Lyft-Uber-Price-Prediction

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IMPORTING DATASETS AND CLEANING THEM

Importing dataset cab_rides

```
cab_rides <-
read.csv("C:/Users/AJAY/Downloads/Multivariate/project/cab_rides.csv")
summary(cab_rides)
```

```
##     distance     cab_type        time_stamp
##  Min.   :0.020   Lyft:307408   Min.   :1.543e+12
##  1st Qu.:1.280   Uber:385663   1st Qu.:1.543e+12
##  Median :2.160                 Median :1.544e+12
##  Mean   :2.189                 Mean   :1.544e+12
##  3rd Qu.:2.920                 3rd Qu.:1.545e+12
##  Max.   :7.860                 Max.   :1.545e+12
##
##                destination                      source          price
##  Financial District: 58851   Financial District: 58857   Min.   : 2.50
##  Theatre District  : 57798   Theatre District  : 57813   1st Qu.: 9.00
##  Back Bay          : 57780   Back Bay          : 57792   Median :13.50
##  Boston University : 57764   Boston University : 57764   Mean   :16.55
##  Haymarket Square  : 57764   North End         : 57763   3rd Qu.:22.50
##  Fenway            : 57757   Fenway            : 57757   Max.   :97.50
##  (Other)           :345357   (Other)           :345325   NA's   :55095
##  surge_multiplier                                     id
##  Min.   :1.000    00005b8c-5647-4104-9ac6-94fa6a40f3c3:     1
##  1st Qu.:1.000    00006eeb-0183-40c1-8198-c441d3c8a734:     1
##  Median :1.000    00008b42-5ecc-4f66-b4b9-b22a331634e6:     1
##  Mean   :1.014    000094c0-00c4-43f1-ae1b-4693eec2a580:     1
##  3rd Qu.:1.000    0000a8b2-e4d3-4227-8374-af8a2366e475:     1
##  Max.   :3.000    0000b5d6-59be-4534-b371-8214334d94f0:     1
##                   (Other)                               :693065
##                                 product_id           name
##  6d318bcc-22a3-4af6-bddd-b409bfce1546: 55096   Black SUV: 55096
##  6f72dfc5-27f1-42e8-84db-ccc7a75f6969: 55096   UberXL   : 55096
##  9a0e7b09-b92b-4c41-9779-2ad22b4d779d: 55096   WAV      : 55096
##  6c84fd89-3f11-4782-9b50-97c468b19529: 55095   Black    : 55095
##  8cf7e821-f0d3-49c6-8eba-e679c0ebcf6a: 55095   Taxi     : 55095
##  55c66225-fbe7-4fd5-9072-eab1ece5e23e: 55094   UberX    : 55094
##  (Other)                             :362499   (Other)  :362499
```

```
cab_data<-cab_rides
```

Creating a date_time column

```
cab_data$date_time<-as.POSIXct((cab_data$time_stamp/1000),origin = "1970-01-01 00:53:20", tz="GMT")
```

Importing dataset weather

```
weather <-
read.csv("C:/Users/AJAY/Downloads/Multivariate/project/weather.xls")
summary(weather)
```

```
##      ï..temp                      location    clouds
##  Min.   :19.62   Back Bay           : 523   Min.   :0.0000
##  1st Qu.:36.08   Beacon Hill        : 523   1st Qu.:0.4400
##  Median :40.13   Boston University  : 523   Median :0.7800
##  Mean   :39.09   Fenway             : 523   Mean   :0.6778
##  3rd Qu.:42.83   Financial District : 523   3rd Qu.:0.9700
##  Max.   :55.41   Haymarket Square   : 523   Max.   :1.0000
##                  (Other)            :3138
##     pressure          rain           time_stamp           humidity
##  Min.   : 988.2   Min.   :0.000   Min.   :1.543e+09   Min.   :0.450
##  1st Qu.: 997.7   1st Qu.:0.005   1st Qu.:1.543e+09   1st Qu.:0.670
##  Median :1007.7   Median :0.015   Median :1.544e+09   Median :0.760
##  Mean   :1008.4   Mean   :0.058   Mean   :1.544e+09   Mean   :0.764
##  3rd Qu.:1018.5   3rd Qu.:0.061   3rd Qu.:1.545e+09   3rd Qu.:0.890
##  Max.   :1035.1   Max.   :0.781   Max.   :1.545e+09   Max.   :0.990
##                   NA's   :5382
##       wind
##  Min.   : 0.290
##  1st Qu.: 3.518
##  Median : 6.570
##  Mean   : 6.803
##  3rd Qu.: 9.920
##  Max.   :18.180
##
```

```
str(weather)
```

```
## 'data.frame':    6276 obs. of  8 variables:
##  $ ï..temp   : num  42.4 42.4 42.5 42.1 43.1 ...
##  $ location  : Factor w/ 12 levels "Back Bay","Beacon Hill",..: 1 2 3 4 5 6 7 8 9 10 ...
##  $ clouds    : num  1 1 1 1 1 1 1 1 1 1 ...
##  $ pressure  : num  1012 1012 1012 1012 1012 ...
##  $ rain      : num  0.1228 0.1846 0.1089 0.0969 0.1786 ...
##  $ time_stamp: int  1545003901 1545003901 1545003901 1545003901 1545003901 1545003901 1545003901 1545003901 1545003901 1545003901 ...
```

```
## $ humidity : num 0.77 0.76 0.76 0.77 0.75 0.77 0.77 0.77 0.78 0.75 ...
## $ wind : num 11.2 11.3 11.1 11.1 11.5 ...

weather_data<-weather
```

creating a date_time column in weather_data

```
weather_data$date_time<-as.POSIXct(weather_data$time_stamp,origin = "1970-01-01 00:53:20", tz="GMT")
str(weather_data)

## 'data.frame': 6276 obs. of 9 variables:
## $ ï..temp : num 42.4 42.4 42.5 42.1 43.1 ...
## $ location : Factor w/ 12 levels "Back Bay","Beacon Hill",..: 1 2 3 4 5 6 7 8 9 10 ...
## $ clouds : num 1 1 1 1 1 1 1 1 1 1 ...
## $ pressure : num 1012 1012 1012 1012 1012 ...
## $ rain : num 0.1228 0.1846 0.1089 0.0969 0.1786 ...
## $ time_stamp: int 1545003901 1545003901 1545003901 1545003901 1545003901 1545003901 1545003901 1545003901 1545003901 1545003901 ...
## $ humidity : num 0.77 0.76 0.76 0.77 0.75 0.77 0.77 0.77 0.78 0.75 ...
## $ wind : num 11.2 11.3 11.1 11.1 11.5 ...
## $ date_time : POSIXct, format: "2018-12-17 00:38:21" "2018-12-17 00:38:21" ...
```

merge the datasets to reflect the same time for a location

```
cab_data$merge_date<-paste(cab_data$source,"-",as.Date(cab_data$date_time),"-",format(cab_data$date_time,"%H:%M:%S"))
weather_data$merge_date<-paste(weather_data$location,"-",as.Date(weather_data$date_time),"-",format(weather_data$date_time,"%H:%M:%S"))

#making those values as characters
weather_data$merge_date<-as.character(weather_data$merge_date)
cab_data$merge_date<-as.character(cab_data$merge_date)
```

verify that merge_date has unique values.

```
weather_data<-subset(weather_data,!duplicated(weather_data$merge_date))
isTRUE(duplicated(weather_data$merge_date))

## [1] FALSE
```

Merging both the dataframes.

```
merge_data<-merge(x=weather_data, y=cab_data,by='merge_date', all.x=TRUE)
str(merge_data)
```

```
## 'data.frame':    9306 obs. of  21 variables:
##  $ merge_date      : chr  "Back Bay - 2018-11-26 - 04:34:05" "Back Bay - 2018-11-26 - 05:34:13" "Back Bay - 2018-11-26 - 05:34:58" "Back Bay - 2018-11-26 - 05:36:38" ...
##  $ ï..temp         : num  41 40.6 40.6 40.6 40.6 ...
##  $ location        : Factor w/ 12 levels "Back Bay","Beacon Hill",..: 1 1 1 1 1 1 1 1 1 1 ...
##  $ clouds          : num  0.87 0.86 0.86 0.86 0.86 0.95 0.95 0.94 0.93 0.93 ...
##  $ pressure        : num  1014 1014 1014 1014 1014 ...
##  $ rain            : num  NA NA NA NA NA NA NA NA NA NA ...
##  $ time_stamp.x    : int  1543203645 1543207253 1543207298 1543207398 1543207398 1543207777 1543207777 1543208142 1543208578 1543209183 ...
##  $ humidity        : num  0.92 0.93 0.93 0.93 0.93 0.92 0.92 0.92 0.92 0.92 ...
##  $ wind            : num  1.46 2.57 2.59 2.65 2.65 2.59 2.59 2.83 3 3.01 ...
##  $ date_time.x     : POSIXct, format: "2018-11-26 04:34:05" "2018-11-26 05:34:13" ...
##  $ distance        : num  NA NA 1.44 1.36 1.22 1.34 1.1 NA NA NA ...
##  $ cab_type        : Factor w/ 2 levels "Lyft","Uber": NA NA 2 1 2 2 2 NA NA NA ...
##  $ time_stamp.y    : num  NA NA 1.54e+12 1.54e+12 1.54e+12 ...
##  $ destination     : Factor w/ 12 levels "Back Bay","Beacon Hill",..: NA NA 3 10 9 4 9 NA NA NA ...
##  $ source          : Factor w/ 12 levels "Back Bay","Beacon Hill",..: NA NA 1 1 1 1 1 NA NA NA ...
##  $ price           : num  NA NA 8.5 16.5 NA 26.5 7.5 NA NA NA ...
##  $ surge_multiplier: num  NA NA 1 1 1 1 1 NA NA NA ...
##  $ id              : Factor w/ 693071 levels "00005b8c-5647-4104-9ac6-94fa6a40f3c3",..: NA NA 548701 610037 513190 566219 94420 NA NA NA ...
##  $ product_id      : Factor w/ 13 levels "55c66225-fbe7-4fd5-9072-eab1ece5e23e",..: NA NA 7 10 5 3 1 NA NA NA ...
##  $ name            : Factor w/ 13 levels "Black","Black SUV",..: NA NA 13 4 9 2 11 NA NA NA ...
##  $ date_time.y     : POSIXct, format: NA NA ...
```

