## ********************************************************

## Note: As of version 1.0.0, cowplot does not change the

##   default ggplot2 theme anymore. To recover the previous

##   behavior, execute:
##   theme_set(theme_cowplot())

## ********************************************************

library(tidyverse)

## Warning: package 'tidyverse' was built under R version 3.6.2

## -- Attaching packages -----------------------------------------------------
------- tidyverse 1.3.0 --

## v tibble  2.1.3     v dplyr   0.8.4
## v tidyr   1.0.2     v stringr 1.4.0
## v readr   1.3.1     v forcats 0.4.0
## v purrr   0.3.3

## Warning: package 'tidyr' was built under R version 3.6.2

## Warning: package 'purrr' was built under R version 3.6.2

## Warning: package 'dplyr' was built under R version 3.6.2

## Warning: package 'forcats' was built under R version 3.6.2

## -- Conflicts --------------------------------------------------------------
- tidyverse_conflicts() --
## x dplyr::between()   masks data.table::between()
## x dplyr::filter()    masks stats::filter()
## x dplyr::first()     masks data.table::first()
## x dplyr::lag()       masks stats::lag()
## x dplyr::last()      masks data.table::last()
## x purrr::transpose() masks data.table::transpose()

library(psych)

## Warning: package 'psych' was built under R version 3.6.2

##
## Attaching package: 'psych'

## The following objects are masked from 'package:ggplot2':
##
##     %+%, alpha
```

```r
library(e1071)

## Warning: package 'e1071' was built under R version 3.6.2

library(dplyr)
library(corrplot)

## Warning: package 'corrplot' was built under R version 3.6.2

## corrplot 0.84 loaded

library(GGally)

## Warning: package 'GGally' was built under R version 3.6.2

## Registered S3 method overwritten by 'GGally':
##   method from
##   +.gg   ggplot2

##
## Attaching package: 'GGally'

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

## The following object is masked from 'package:fma':
##
##     pigs

library(reshape2)

##
## Attaching package: 'reshape2'

## The following object is masked from 'package:tidyr':
##
##     smiths

## The following objects are masked from 'package:data.table':
##
##     dcast, melt

AirbnbIstanbul <- read.csv("C:/Pritesh/Rutgers/Courses/Projects/MVA/Dataset/A
irbnbIstanbul.csv", stringsAsFactors=FALSE)
Istanbul <- copy(AirbnbIstanbul)
class(Istanbul)

## [1] "data.frame"

setDT(Istanbul)

str(Istanbul)
```

```
## Classes 'data.table' and 'data.frame':   16251 obs. of  16 variables:
##  $ id                            : int  4826 20815 25436 27271 28277 28308 28318 29241 30697 33368 ...
##  $ name                          : chr  "The Place" "The Bosphorus from The Comfy Hill" "House for vacation rental furnutare" "LOVELY APT. IN PERFECT LOCATION" ...
##  $ host_id                       : int  6603 78838 105823 117026 121607 121695 121721 125742 132137 135136 ...
##  $ host_name                     : chr  "Kaan" "GÃ¼lder" "Yesim" "Mutlu" ...
##  $ neighbourhood_group           : logi  NA NA NA NA NA NA ...
##  $ neighbourhood                 : chr  "Uskudar" "Besiktas" "Besiktas" "Beyoglu" ...
##  $ latitude                      : num  41.1 41.1 41.1 41 41 ...
##  $ longitude                     : num  29.1 29 29 29 29 ...
##  $ room_type                     : chr  "Entire home/apt" "Entire home/apt" "Entire home/apt" "Entire home/apt" ...
##  $ price                         : int  554 100 211 237 591 237 633 264 596 295 ...
##  $ minimum_nights                : int  1 30 21 5 3 1 3 3 1 2 ...
##  $ number_of_reviews             : int  1 41 0 2 0 0 0 0 1 1 ...
##  $ last_review                   : chr  "2009-06-01" "2018-11-07" "" "2018-05-04" ...
##  $ reviews_per_month             : num  0.01 0.38 NA 0.04 NA NA NA NA 0.01 0.02 ...
##  $ calculated_host_listings_count: int  1 2 1 1 13 1 1 1 1 2 ...
##  $ availability_365              : int  365 49 83 228 356 365 365 365 365 232 ...
##  - attr(*, ".internal.selfref")=<externalptr>
```

Factoring categorical variables

```
Istanbul[,room_type:=factor(room_type)]
Istanbul[,neighbourhood:=factor(neighbourhood)]
Istanbul[,last_review:=as.Date(last_review,'%Y-%m-%d')] ## converting last_review to date datatype

# datatypes looks better now. hence will see again for NA values
grep ('NA',Istanbul) # 2, 5, 13 and 14 column have NA values

## [1]  2  5 13 14

Istanbul[is.na(neighbourhood_group),NROW(neighbourhood_group)] # entire obs. is blank, will drop this var

## [1] 16251

Istanbul[is.na(last_review),NROW(last_review)] ## there are 8484 NA values

## [1] 8484
```

```
Istanbul[is.na(reviews_per_month),NROW(reviews_per_month)] ## there are 8484
NA values
```

```
## [1] 8484
```

```
Istanbul$neighbourhood_group <- NULL ## removing neighbourhood_group column
Istanbul[is.na(reviews_per_month),reviews_per_month:=0] ## nearly 50% of the
dataset is filled with NA.
# hence we can't simply remove these many rows. Hence imputing with 0 values.

nrow(Istanbul[price > 1000]) ## price > 1000
```

```
## [1] 613
```

```
#Only 613 rows out of 16251 have Price>1000 which are outliers as seen in EDA
, we can remove those records