Handling Missing values

```
#Filling NA values in price
merge_data$rain[is.na(merge_data$rain)]<-0

#Extracting the numerical columns in a new dataframe "df"
merge_data$temp<-merge_data[,c(2)] #renaming a column
df<-merge_data[,c(4,5,6,8,9,10,11,17,22,16)]

#Data preparation
#Dealing with missing values
summary(merge_data)
```

```
##   merge_date          ï..temp                          location
##  Length:9306        Min.   :19.62   Haymarket Square       : 843
##  Class :character   1st Qu.:36.74   North Station          : 801
##  Mode  :character   Median :39.73   Theatre District       : 800
##                     Mean   :39.12   Northeastern University: 788
##                     3rd Qu.:41.86   North End              : 771
##                     Max.   :55.41   Fenway                 : 771
##                                     (Other)                 4531
##      clouds          pressure          rain          time_stamp.x
##  Min.   :0.0000   Min.   : 988.2   Min.   :0.00000   Min ....1.543e+09
##  1st Qu.:0.4500   1st Qu.: 992.2   1st Qu.:0.00000   1st Qu  1.543e+09
##  Median :0.7700   Median :1002.2   Median :0.00000   Median :1.543e+09
##  Mean   :0.6799   Mean   :1005.2   Mean   :0.01197   Mean :1.544e+09
##  3rd Qu.:0.9700   3rd Qu.:1014.4   3rd Qu.:0.00000   3rd Qu  1.544e+09
##  Max.   :1.0000   Max.   :1035.1   Max.   :0.78070   Max ....1.545e+09
##
##     humidity           wind         date_time.x
##  Min.   :0.4500  Min.   : 0.290   Min.   :2018-11-26 04:34:04
##  1st Qu.:0.6700  1st Qu.: 4.183  1st Qu.:2018-11-28 01:38:42
## Median :0.7500 Median : 7.490 Median :2018-11-28 23:55:29
##  Mean   :0.7623  Mean   : 7.212   Mean   :2018-12-01 23:49:51
##  3rd Qu.:0.8800  3rd Qu.: 9.990  3rd Qu.:2018-12-02 09:31:14
##  Max.   :0.9900  Max.   :18.180   Max.   :2018-12-18 19:38:22
##
##     distance     cab_type     time_stamp.y                 destination
##  Min.   :0.020   Lyft:1732   Min.   :1.543e+12   Fenway             : 344
## 1st Qu.:1.250   Uber:2134   1st Qu.:1.543e+12   Financial District: 342
##  Median :2.140   NA's:5440   Median :1.543e+12   Back Bay          : 337
##  Mean   :2.168               Mean   :1.543e+12   Beacon Hill    : 335 ##
3rd Qu.:2.947                3rd Qu.:1.543e+12    South Station    : 334
##  Max.   :7.460               Max.   :1.545e+12   (Other)            2174
##  NA's   :5440                NA's   :5440        NA's                5440
##                        source          price       surge_multiplier
##  Haymarket Square       : 392   Min.   : 2.50   Min.   :1.000
##  North Station          : 351   1st Qu.: 9.00   1st Qu.:1.000
##  Theatre District       : 344   Median :13.50   Median :1.000
##  Northeastern University: 329   Mean   :16.67   Mean   :1.018
##  North End              : 316   3rd Qu.:22.50   3rd Qu.:1.000
##  (Other)                :2134   Max.   :92.00   Max.   :2.000
##  NA's                   :5440   NA's   :5758    NA's    5440
##                                       id
##  000baa63-5e1c-4f9d-891c-e4e78e830199:   1
##  002b15bc-b433-44a4-8174-b8ac95caebf8:   1
##  00423464-fb1b-4e96-9154-b55a00854181:   1
##  00552d6f-c5fa-4006-962a-4613097afabe:   1
##  005ca94d-9dad-4b34-a8ce-82a6de9058b4:   1
##  (Other)                             3861
##  NA's                                5440
##                               product_id          name
##  8cf7e821-f0d3-49c6-8eba-e679c0ebcf6a: 318   Taxi     : 318
```

```
##  6d318bcc-22a3-4af6-bddd-b409bfce1546: 308   Black SUV: 308
##  6c84fd89-3f11-4782-9b50-97c468b19529: 307   Black    : 307
##  6f72dfc5-27f1-42e8-84db-ccc7a75f6969: 306   UberPool : 306
##  997acbb5-e102-41e1-b155-9df7de0a73f2: 306   UberXL   : 306
##  (Other)                              2321   (Other)  :2321
##  NA's                                 5440   NA's      5440
##   date_time.y                          temp
##  Min.  :2018-11-26 04:34:06   Min.    :19.62
##  1st Qu.:2018-11-27 03:08:42  1st Qu.:36.74
##  Median :2018-11-28 14:25:28   Median :39.73
##  Mean   :2018-11-28 08:15:46   Mean   :39.12
##  3rd Qu.:2018-11-29 00:42:54  3rd Qu.:41.86
##  Max.   :2018-12-16 20:38:27   Max.   :55.41
##  NA's  5440
```

```
summary(df)
```

```
##      clouds         pressure          rain            humidity
##  Min.   :0.0000   Min.   : 988.2   Min.   :0.00000   Min.   :0.4500
##  1st Qu.:0.4500   1st Qu.: 992.2   1st Qu.:0.00000   1st Qu.:0.6700
##  Median :0.7700   Median :1002.2   Median :0.00000   Median :0.7500
##  Mean   :0.6799   Mean   :1005.2   Mean   :0.01197   Mean   :0.7623
##  3rd Qu.:0.9700   3rd Qu.:1014.4   3rd Qu.:0.00000   3rd Qu.:0.8800
##  Max.   :1.0000   Max.   :1035.1   Max.   :0.78070   Max.   :0.9900
##
##       wind         date_time.x                      distance
##  Min.   : 0.290   Min.   :2018-11-26 04:34:04   Min.   :0.020
##  1st Qu.: 4.183   1st Qu.:2018-11-28 01:38:42   1st Qu.:1.250
##  Median : 7.490   Median :2018-11-28 23:55:29   Median :2.140
##  Mean   : 7.212   Mean   :2018-12-01 23:49:51   Mean   :2.168
##  3rd Qu.: 9.990   3rd Qu.:2018-12-02 09:31:14   3rd Qu.:2.947
##  Max.   :18.180   Max.   :2018-12-18 19:38:22   Max.   :7.460
##                                                 NA's    5440
##  surge_multiplier      temp           price
##  Min.   :1.000    Min.   :19.62   Min.   : 2.50
##  1st Qu.:1.000    1st Qu.:36.74   1st Qu.: 9.00
##  Median :1.000    Median :39.73   Median :13.50
##  Mean   :1.018    Mean   :39.12   Mean   :16.67
##  3rd Qu.:1.000    3rd Qu.:41.86   3rd Qu.:22.50
##  Max.   :2.000    Max.   :55.41   Max.   :92.00
##  NA's    5440                     NA's    5758
```

```
merge_data$surge_multiplier = ifelse(is.na(merge_data$surge_multiplier),
                                     ave(merge_data$surge_multiplier , FUN =
function(x) mean(x, na.rm = TRUE)),
                                     merge_data$surge_multiplier)

merge_data$price = ifelse(is.na(merge_data$price),
                          ave(merge_data$price , FUN = function(x) mean(x,
na.rm = TRUE)),
```

```
                          merge_data$price)

df$distance = ifelse(is.na(df$distance),
                     ave(df$distance , FUN = function(x) mean(x, na.rm = 
TRUE)),
                     df$distance)

df$surge_multiplier = ifelse(is.na(df$surge_multiplier),
                             ave(df$surge_multiplier , FUN = function(x)
mean(x, na.rm = TRUE)),
                             df$surge_multiplier)

df$price = ifelse(is.na(df$price),
                  ave(df$price , FUN = function(x) mean(x, na.rm = TRUE)),
                  df$price)
```

Checking for null values

```
any(is.na(df))

## [1] FALSE
```

Adding date and time column in the df data set

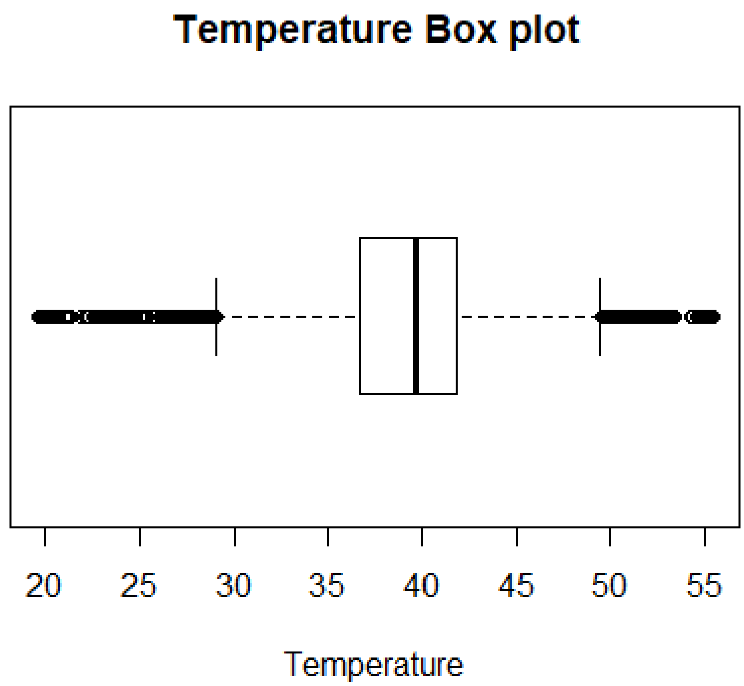
```
df$day<-weekdays(df$date_time)
df$time<-format(df$date_time.x,"%H:%M:%S")
df$date_time<-as.Date(df$date_time.x)
merge_data$day=weekdays(merge_data$date_time.x)
```

Creating a Numeric dataframe

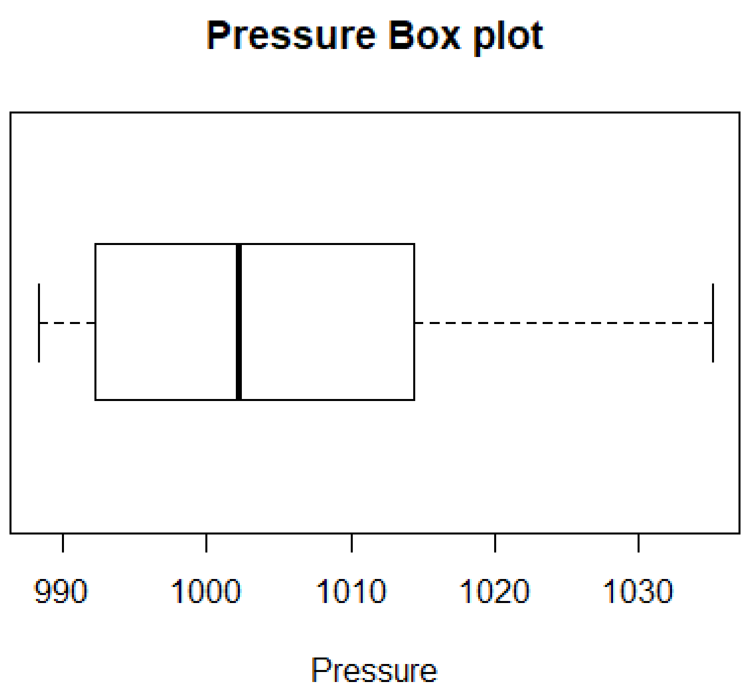
```
x<-df[,c(1,2,3,4,5,7,9)]
str(x)

## 'data.frame':    9306 obs. of  7 variables:
##  $ clouds  : num  0.87 0.86 0.86 0.86 0.86 0.95 0.95 0.94 0.93 0.93 ...
##  $ pressure: num  1014 1014 1014 1014 1014 ...
##  $ rain    : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ humidity: num  0.92 0.93 0.93 0.93 0.93 0.92 0.92 0.92 0.92 0.92 ...
##  $ wind    : num  1.46 2.57 2.59 2.65 2.65 2.59 2.59 2.83 3 3.01 ...
##  $ distance: num  2.17 2.17 1.44 1.36 1.22 ...
##  $ temp    : num  41 40.6 40.6 40.6 40.6 ...
```