Istanbul <- Istanbul[price < 1000] # removing outliers [1] 15638    15
dim(Istanbul)
```

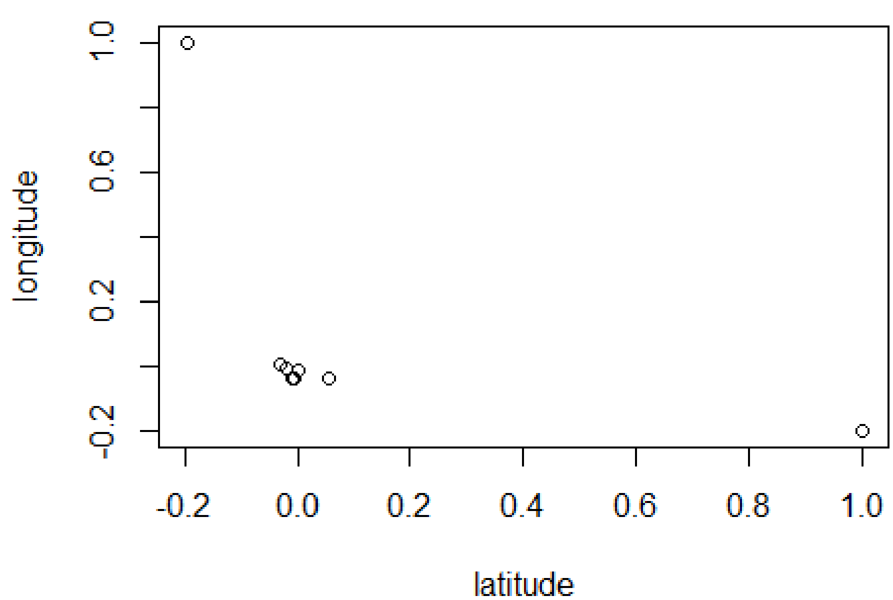
```
## [1] 15638    15
```

Creating new data table with all the quantitative column named Istanbul_factor

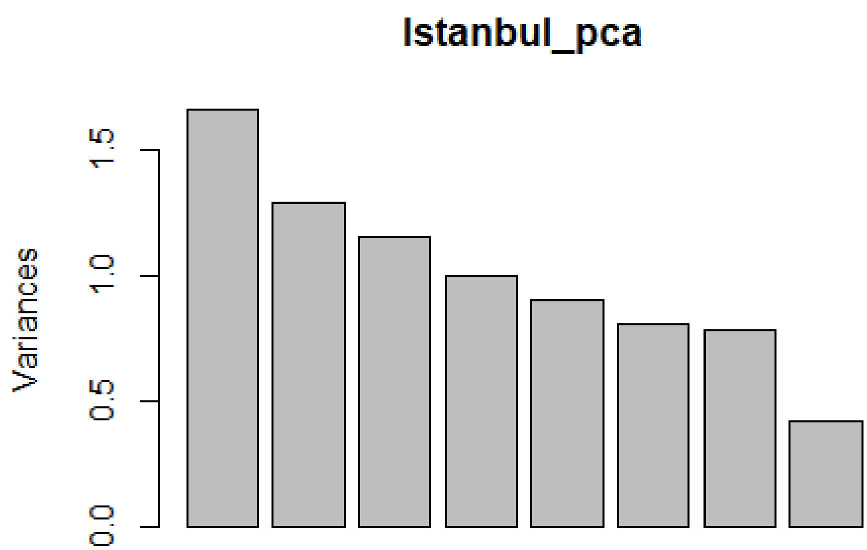
```
Istanbul_factor <- Istanbul[,c("latitude","longitude","price","minimum_nights
","number_of_reviews","reviews_per_month","calculated_host_listings_count","a
vailability_365")]
corrm.Istanbul <- cor(Istanbul_factor)
corrm.Istanbul
```

```
##                                   latitude    longitude        price
## latitude                        1.000000000 -0.197168094  0.054487580
## longitude                      -0.197168094  1.000000000 -0.035045643
## price                           0.054487580 -0.035045643  1.000000000
## minimum_nights                  0.001806824 -0.008447202  0.003237415
## number_of_reviews              -0.020171577 -0.002091917  0.020700048
## reviews_per_month              -0.030645872  0.009699078 -0.025490933
## calculated_host_listings_count -0.009835884 -0.034267106  0.079463904
## availability_365               -0.005504686 -0.038766412  0.160241947
##                                minimum_nights number_of_reviews
## latitude                          0.001806824      -0.020171577
## longitude                        -0.008447202      -0.002091917
## price                             0.003237415       0.020700048
## minimum_nights                    1.000000000      -0.013837757
## number_of_reviews                -0.013837757       1.000000000
## reviews_per_month                -0.034105874       0.576543022
## calculated_host_listings_count   -0.017881502       0.181090297
## availability_365                  0.012869263       0.048541558
##                                reviews_per_month calculated_host_listings_
count
```

```
## latitude                              -0.030645872                        -0.0098
35884
## longitude                              0.009699078                        -0.0342
67106
## price                                 -0.025490933                         0.0794
63904
## minimum_nights                        -0.034105874                        -0.0178
81502
## number_of_reviews                      0.576543022                         0.1810
90297
## reviews_per_month                      1.000000000                         0.1081
87924
## calculated_host_listings_count         0.108187924                         1.0000
00000
## availability_365                      -0.007430996                         0.1677
18740
##                                 availability_365
## latitude                            -0.005504686
## longitude                           -0.038766412
## price                                0.160241947
## minimum_nights                       0.012869263
## number_of_reviews                    0.048541558
## reviews_per_month                   -0.007430996
## calculated_host_listings_count       0.167718740
## availability_365                     1.000000000

plot(corrm.Istanbul)
```

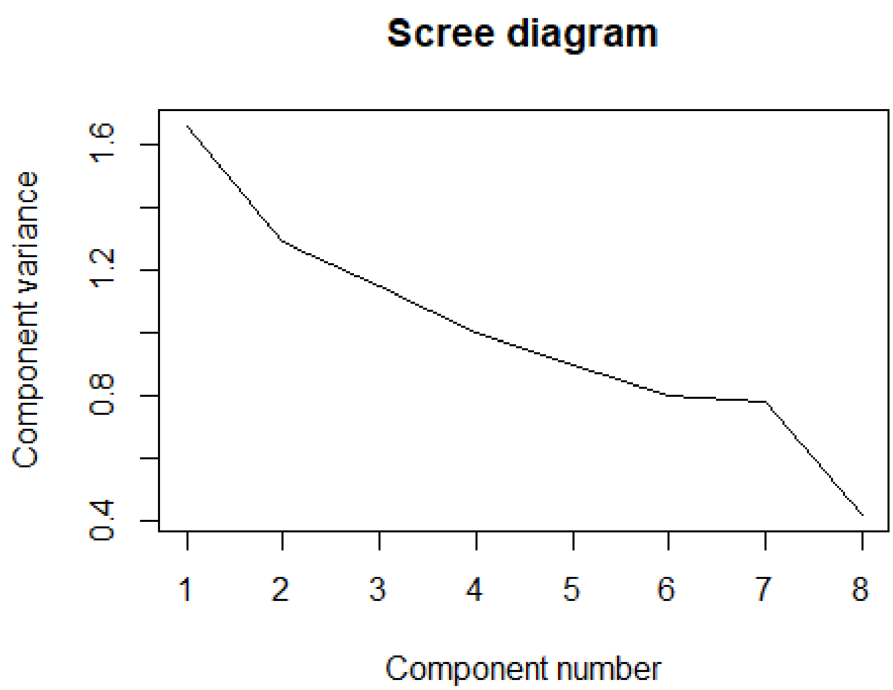


```
Istanbul_pca <- prcomp(Istanbul_factor, scale=TRUE)
summary(Istanbul_pca)

## Importance of components:
##                           PC1    PC2    PC3    PC4    PC5    PC6     PC7
## Standard deviation     1.2880 1.1367 1.0725 0.9995 0.9482 0.8963 0.88367
## Proportion of Variance 0.2074 0.1615 0.1438 0.1249 0.1124 0.1004 0.09761
## Cumulative Proportion  0.2074 0.3689 0.5127 0.6375 0.7499 0.8503 0.94795
##                            PC8
## Standard deviation     0.64529
## Proportion of Variance 0.05205
## Cumulative Proportion  1.00000

plot(Istanbul_pca)
```




```
# A table containing eigenvalues and %'s accounted, follows. Eigenvalues are
the sdev^2
(eigen_Istanbul <- round(Istanbul_pca$sdev^2,2))

## [1] 1.66 1.29 1.15 1.00 0.90 0.80 0.78 0.42

names(eigen_Istanbul) <- paste("PC",1:8,sep="")
eigen_Istanbul

##  PC1  PC2  PC3  PC4  PC5  PC6  PC7  PC8
## 1.66 1.29 1.15 1.00 0.90 0.80 0.78 0.42
```

```r
plot(eigen_Istanbul, xlab = "Component number", ylab = "Component variance",
type = "l", main = "Scree diagram")
```

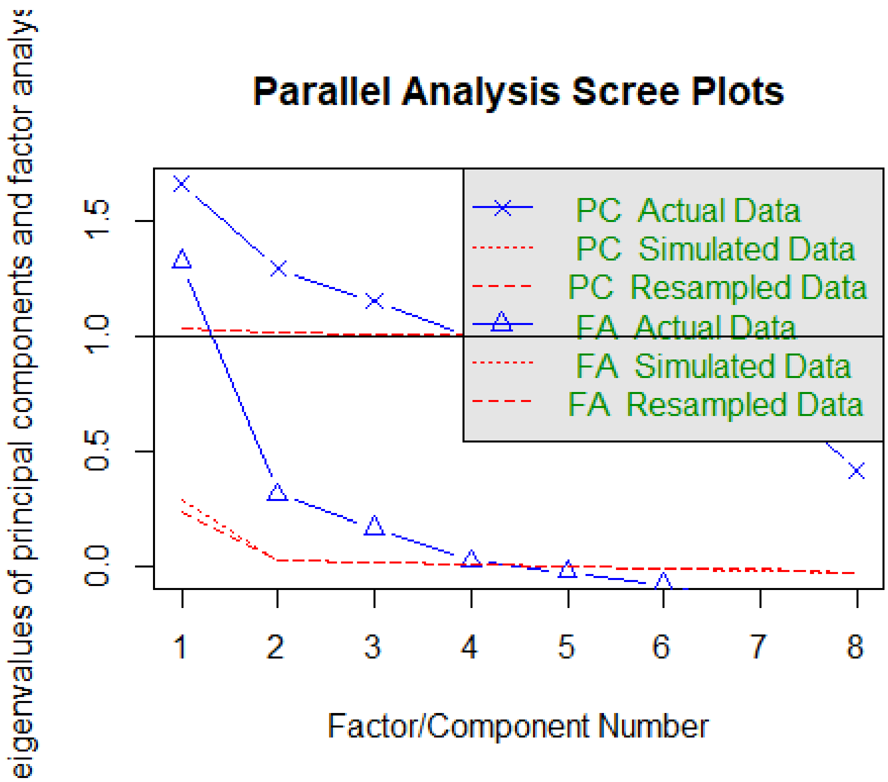


As per scree plot, there should be 7 factors, will see what parallel analysis sugge sts