BOXPLOT

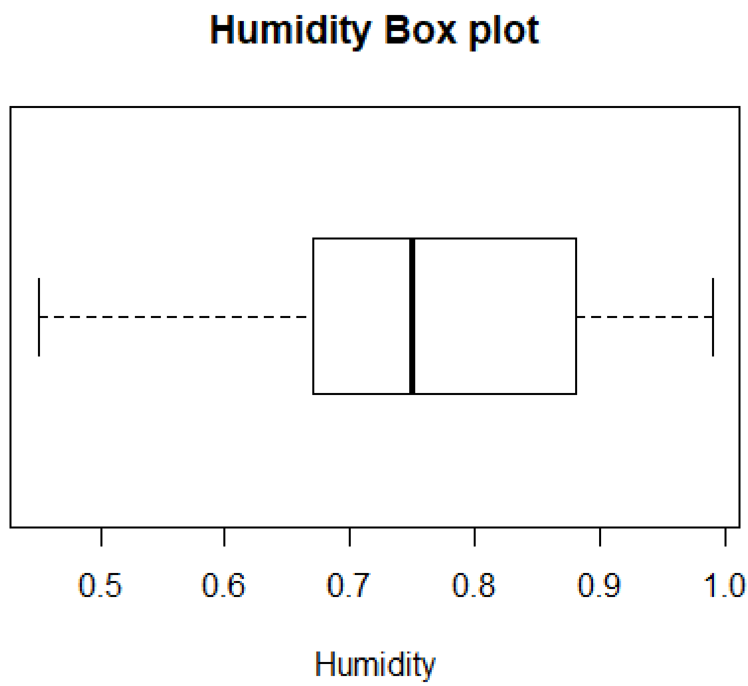
```
boxplot(x$temp, main="Temperature Box plot",yaxt="n", xlab="Temperature",
horizontal=TRUE)
```



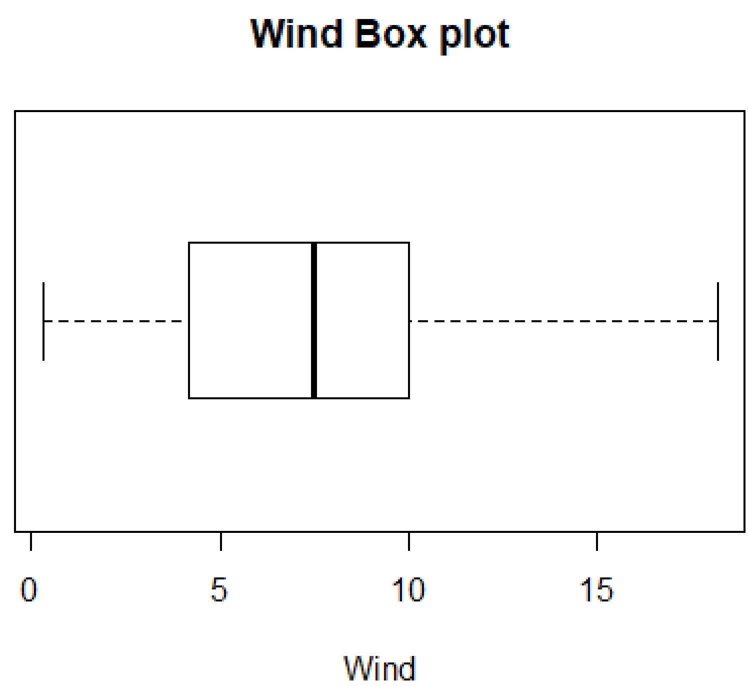

```
boxplot(x$pressure, main="Pressure Box plot",yaxt="n", xlab="Pressure",
horizontal=TRUE)
```



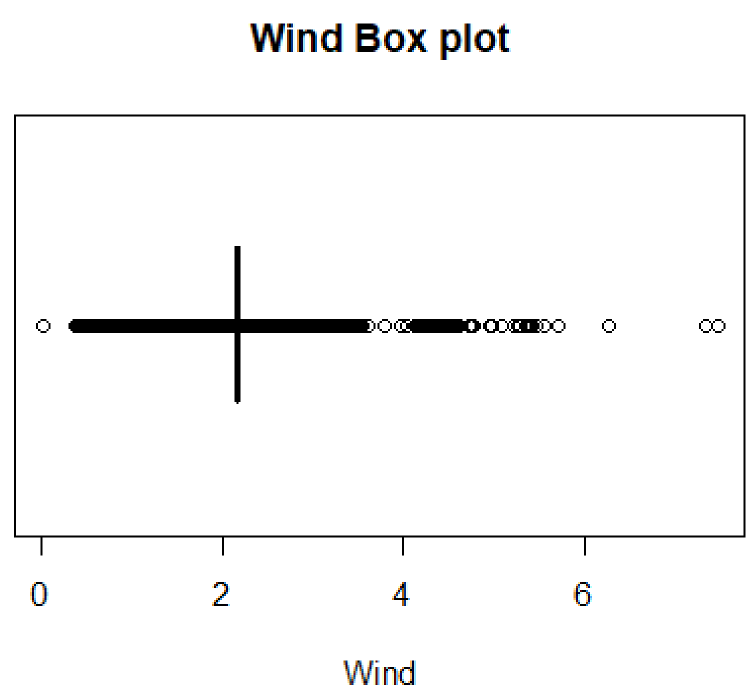
```r
boxplot(x$humidity, main="Humidity Box plot",yaxt="n", xlab="Humidity",
horizontal=TRUE)
```




```r
boxplot(x$wind, main="Wind Box plot",yaxt="n", xlab="Wind", horizontal=TRUE)
```

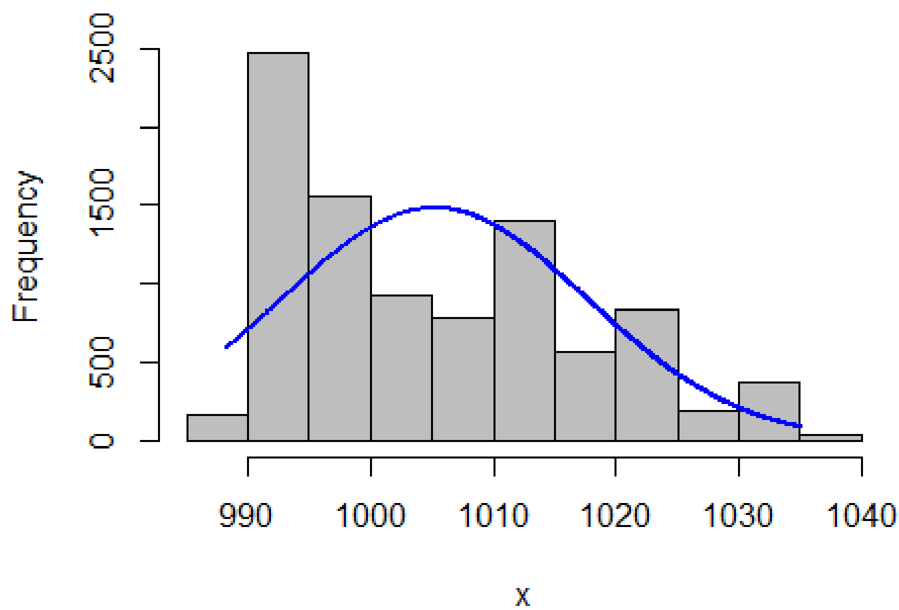



```
boxplot(x$distance, main="Wind Box plot",yaxt="n", xlab="Wind",
horizontal=TRUE)
```

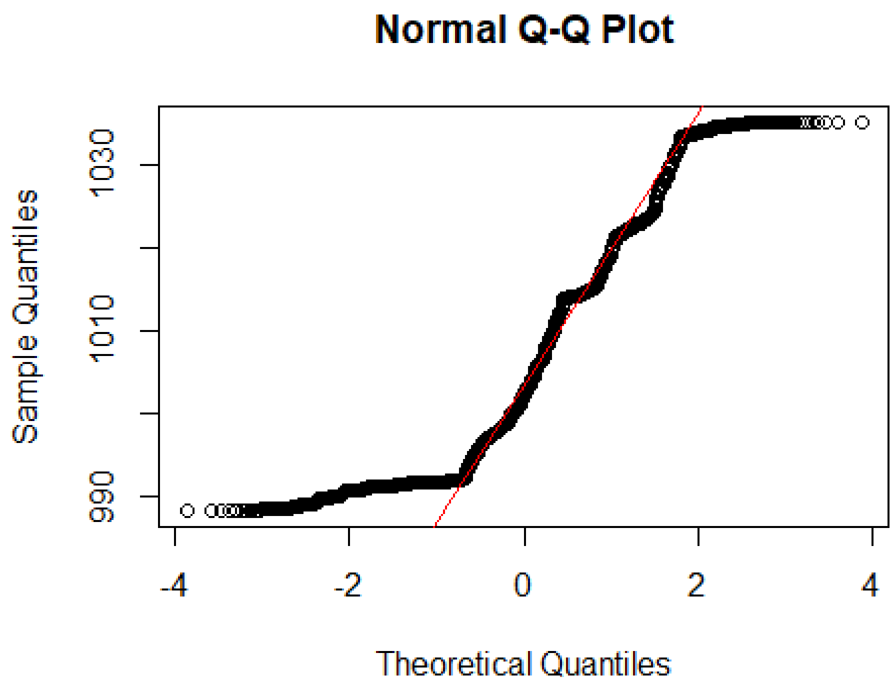


#Q-Q Plot to check normality..

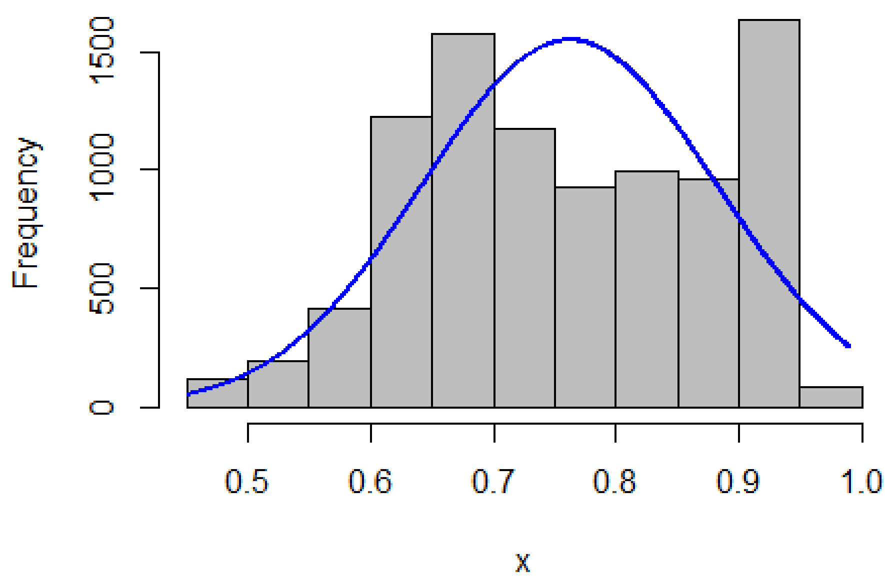
```r
library(rcompanion)

## Warning: package 'rcompanion' was built under R version 3.5.3

plotNormalHistogram(x$pressure)
```



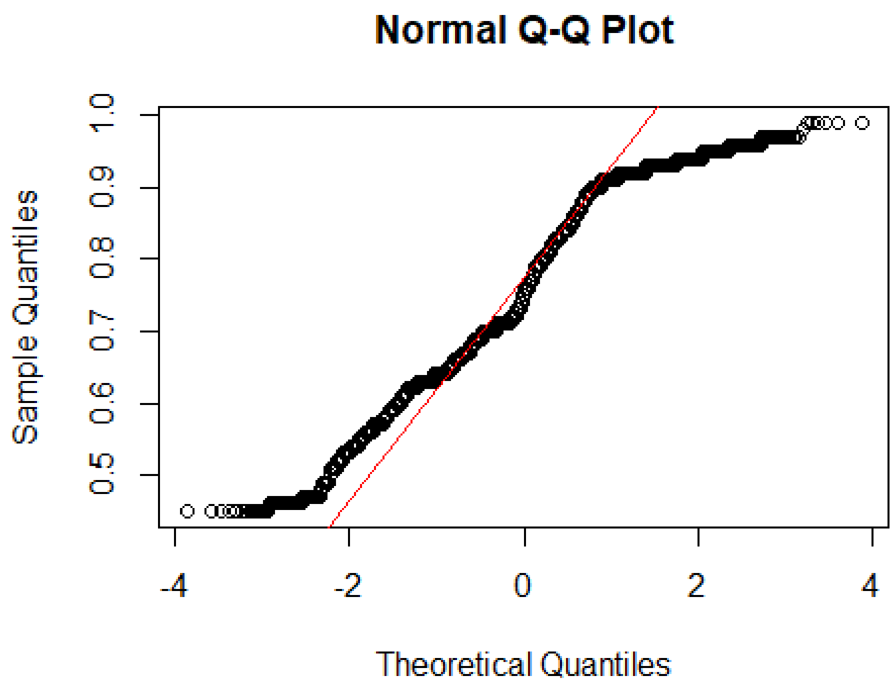

```r
qqnorm(df$pressure)
qqline(df$pressure, col="red")
```



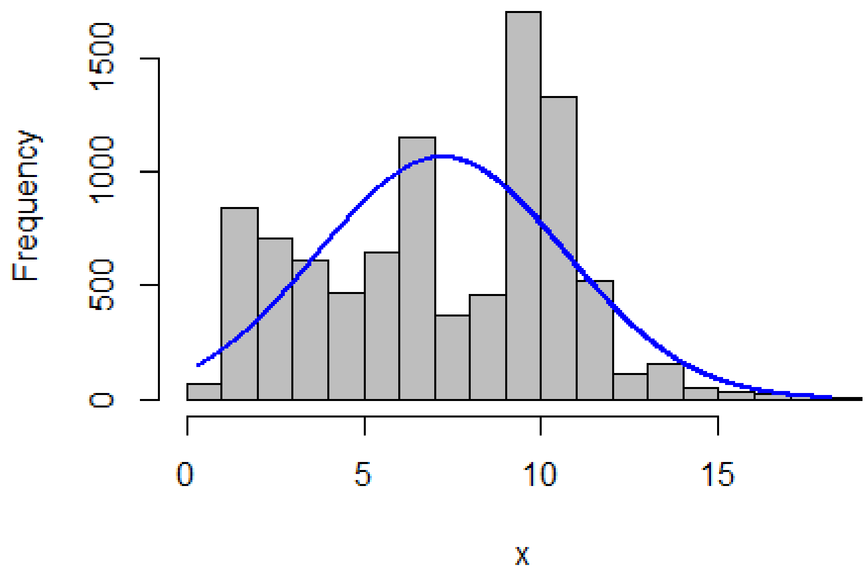

```
plotNormalHistogram(x$humidity)
```



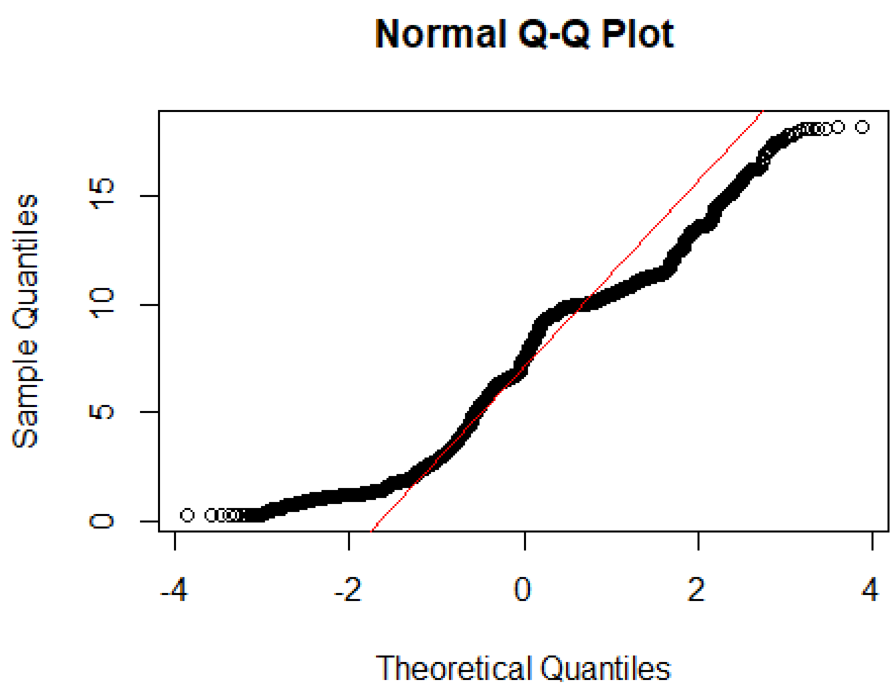
```r
qqnorm(df$humidity)
qqline(df$humidity, col="red")
```



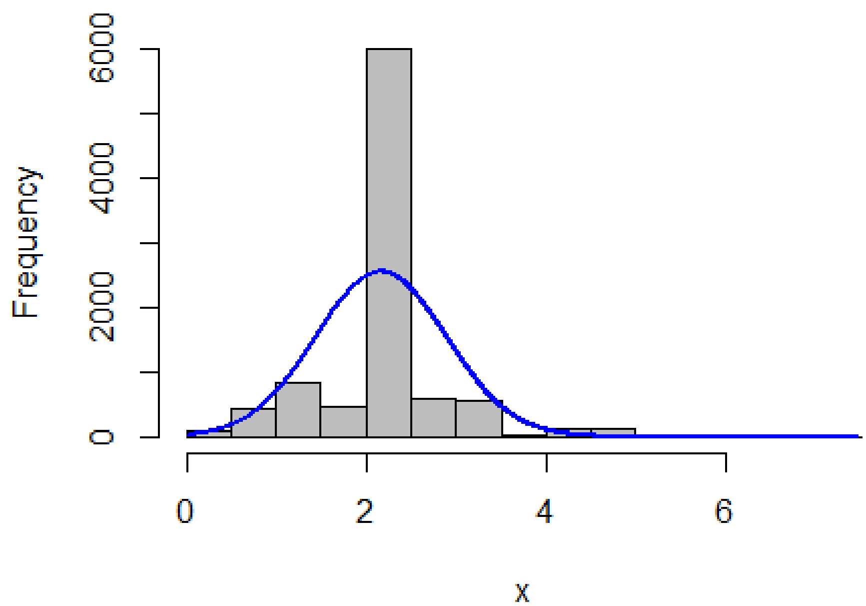

```r
plotNormalHistogram(x$wind)
```



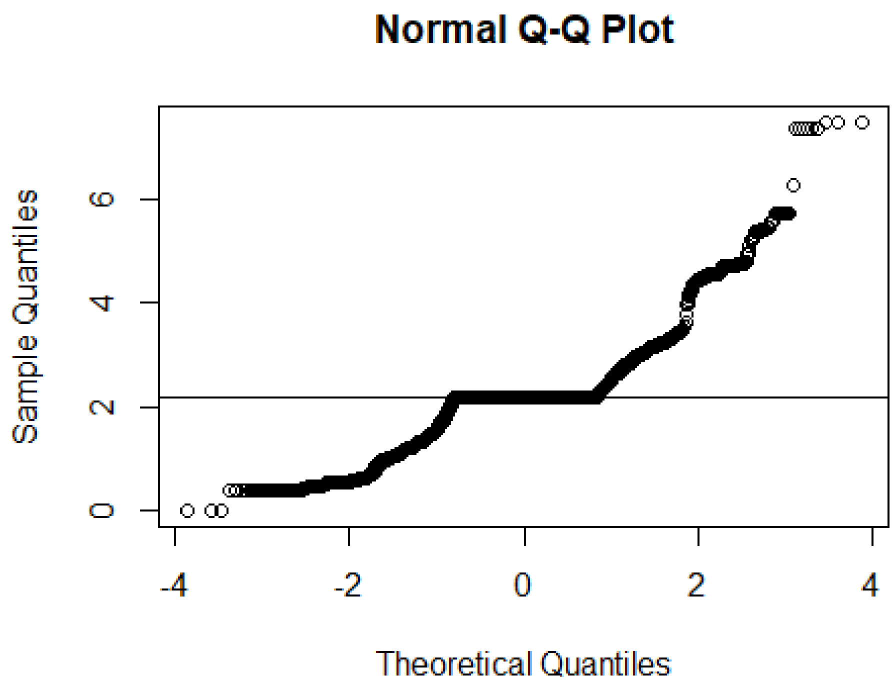

```r
qqnorm(df$wind)
qqline(df$wind, col="red")
```



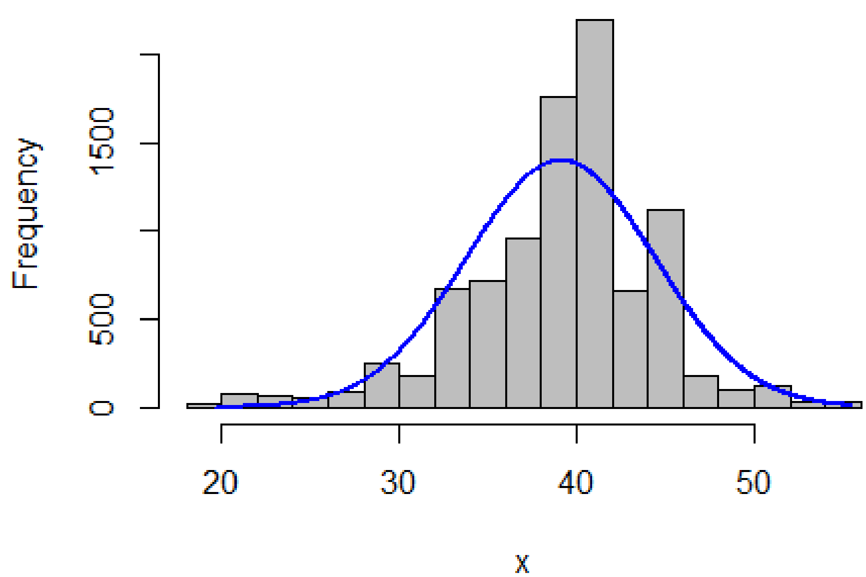
```r
plotNormalHistogram(x$distance)
```