```r
sumlambdas <- sum(eigen_Istanbul) ## eigen values
sumlambdas
```

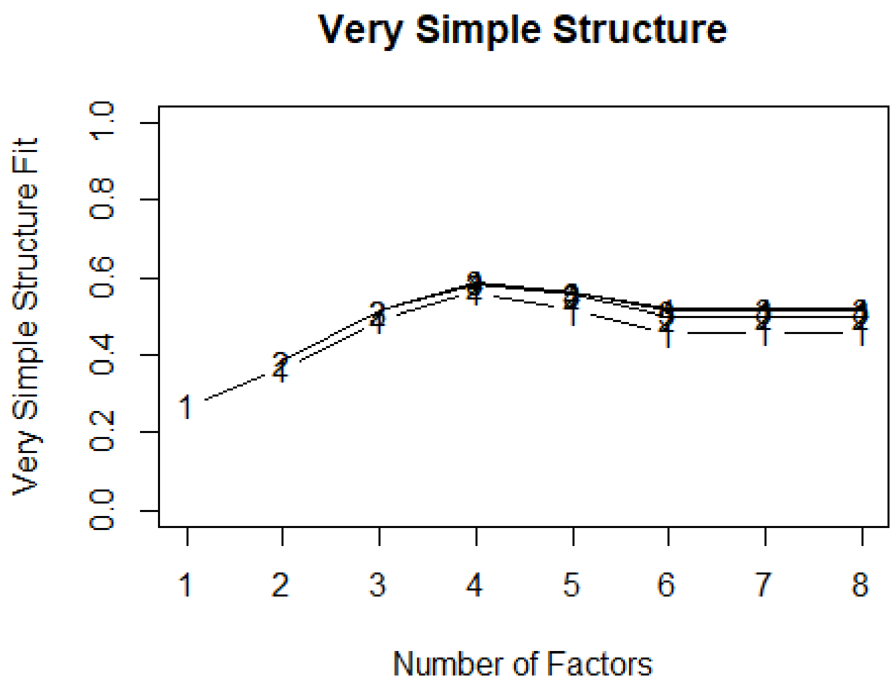
```
## [1] 8
```

```r
fa.parallel(Istanbul_factor)
```



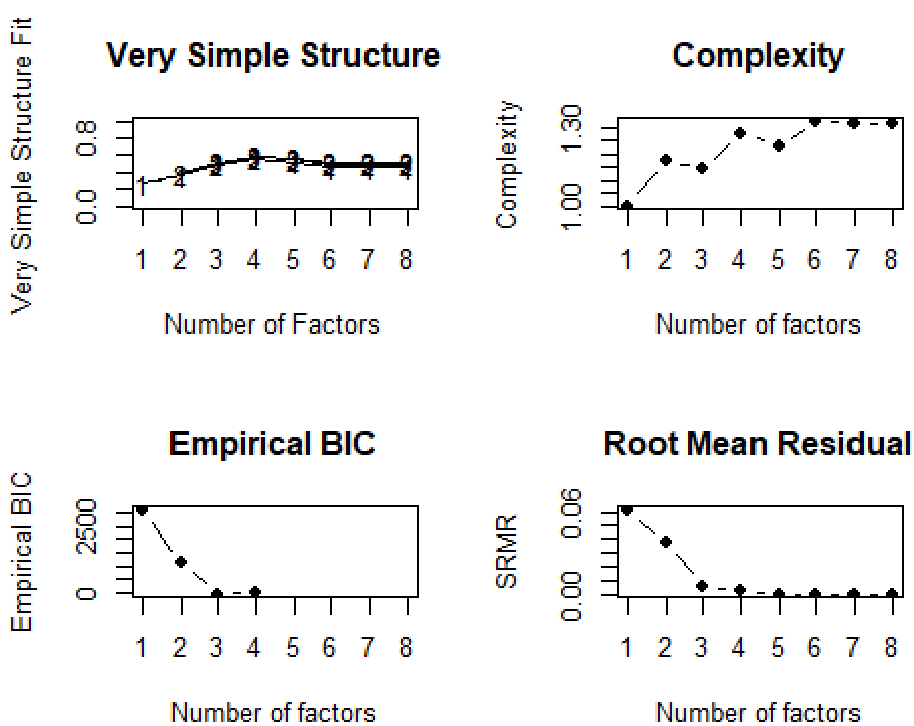
Parallel analysis suggests that the number of factors = 4 and the number of com ponents = 3

```
vss(Istanbul_factor) # See Factor recommendations for a simple structure
```




```
##
## Very Simple Structure
## Call: vss(x = Istanbul_factor)
## VSS complexity 1 achieves a maximimum of 0.56  with  4  factors
## VSS complexity 2 achieves a maximimum of 0.58  with  4  factors
##
## The Velicer MAP achieves a minimum of NA  with  1  factors
## BIC achieves a minimum of  NA  with  3  factors
## Sample Size adjusted BIC achieves a minimum of  NA  with  3  factors
##
## Statistics by number of factors
##   vss1 vss2   map dof   chisq     prob sqresid  fit  RMSEA  BIC SABIC comp
lex
## 1 0.27 0.00 0.032  20 1.7e+03  0.0e+00     6.5 0.27 0.0726 1477  1540
1.0
## 2 0.36 0.38 0.056  13 6.8e+02 6.1e-137     5.5 0.38 0.0573  555   596
1.2
## 3 0.49 0.51 0.095   7 2.9e+01  1.3e-04     4.4 0.51 0.0142  -38   -16
1.1
## 4 0.56 0.58 0.153   2 2.6e+00  2.8e-01     3.7 0.59 0.0043  -17   -10
1.3
## 5 0.51 0.56 0.259  -2 1.2e-06       NA     3.9 0.56     NA   NA    NA
1.2
## 6 0.46 0.50 0.532  -5 1.2e-07       NA     4.3 0.52     NA   NA    NA
1.3
## 7 0.46 0.50 1.000  -7 3.6e-09       NA     4.3 0.52     NA   NA    NA
1.3
```

```
## 8 0.46 0.50    NA   -8 3.6e-09       NA      4.3 0.52     NA    NA     NA
1.3
##     eChisq    SRMR   eCRMS  eBIC
## 1 3.3e+03 6.2e-02 0.0728 3120
## 2 1.3e+03 3.8e-02 0.0555 1125
## 3 3.1e+01 5.9e-03 0.0118  -37
## 4 3.3e+00 1.9e-03 0.0072  -16
## 5 1.1e-06 1.1e-06     NA   NA
## 6 1.4e-07 4.0e-07     NA   NA
## 7 3.2e-09 6.0e-08     NA   NA
## 8 3.2e-09 6.0e-08     NA   NA

# VSS complexity 1 achieves a maximimum of 0.56  with  4  factors
# VSS complexity 2 achieves a maximimum of 0.58  with  4  factors
#
# The Velicer MAP achieves a minimum of NA  with  1  factors
# BIC achieves a minimum of  NA  with  3  factors
# Sample Size adjusted BIC achieves a minimum of  NA  with  3  factors

nfactors(Istanbul_factor)
```




```
##
## Number of factors
## Call: vss(x = x, n = n, rotate = rotate, diagonal = diagonal, fm = fm,
##     n.obs = n.obs, plot = FALSE, title = title, use = use, cor = cor)
## VSS complexity 1 achieves a maximimum of 0.56  with  4  factors
## VSS complexity 2 achieves a maximimum of 0.58  with  4  factors
```

```
## The Velicer MAP achieves a minimum of 0.03  with  1  factors
## Empirical BIC achieves a minimum of  -36.95  with  3  factors
## Sample Size adjusted BIC achieves a minimum of  -16.19  with  3  factors
##
## Statistics by number of factors
##   vss1 vss2   map dof   chisq     prob sqresid  fit  RMSEA  BIC SABIC comp
lex
## 1 0.27 0.00 0.032  20 1.7e+03  0.0e+00     6.5 0.27 0.0726 1477  1540
1.0
## 2 0.36 0.38 0.056  13 6.8e+02 6.1e-137     5.5 0.38 0.0573  555   596
1.2
## 3 0.49 0.51 0.095   7 2.9e+01  1.3e-04     4.4 0.51 0.0142  -38   -16
1.1
## 4 0.56 0.58 0.153   2 2.6e+00  2.8e-01     3.7 0.59 0.0043  -17   -10
1.3
## 5 0.51 0.56 0.259  -2 1.2e-06       NA     3.9 0.56     NA   NA    NA
1.2
## 6 0.46 0.50 0.532  -5 1.2e-07       NA     4.3 0.52     NA   NA    NA
1.3
## 7 0.46 0.50 1.000  -7 3.6e-09       NA     4.3 0.52     NA   NA    NA
1.3
## 8 0.46 0.50    NA  -8 3.6e-09       NA     4.3 0.52     NA   NA    NA
1.3
##    eChisq    SRMR  eCRMS eBIC
## 1 3.3e+03 6.2e-02 0.0728 3120
## 2 1.3e+03 3.8e-02 0.0555 1125
## 3 3.1e+01 5.9e-03 0.0118  -37
## 4 3.3e+00 1.9e-03 0.0072  -16
## 5 1.1e-06 1.1e-06     NA   NA
## 6 1.4e-07 4.0e-07     NA   NA
## 7 3.2e-09 6.0e-08     NA   NA
## 8 3.2e-09 6.0e-08     NA   NA
```

nfactors suggests we can either go with 3 factors or 4 factors

```
# Part 1, with four factors
library(psych)
fit.pc4 <- principal(Istanbul_factor, nfactors=4, rotate="varimax")
fit.pc4 #4 factors RC1, RC2, RC3, RC4 are created
```

```
## Principal Components Analysis
## Call: principal(r = Istanbul_factor, nfactors = 4, rotate = "varimax")
## Standardized loadings (pattern matrix) based upon correlation matrix
##                                  RC1   RC2   RC3   RC4   h2     u2 com
## latitude                       -0.03 -0.02  0.78 -0.02 0.61 0.3877 1.0
## longitude                      -0.02 -0.07 -0.76 -0.02 0.58 0.4181 1.0
## price                          -0.09  0.62  0.11  0.00 0.41 0.5926 1.1
## minimum_nights                 -0.01  0.00  0.00  1.00 0.99 0.0055 1.0
## number_of_reviews               0.88  0.09  0.00  0.01 0.77 0.2263 1.0
## reviews_per_month               0.87 -0.04 -0.01 -0.02 0.77 0.2320 1.0
```