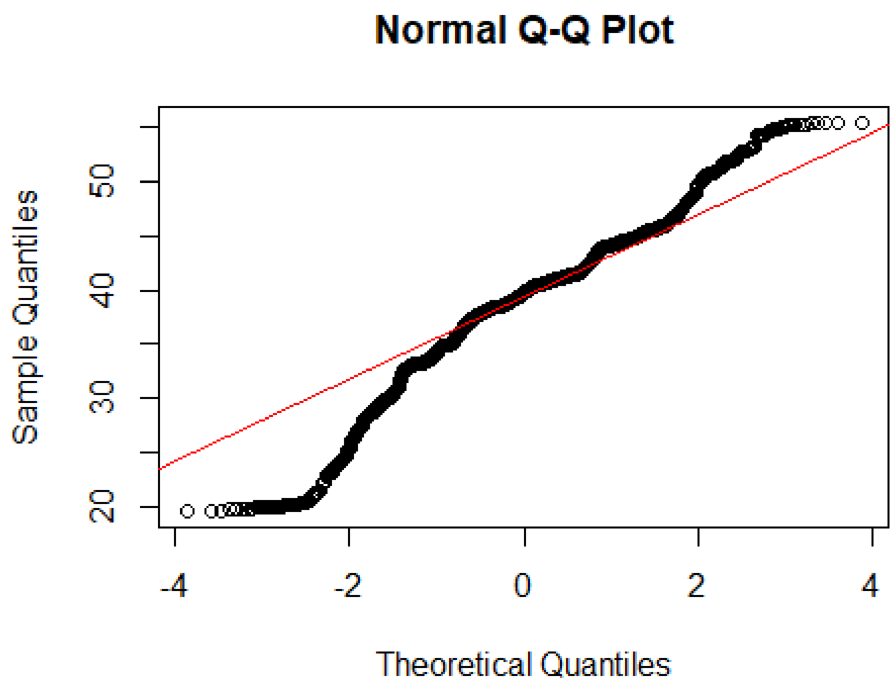

```r
qqnorm(df$distance)
qqline(df$distance)
```




```r
plotNormalHistogram(x$temp)
```



```r
qqnorm(df$temp)
qqline(df$temp, col="red")
```



Deviation from normality can be observed in our variables. Let's check for multivariate analysis using chi-squre plot

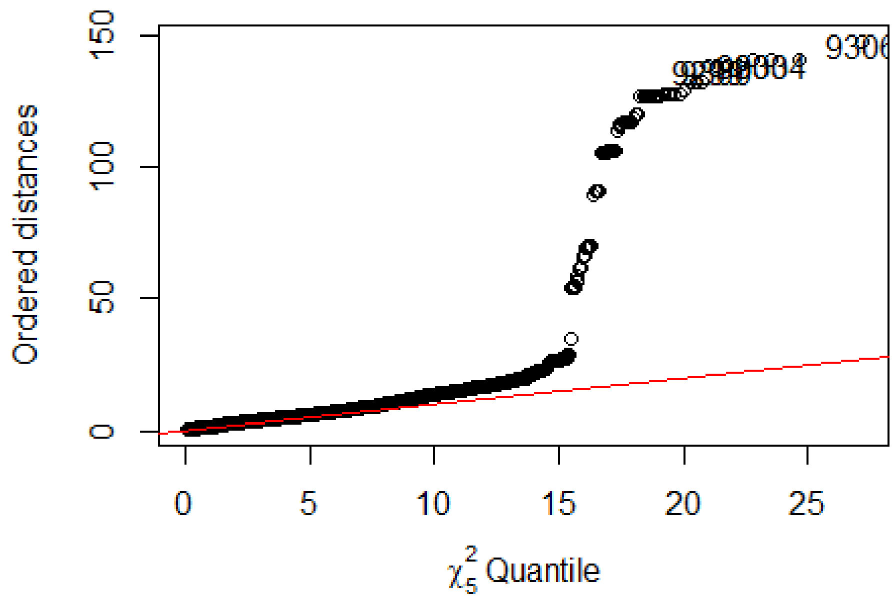
CORRELATION, COVARIANCE AND DISTANCE

```r
#We are calculating for: clouds, pressure, rain, humidity, wind, distance, surge_multiplier, temp, price
covariance<-cov(x) #variamce-covariance matrix created
correlation<-cor(x) #standardized
#colmeans
cm<-colMeans(x)
distance<-dist(scale(x,center=FALSE))
#Calculating di(generalized distance for all observations of our data)
d <- apply(x, MARGIN = 1, function(x) + t(x - cm) %*% solve(covariance) %*% (x - cm))
```

The sorted distance are now plotted against the appropriate quantiles of the chi-distribution

```r
plot(qc <- qchisq((1:nrow(x) - 1/2) / nrow(x), df = 5), sd <- sort(d),xlab = expression(paste(chi[5]^2, " Quantile")),ylab = "Ordered distances")
oups <- which(rank(abs(qc - sd), ties = "random") > nrow(x) - 5)
```

```
text(qc[oups], sd[oups] - 1.5,oups)
abline(a=0,b=1,col="red")
```

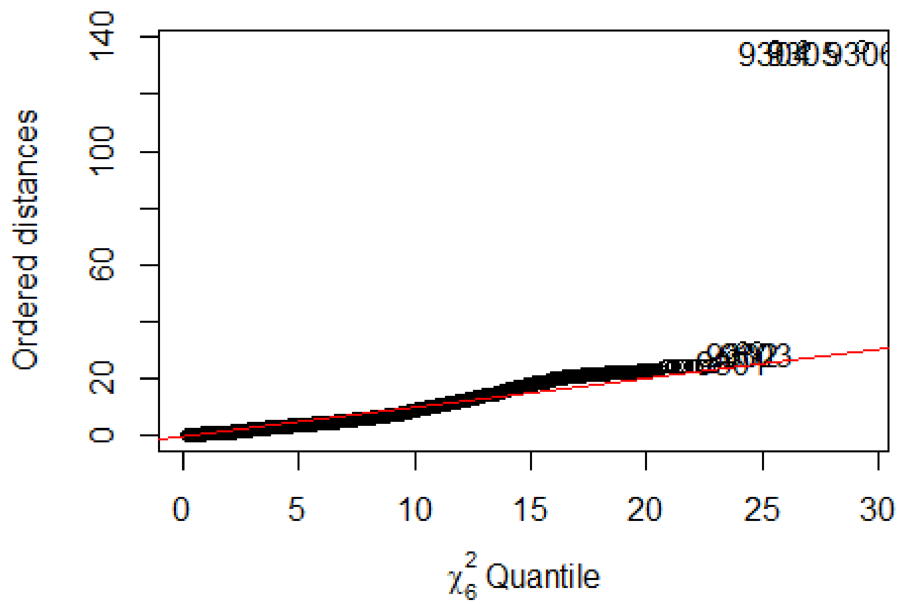



```
#Our observations seems to deviate from linearity after a certain point
```

There is a complete deviation from Normality. We will apply the log transformation on our dataset.

```
#x_new<-x+1
#x_new=log(x - (min(x) - 1))
x_new<-log(x[,c(2,4,5,6,7)])

covariance<-cov(x_new) #variamce-covariance matrix created
correlation<-cor(x_new) #standardized
#colmeans
cm<-colMeans(x_new)
distance<-dist(scale(x_new,center=FALSE))
#Calculating di(generalized distance for all observations of our data)
d <- apply(x_new, MARGIN = 1, function(x_new) + t(x_new - cm) %*%
solve(covariance) %*% (x_new - cm))

plot(qc <- qchisq((1:nrow(x_new) - 1/2) / nrow(x_new), df = 6), sd <-
sort(d),xlab = expression(paste(chi[6]^2, " Quantile")),ylab = "Ordered
distances")
oups <- which(rank(abs(qc - sd), ties = "random") > nrow(x) - 6)
```

```
text(qc[oups], sd[oups] - 1.5,oups)
abline(a=0,b=1,col="red")
```



We have normalized the data..

Pca || T-test || F-test

Get the Correlations between the measurements

```
cor(x_new)

##             pressure     humidity        wind     distance         temp
## pressure  1.00000000  0.037667720 -0.57053758  0.091084564 -0.190802751
## humidity  0.03766772  1.000000000 -0.34918388  0.007457245  0.342394254
## wind     -0.57053758 -0.349183876  1.00000000 -0.036561758  0.107101055
## distance  0.09108456  0.007457245 -0.03656176  1.000000000 -0.002908013
## temp     -0.19080275  0.342394254  0.10710106 -0.002908013  1.000000000

sapply(x_new, sd, na.rm = TRUE)

##   pressure   humidity       wind   distance       temp
## 0.01242771 0.16241660 0.67116505 0.39696563 0.14798758

#There are not considerable differences between these standard deviations..
Still let's see the PCAs.
```

Using prcomp to compute the principal components (eigenvalues and eigenvectors).

With scale=TRUE, variable means are set to zero, and variances set to one

```
x_pca <- prcomp(x_new,scale=TRUE)
x_pca

## Standard deviations (1, .., p=5):
## [1] 1.3050862 1.1732928 0.9966622 0.7718227 0.5754028
##
## Rotation (n x k) = (5 x 5):
##                 PC1         PC2         PC3         PC4         PC5
## pressure -0.6258199  0.23938719 -0.01737613  0.51939957 -0.53006170
## humidity -0.3194217 -0.65993093 -0.04083935 -0.52331376 -0.43236070
## wind      0.6908793  0.04300622  0.11994313  0.09716528 -0.70498852
## distance -0.1208578  0.04613105  0.98636820 -0.09381744  0.03926031
## temp      0.1199934 -0.70937108  0.10354529  0.66190935  0.18316287

summary(x_pca)

## Importance of components:
##                           PC1    PC2    PC3    PC4     PC5
## Standard deviation     1.3051 1.1733 0.9967 0.7718 0.57540
## Proportion of Variance 0.3407 0.2753 0.1987 0.1191 0.06622
## Cumulative Proportion  0.3407 0.6160 0.8146 0.9338 1.00000

#x_pca$rotation
```

We see that the first four components account for nearly 80% of the total variance.

sample scores stored in x_pca$x # singular values (square roots of eigenvalues) stored in x_pca$sdev

loadings (eigenvectors) are stored in x_pca$rotation # variable means stored in x_pca$center

variable standard deviations stored in x_pca$scale

A table containing eigenvalues and %'s accounted, follows

Eigenvalues are sdev^2

```
(eigen_x <- x_pca$sdev^2)

## [1] 1.7032500 1.3766159 0.9933355 0.5957103 0.3310884

names(eigen_x) <- paste("PC",1:5,sep="")
eigen_x

##       PC1       PC2       PC3       PC4       PC5
## 1.7032500 1.3766159 0.9933355 0.5957103 0.3310884

sumlambdas <- sum(eigen_x)
sumlambdas #total sample variance

## [1] 5

propvar <- eigen_x/sumlambdas
propvar

##        PC1        PC2        PC3        PC4        PC5
## 0.34065000 0.27532318 0.19866709 0.11914205 0.06621768

cumvar_x <- cumsum(propvar)
cumvar_x

##       PC1       PC2       PC3       PC4       PC5
## 0.3406500 0.6159732 0.8146403 0.9337823 1.0000000

matlambdas <- rbind(eigen_x,propvar,cumvar_x)
rownames(matlambdas) <- c("Eigenvalues","Prop. variance","Cum. prop.
```

```
variance")
round(matlambdas,4)

##                         PC1    PC2    PC3    PC4    PC5
## Eigenvalues          1.7033 1.3766 0.9933 0.5957 0.3311
## Prop. variance       0.3407 0.2753 0.1987 0.1191 0.0662
## Cum. prop. variance 0.3407 0.6160 0.8146 0.9338 1.0000
```