```
## calculated_host_listings_count  0.28  0.57 -0.02 -0.06 0.40 0.5989 1.5
## availability_365               -0.03  0.75 -0.04  0.05 0.56 0.4387 1.0
##
##                        RC1  RC2  RC3  RC4
## SS loadings           1.62 1.28 1.20 1.00
## Proportion Var        0.20 0.16 0.15 0.13
## Cumulative Var        0.20 0.36 0.51 0.64
## Proportion Explained  0.32 0.25 0.24 0.20
## Cumulative Proportion 0.32 0.57 0.80 1.00
##
## Mean item complexity =  1.1
## Test of the hypothesis that 4 components are sufficient.
##
## The root mean square of the residuals (RMSR) is  0.13
##  with the empirical chi square  14145.13  with prob <  0
##
## Fit based upon off diagonal values = 0.08
```

```
round(fit.pc4$values, 3)
```

```
## [1] 1.659 1.292 1.150 0.999 0.899 0.803 0.781 0.416
```

```
#Above are factor values for all 8 variables
fit.pc4$loadings
```

```
##
## Loadings:
##                                RC1    RC2    RC3    RC4
## latitude                                     0.781
## longitude                                   -0.759
## price                                 0.623  0.105
## minimum_nights                                      0.997
## number_of_reviews               0.875
## reviews_per_month               0.875
## calculated_host_listings_count  0.278  0.565
## availability_365                      0.746
##
##                  RC1   RC2   RC3   RC4
## SS loadings    1.620 1.278 1.200 1.002
## Proportion Var 0.202 0.160 0.150 0.125
## Cumulative Var 0.202 0.362 0.512 0.638
```

```
# Above are the Loadings for all 8 variables

for (i in c(1,2,3,4)) { print(fit.pc4$loadings[[1,i]])}
```

```
## [1] -0.03077102
## [1] -0.02069587
## [1] 0.7814196
## [1] -0.01709352
```

Communalities

```r
fit.pc4$communality
```

```
##                      latitude                     longitude 
##                     0.6122840                     0.5818972 
##                         price                minimum_nights 
##                     0.4074236                     0.9945396 
##             number_of_reviews             reviews_per_month 
##                     0.7737051                     0.7679744 
## calculated_host_listings_count              availability_365 
##                     0.4010889                     0.5612598
```

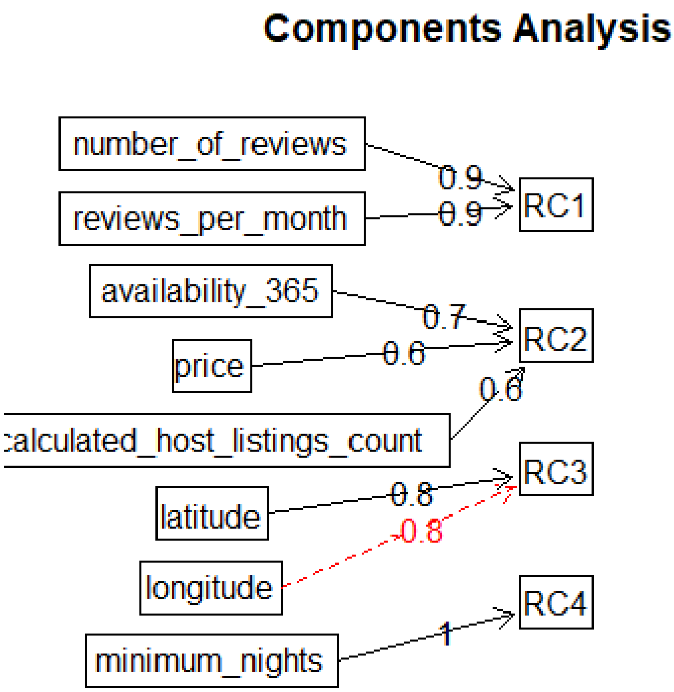
```r
#Above are the communalities for all 8 variabbles
```

Rotated factor scores

```r
head(fit.pc4$scores)
```

```
##             RC1        RC2        RC3         RC4
## [1,] -0.7188928  1.2150301 0.14835545 -0.11114975
## [2,]  0.9190461 -1.3792418 0.41991784  0.85933486
## [3,] -0.4308853 -0.9829675 0.56648630  0.49807054
## [4,] -0.4308808 -0.2203644 0.13281517  0.02074727
## [5,] -0.5315036  1.9813454 0.30817477 -0.12110005
## [6,] -0.5697539  0.3782424 0.04495653 -0.07605584
```

```r
fa.diagram(fit.pc4) # To Visualize the relationship and mapping between varia
bles and factors with weights
```



Above, output gives weigths going in RCs
red line indicates negative relation

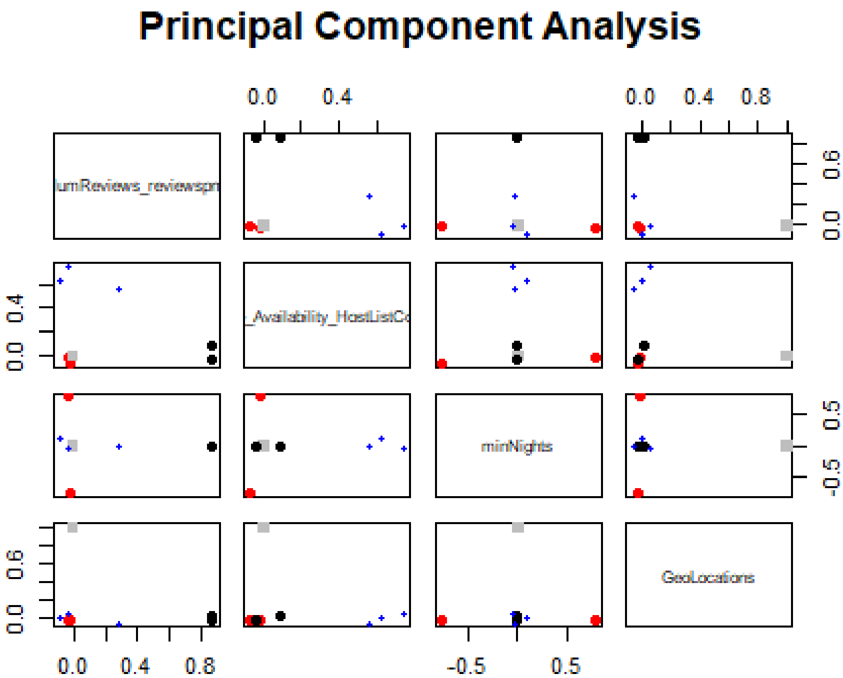
As per above diagram, all the factors have significant contribution and so its better not to loose any of 4 factors
So we will take all four RC1, RC2, RC3 and RC4 as inputs for our models

Above factor analysis, we can conclude to reduce number of variables from 8 to 4 in our input dataset.

```
#Now lets rename these factors as per their contributing variables
colnames(fit.pc4$loadings) <- c("NumReviews_reviewspm","Prie_Availability_HostListCount","minNights","GeoLocations")
fit.pc4$loadings

##
## Loadings:
##                                  NumReviews_reviewspm
## latitude
## longitude
## price
## minimum_nights
## number_of_reviews                  0.875
## reviews_per_month                  0.875
## calculated_host_listings_count    0.278
```

```
## availability_365
##                                Prie_Availability_HostListCount minNights
## latitude                                                         0.781
## longitude                                                       -0.759
## price                           0.623                            0.105
## minimum_nights
## number_of_reviews
## reviews_per_month
## calculated_host_listings_count  0.565
## availability_365                0.746
##                                GeoLocations
## latitude
## longitude
## price
## minimum_nights                  0.997
## number_of_reviews
## reviews_per_month
## calculated_host_listings_count
## availability_365
##
##                  NumReviews_reviewspm Prie_Availability_HostListCount minNig
hts
## SS loadings                     1.620                           1.278     1.
200
## Proportion Var                  0.202                           0.160     0.
150
## Cumulative Var                  0.202                           0.362     0.
512
##                  GeoLocations
## SS loadings             1.002
## Proportion Var          0.125
## Cumulative Var          0.638
```

```r
#Plotting the correlation beyween these factors
plot(fit.pc4)
```




```r
# Part 2, with three factors
library(psych)
fit.pc3 <- principal(Istanbul_factor, nfactors=3, rotate="varimax")
fit.pc3 #3 factors RC1, RC2, RC3 are created
```

```
## Principal Components Analysis
## Call: principal(r = Istanbul_factor, nfactors = 3, rotate = "varimax")
## Standardized loadings (pattern matrix) based upon correlation matrix
##                                  RC1   RC2   RC3     h2   u2 com
## latitude                       -0.04 -0.03  0.78 0.6115 0.39 1.0
## longitude                       0.00 -0.07 -0.76 0.5818 0.42 1.0
## price                          -0.14  0.61  0.10 0.4063 0.59 1.2
## minimum_nights                 -0.09  0.03  0.01 0.0087 0.99 1.4
## number_of_reviews               0.86  0.15  0.02 0.7690 0.23 1.1
## reviews_per_month               0.87  0.02  0.01 0.7661 0.23 1.0
## calculated_host_listings_count  0.24  0.58 -0.02 0.3969 0.60 1.3
## availability_365               -0.09  0.74 -0.04 0.5610 0.44 1.0
##
##                        RC1  RC2  RC3
## SS loadings           1.60 1.30 1.20
## Proportion Var        0.20 0.16 0.15
## Cumulative Var        0.20 0.36 0.51
## Proportion Explained  0.39 0.32 0.29
## Cumulative Proportion 0.39 0.71 1.00
##
## Mean item complexity =  1.1
## Test of the hypothesis that 3 components are sufficient.
```

```
##
## The root mean square of the residuals (RMSR) is  0.13
##  with the empirical chi square  14219.67  with prob <  0
##
## Fit based upon off diagonal values = 0.07
```