Sample scores stored in x_pca$x

We need to calculate the scores on each of these components for each individual in our sample.

```
#x_pca$x
xtyp_pca <- cbind(data.frame(df$price),x_pca$x)
str(xtyp_pca)

## 'data.frame':    9306 obs. of  6 variables:
##  $ df.price: num  16.7 16.7 8.5 16.5 16.7 ...
##  $ PC1     : num  -2.29 -1.73 -1.6 -1.56 -1.52 ...
##  $ PC2     : num  -1.003 -0.967 -1.014 -1.017 -1.029 ...
##  $ PC3     : num  -0.1144 -0.0228 -1.0382 -1.1765 -1.4464 ...
##  $ PC4     : num  -0.225 -0.232 -0.134 -0.12 -0.094 ...
##  $ PC5     : num  0.647 0.021 -0.0276 -0.0579 -0.0686 ...

#xtyp_pca
```

Merging price column

```
colnames(xtyp_pca)[colnames(xtyp_pca)=="df.price"] <- "price"
str(xtyp_pca)

## 'data.frame':    9306 obs. of  6 variables:
##  $ price: num  16.7 16.7 8.5 16.5 16.7 ...
##  $ PC1  : num  -2.29 -1.73 -1.6 -1.56 -1.52 ...
##  $ PC2  : num  -1.003 -0.967 -1.014 -1.017 -1.029 ...
##  $ PC3  : num  -0.1144 -0.0228 -1.0382 -1.1765 -1.4464 ...
##  $ PC4  : num  -0.225 -0.232 -0.134 -0.12 -0.094 ...
##  $ PC5  : num  0.647 0.021 -0.0276 -0.0579 -0.0686 ...
```

Sample scores stoted. x_pca$x

T-Test– We see that true difference in all the means is different from zero.

```
t.test(xtyp_pca$PC1,xtyp_pca$price,var.equal = TRUE)
```

```
##
##  Two Sample t-test
##
## data:  xtyp_pca$PC1 and xtyp_pca$price
## t = -265.73, df = 18610, p-value < 2.2e-16
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -16.79675 -16.55077
## sample estimates:
##     mean of x     mean of y
## -1.534642e-14  1.667376e+01
```

```
t.test(xtyp_pca$PC2,xtyp_pca$price,var.equal = TRUE)
```

```
##
##  Two Sample t-test
##
## data:  xtyp_pca$PC2 and xtyp_pca$price
## t = -266.92, df = 18610, p-value < 2.2e-16
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -16.79620 -16.55132
## sample estimates:
##    mean of x    mean of y
## 4.850155e-15 1.667376e+01
```

```
t.test(xtyp_pca$PC3,xtyp_pca$price,var.equal = TRUE)
```

```
##
##  Two Sample t-test
##
## data:  xtyp_pca$PC3 and xtyp_pca$price
## t = -268.34, df = 18610, p-value < 2.2e-16
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -16.79555 -16.55197
## sample estimates:
##     mean of x     mean of y
## -3.485127e-16  1.667376e+01
```

```
t.test(xtyp_pca$PC4,xtyp_pca$price,var.equal = TRUE)
```

```
##
##  Two Sample t-test
##
## data:  xtyp_pca$PC4 and xtyp_pca$price
## t = -269.84, df = 18610, p-value < 2.2e-16
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -16.79488 -16.55264
## sample estimates:
```

```
##    mean of x    mean of y
## 1.371754e-14 1.667376e+01

t.test(xtyp_pca$PC5,xtyp_pca$price,var.equal = TRUE)

##
##  Two Sample t-test
##
## data:  xtyp_pca$PC5 and xtyp_pca$price
## t = -270.85, df = 18610, p-value < 2.2e-16
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -16.79443 -16.55309
## sample estimates:
##     mean of x     mean of y
## -1.304992e-14  1.667376e+01

#F-Test #Testing Variation
```

Variance Test- Test for variance

```
var.test(xtyp_pca$PC1,xtyp_pca$price)

##
##  F test to compare two variances
##
## data:  xtyp_pca$PC1 and xtyp_pca$price
## F = 0.048752, num df = 9305, denom df = 9305, p-value < 2.2e-16
## alternative hypothesis: true ratio of variances is not equal to 1
## 95 percent confidence interval:
##  0.04681082 0.05077444
## sample estimates:
## ratio of variances
##         0.04875236

var.test(xtyp_pca$PC2,xtyp_pca$price)

##
##  F test to compare two variances
##
## data:  xtyp_pca$PC2 and xtyp_pca$price
## F = 0.039403, num df = 9305, denom df = 9305, p-value < 2.2e-16
## alternative hypothesis: true ratio of variances is not equal to 1
## 95 percent confidence interval:
##  0.03783386 0.04103737
## sample estimates:
## ratio of variances
##         0.03940307

var.test(xtyp_pca$PC3,xtyp_pca$price)
```

```
##
##  F test to compare two variances
##
## data:  xtyp_pca$PC3 and xtyp_pca$price
## F = 0.028432, num df = 9305, denom df = 9305, p-value < 2.2e-16
## alternative hypothesis: true ratio of variances is not equal to 1
## 95 percent confidence interval:
##  0.02730007 0.02961165
## sample estimates:
## ratio of variances
##         0.02843238
```

```
var.test(xtyp_pca$PC4,xtyp_pca$price)
```

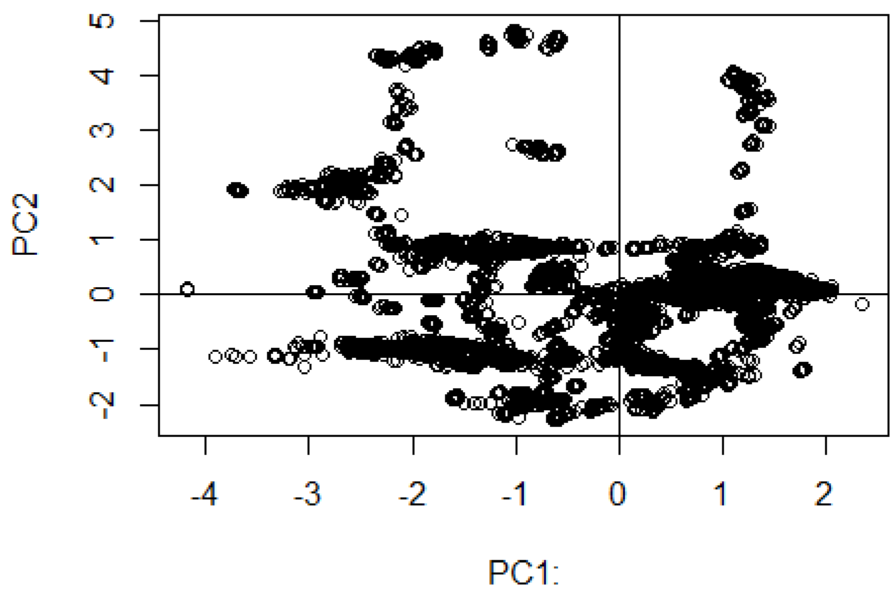
```
##
##  F test to compare two variances
##
## data:  xtyp_pca$PC4 and xtyp_pca$price
## F = 0.017051, num df = 9305, denom df = 9305, p-value < 2.2e-16
## alternative hypothesis: true ratio of variances is not equal to 1
## 95 percent confidence interval:
##  0.01637204 0.01775832
## sample estimates:
## ratio of variances
##          0.0170511
```

```
var.test(xtyp_pca$PC5,xtyp_pca$price)
```

```
##
##  F test to compare two variances
##
## data:  xtyp_pca$PC5 and xtyp_pca$price
## F = 0.0094768, num df = 9305, denom df = 9305, p-value < 2.2e-16
## alternative hypothesis: true ratio of variances is not equal to 1
## 95 percent confidence interval:
##  0.009099379 0.009869852
## sample estimates:
## ratio of variances
##        0.009476789
```

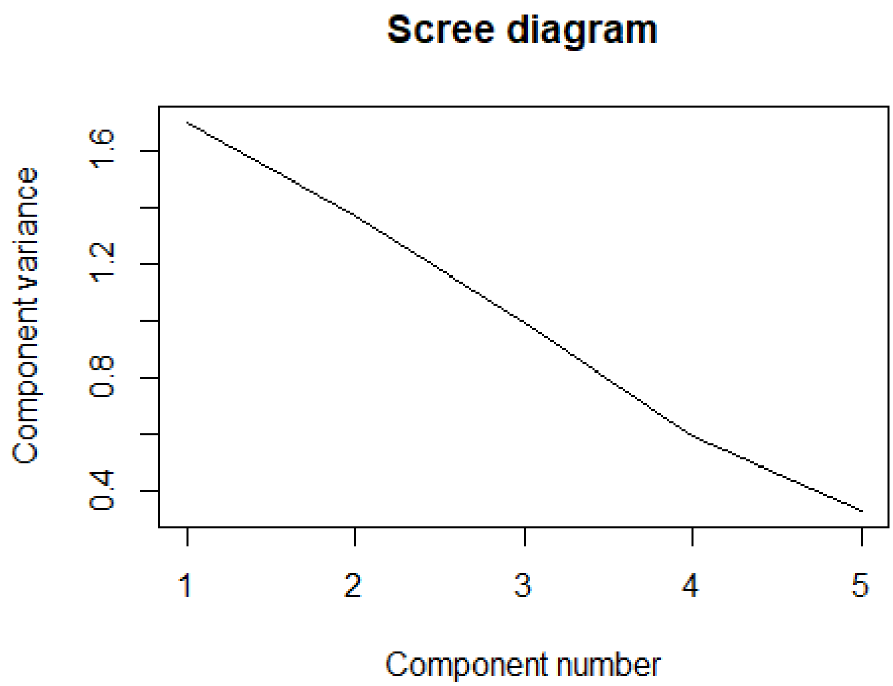
Plotting the scores of Pricipal Component 1 and Principal component 2

```
plot(xtyp_pca$PC1, xtyp_pca$PC2,xlab="PC1:", ylab="PC2")
abline(h=0)
abline(v=0)
```



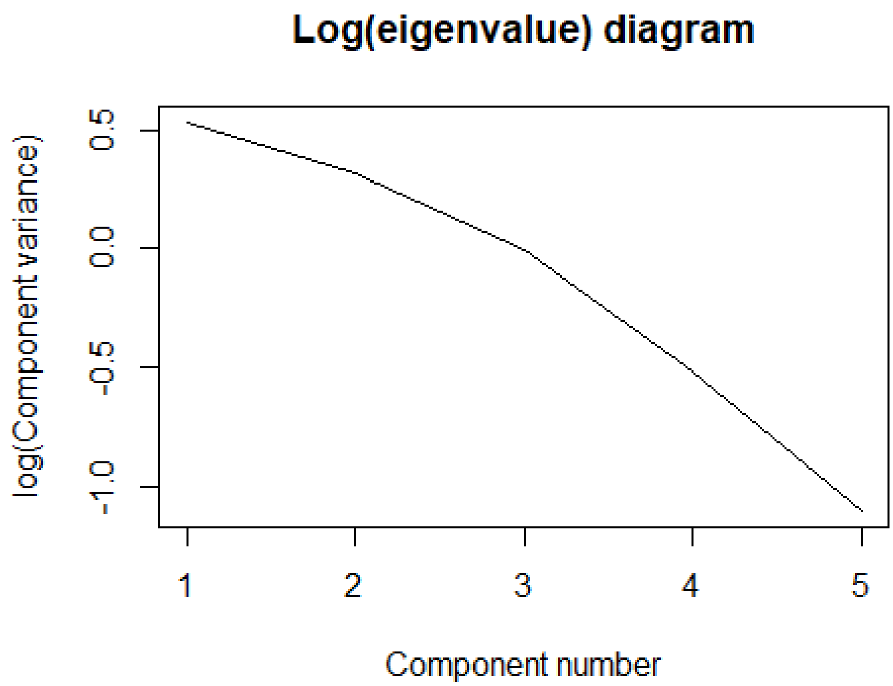
Plotting the Variance of Principal Components

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



#Plotting the Log variance of COmponents

```
plot(log(eigen_x), xlab = "Component number",ylab = "log(Component
variance)", type="l",main = "Log(eigenvalue) diagram")
```

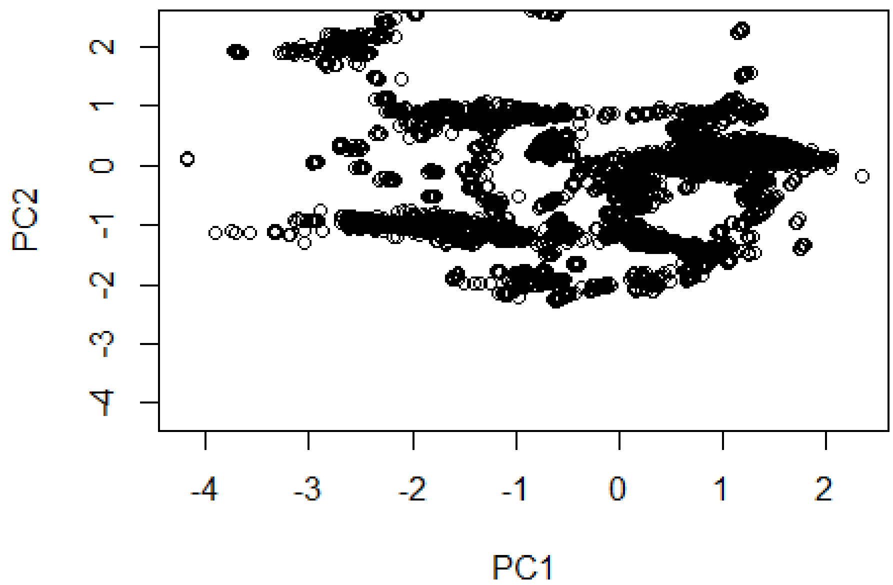


#Variance of the principal components

```
#View(x_pca)
diag(cov(x_pca$x))

##       PC1       PC2       PC3       PC4       PC5
## 1.7032500 1.3766159 0.9933355 0.5957103 0.3310884

#x_pca$x[,1]
#x_pca$x
```

Plotting the scores

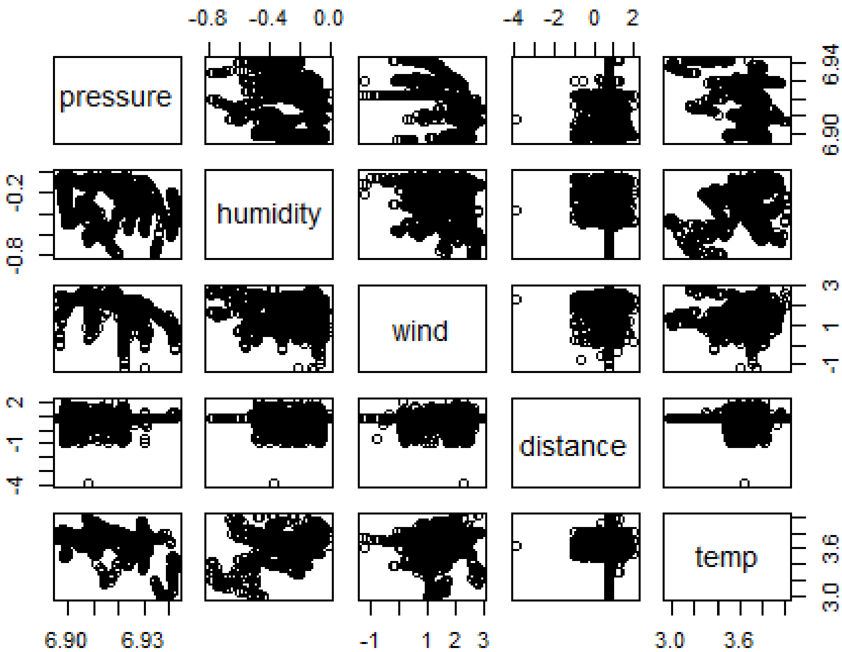
```
xlim <- range(x_pca$x[,1])
plot(x_pca$x,xlim=xlim,ylim=xlim)
```




```
#x_pca$rotation[,1]
#x_pca$rotation
```

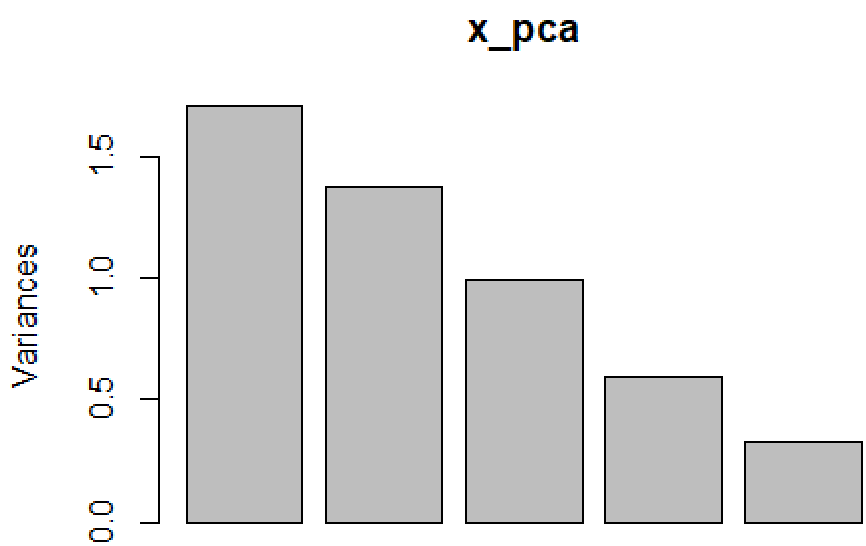
Scatter plot matrix of the actual data

```
plot(x_new)
```

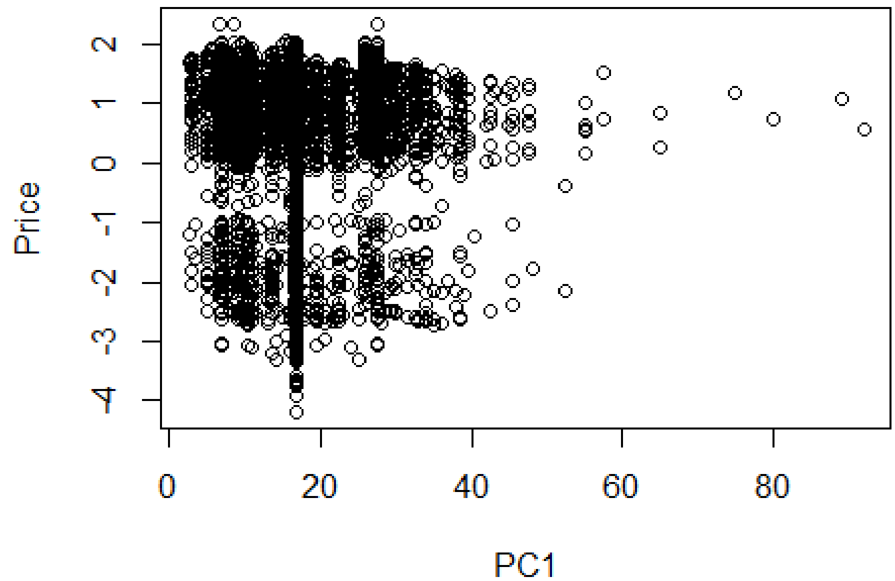


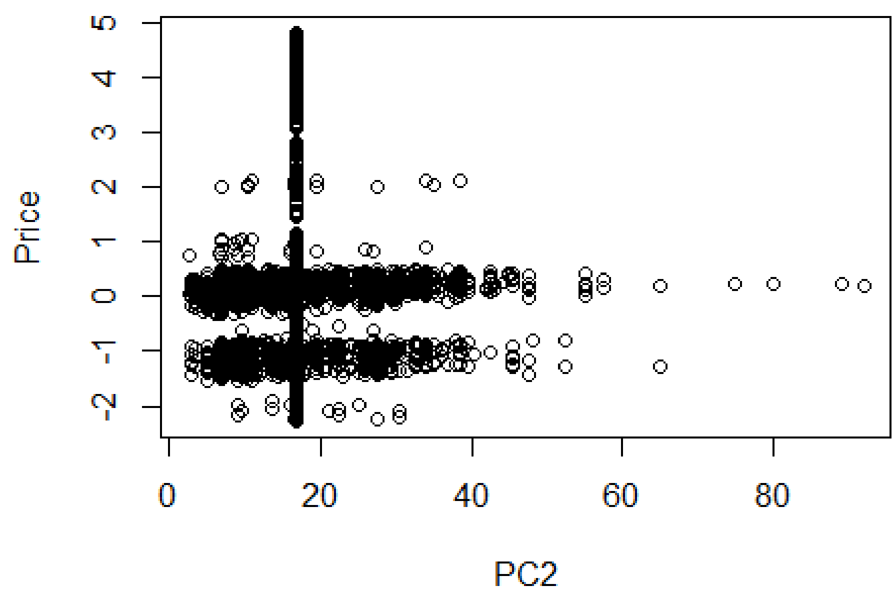
Variance plot for each component. We can see that all components play a dominant role.