```
round(fit.pc3$values, 3)
```

```
## [1] 1.659 1.292 1.150 0.999 0.899 0.803 0.781 0.416
```

```
#Above are factor values for all 8 variables

fit.pc3$loadings
```

```
##
## Loadings:
##                                RC1    RC2    RC3   
## latitude                                     0.780
## longitude                                   -0.760
## price                          -0.140  0.613  0.104
## minimum_nights                                      
## number_of_reviews               0.863  0.154        
## reviews_per_month               0.875               
## calculated_host_listings_count  0.240  0.582        
## availability_365                       0.743        
##
##                  RC1   RC2   RC3
## SS loadings    1.605 1.297 1.199
## Proportion Var 0.201 0.162 0.150
## Cumulative Var 0.201 0.363 0.513
```

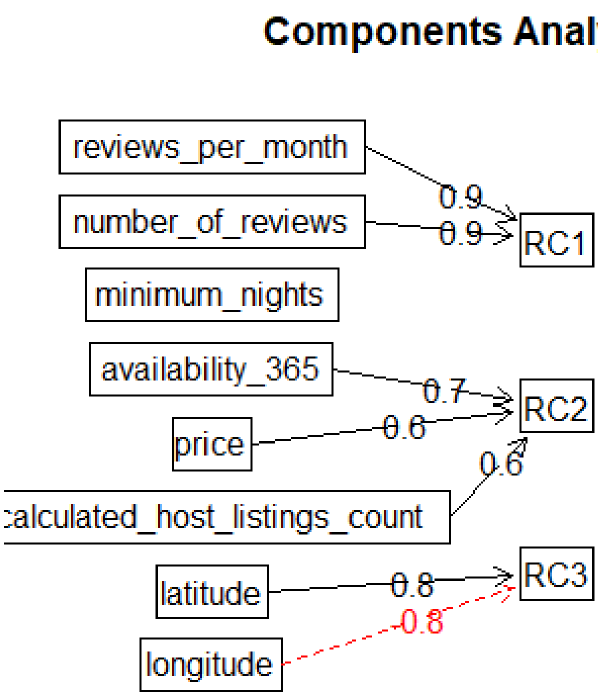
```
# Above are the Loadings for all 8 variables

for (i in c(1,2,3)) { print(fit.pc3$loadings[[1,i]])}
```

```
## [1] -0.04497776
## [1] -0.02607995
## [1] 0.7802823
```

```
# Communalities
fit.pc3$communality
```

```
##                       latitude                      longitude 
##                    0.611543631                    0.581767090 
##                          price                 minimum_nights 
##                    0.406251294                    0.008702142 
##              number_of_reviews              reviews_per_month 
##                    0.769040100                    0.766133759 
## calculated_host_listings_count               availability_365 
##                    0.396866242                    0.560965370 
```

```
#Above are the communalities for all 8 variabbles


fa.diagram(fit.pc3) # To Visualize the relationship and mapping between varia
bles and factors with weights
```



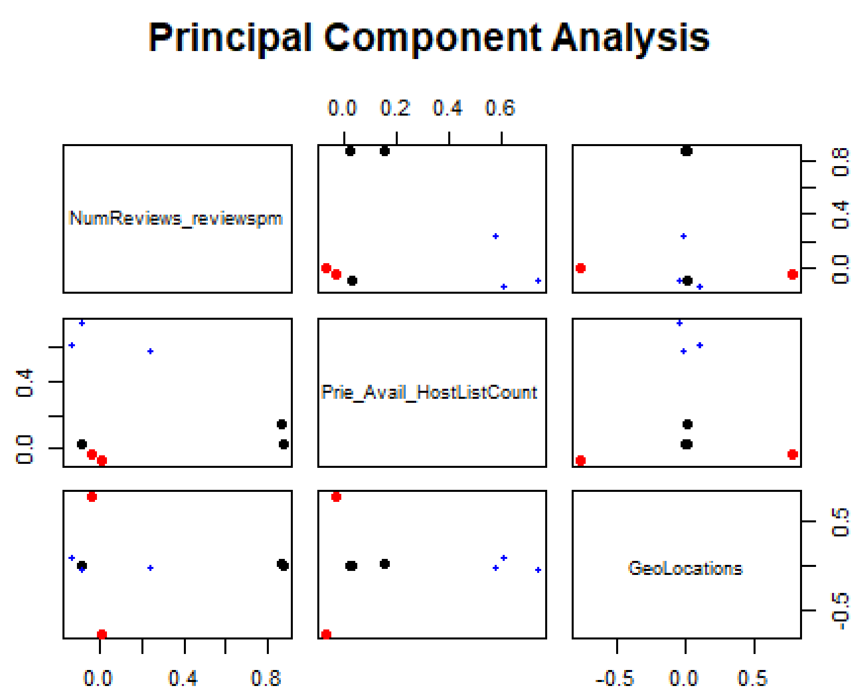
Above, output gives weights going in RCs
red line indicates negative relation

As per above diagram, all the factors have significant contribution and so
its better not to loose any of 3 factors
So we will take all four RC1, RC2 and RC3 as inputs for our models
We can see that minimum_nights doesn't have any contribution, hence we can consider dropping this variable

From Above factor analysis, we can conclude to reduce number of variables from 8 to 3 in our input dataset.

```
#Now lets rename these factors as per their contributing variables
colnames(fit.pc3$loadings) <- c("NumReviews_reviewspm","Prie_Avail_HostListCo
unt","GeoLocations")
fit.pc3$loadings

##
## Loadings:
```

```
##                                    NumReviews_reviewspm Prie_Avail_HostListCou
nt
## latitude
## longitude
## price                              -0.140                0.613
## minimum_nights
## number_of_reviews                   0.863                0.154
## reviews_per_month                   0.875
## calculated_host_listings_count      0.240                0.582
## availability_365                                         0.743
##                                    GeoLocations
## latitude                            0.780
## longitude                          -0.760
## price                               0.104
## minimum_nights
## number_of_reviews
## reviews_per_month
## calculated_host_listings_count
## availability_365
##
##                 NumReviews_reviewspm Prie_Avail_HostListCount GeoLocations
## SS loadings                    1.605                    1.297        1.199
## Proportion Var                 0.201                    0.162        0.150
## Cumulative Var                 0.201                    0.363        0.513

#Plotting the correlation beyween these factors
plot(fit.pc3)
```



- **If we use only 3 variables then we are losing variance from the column : 'minimum_nights' which will cause loss of information.**
- **Thus, we use factor analysis with 4 factors: RC1, RC2, RC3 and RC4 as inputs for our model.**
- **As per this factor analysis, we can have reduced number of variables from 8 to 4 in our input dataset.**