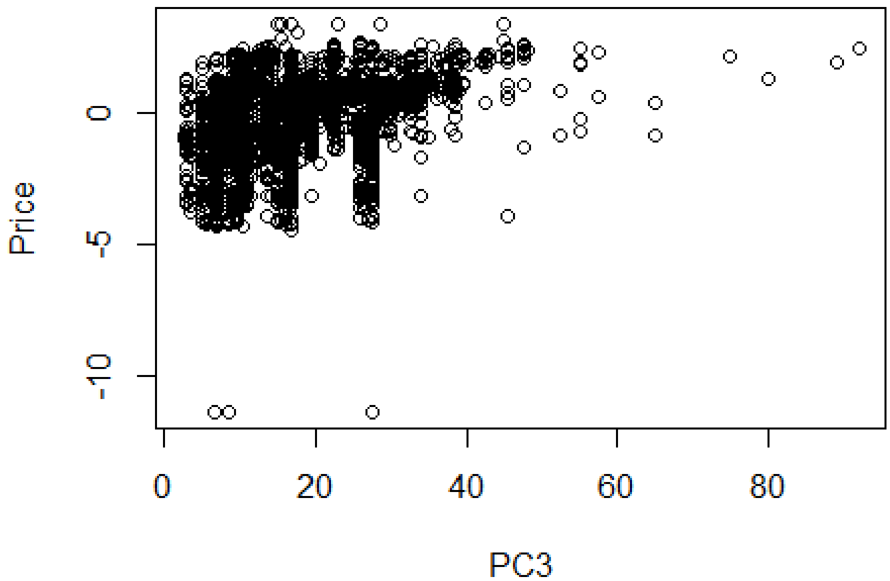
```
plot(x_pca)
```

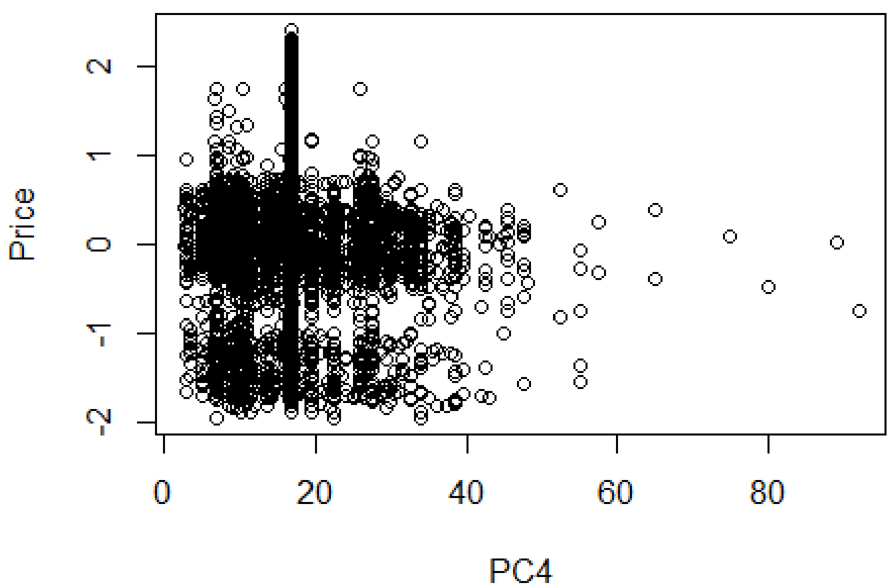


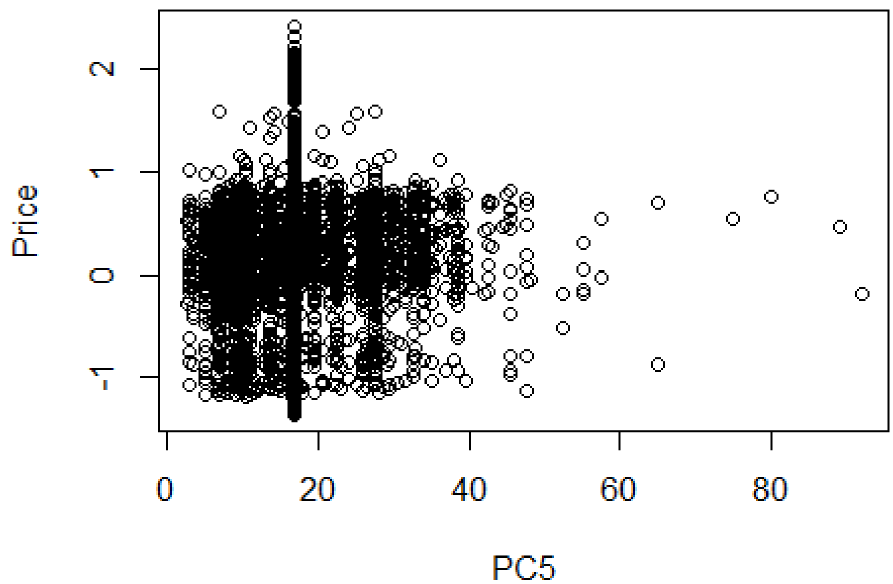

```
#get the original value of the data based on PCA
center <- x_pca$center
scale <- x_pca$scale
new_x <- as.matrix(x_new)
#drop(scale(new_x,center=center, scale=scale)%*%x_pca$rotation[,1])
#predict(x_pca)[,1]
#The aboved two gives us the same thing. predict is a good function to know.

x_new$price<-df$price
out <- sapply(1:5,
function(i){plot(x_new$price,x_pca$x[,i],xlab=paste("PC",i,sep=""),
                                    ylab="Price")})
```


Price
PC1
2
1
0
-1
-2
-3
-4
0
20
40
60
80

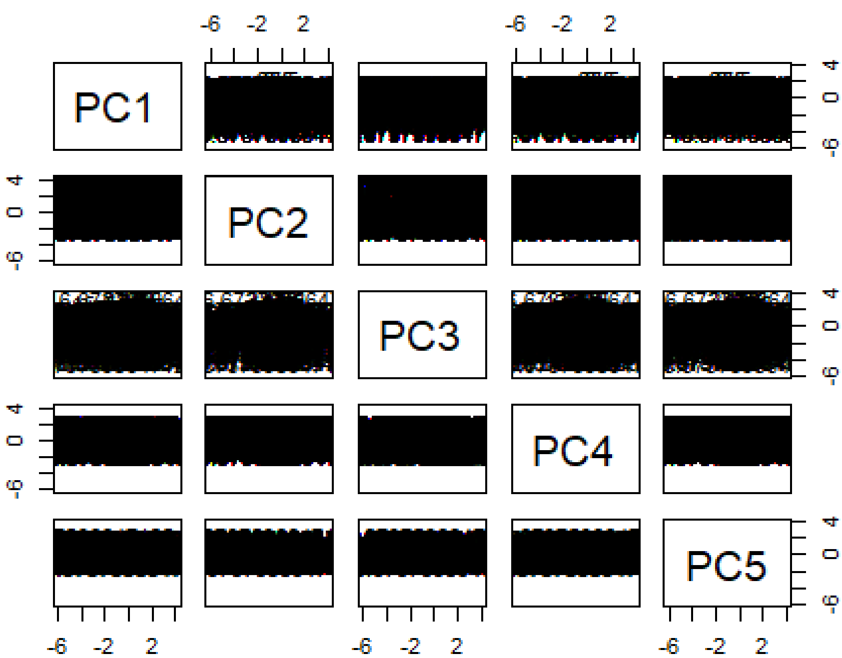

Price
PC2
5
4
3
2
1
0
-1
-2
0
20
40
60
80


Price
0
-5
-10
0
20
40
60
80
PC3


Price
2
1
0
-1
-2
0
20
40
60
80
PC4




```
pairs(x_pca$x[,1:5], ylim = c(-6,4),xlim = c(-
6,4),panel=function(x,y,...){text(x,y,x_new$price)})
```



CLuster Analysis

```
#install.packages("cluster",
#lib="/Library/Frameworks/R.framework/Versions/3.5/Resources/library")
library(cluster)

## Warning: package 'cluster' was built under R version 3.5.3
```

Pulling the numerical variables in the “Cluster” dataframe. Scaling the values..

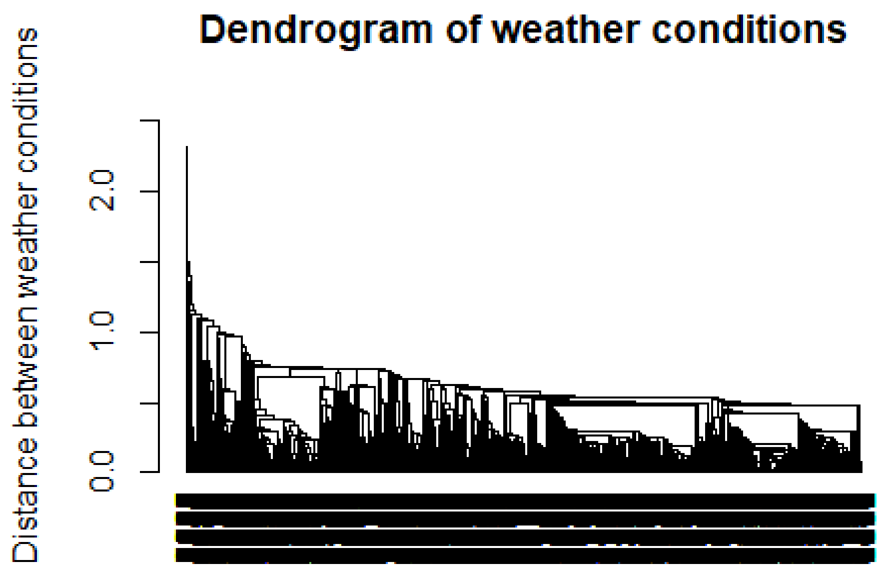
```
cluster <- df[,c(1,2,4,5,7,9)]
matstd.cluster <- scale(cluster)
dim(matstd.cluster)

## [1] 9306    6
```

Calculating the distance between all observations..

```
dist.cluster <- dist(matstd.cluster, method="euclidean")
length(dist.cluster)

## [1] 43296165
```

Invoking hclust command (cluster analysis by single linkage method)

```
hclust_cluster <- hclust(dist.cluster, method = "single")
par(mar=c(6, 4, 4, 2) + 0.1)
plot(as.dendrogram(hclust_cluster),ylab="Distance between weather
conditions",ylim=c(0,2.5),main="Dendrogram of weather conditions")
```



K-means Clustering for k=2 and then computing the percentage variance

```
#attach(cluster)
matstd.cluster <- scale(cluster)
# Computing the percentage of variation accounted for. Two clusters
kmeans2.cluster <- kmeans(matstd.cluster,2,nstart = 10)
perc.var.2 <- round(100*(1 -
kmeans2.cluster$betweenss/kmeans2.cluster$totss),1)
names(perc.var.2) <- "Perc. 2 clus"
perc.var.2

## Perc. 2 clus
##         75.4
```

Computing the percentage of variation accounted for. Three clusters

```
kmeans3.cluster <- kmeans(matstd.cluster,3,nstart = 10)
perc.var.3 <- round(100*(1 -
kmeans3.cluster$betweenss/kmeans3.cluster$totss),1)
names(perc.var.3) <- "Perc. 3 clus"
perc.var.3

## Perc. 3 clus
##         58.3
```

Computing the percentage of variation accounted for. Four clusters

```
kmeans4.cluster <- kmeans(matstd.cluster,4,nstart = 10)
perc.var.4 <- round(100*(1 -
kmeans4.cluster$betweenss/kmeans4.cluster$totss),1)
names(perc.var.4) <- "Perc. 4 clus"
perc.var.4

## Perc. 4 clus
##         50.9
```

Computing the percentage of variation accounted for. Five clusters

```
kmeans5.cluster <- kmeans(matstd.cluster,5,nstart = 10)
perc.var.5 <- round(100*(1 -
kmeans5.cluster$betweenss/kmeans5.cluster$totss),1)
names(perc.var.5) <- "Perc. 5 clus"
perc.var.5

## Perc. 5 clus
##         44.5
```

Computing the percentage of variation accounted for. Six clusters

```
kmeans6.cluster <- kmeans(matstd.cluster,6,nstart = 10)
perc.var.6 <- round(100*(1 -
kmeans6.cluster$betweenss/kmeans6.cluster$totss),1)
names(perc.var.6) <- "Perc. 6 clus"
perc.var.6

## Perc. 6 clus
##         38.7
```

plots to compare

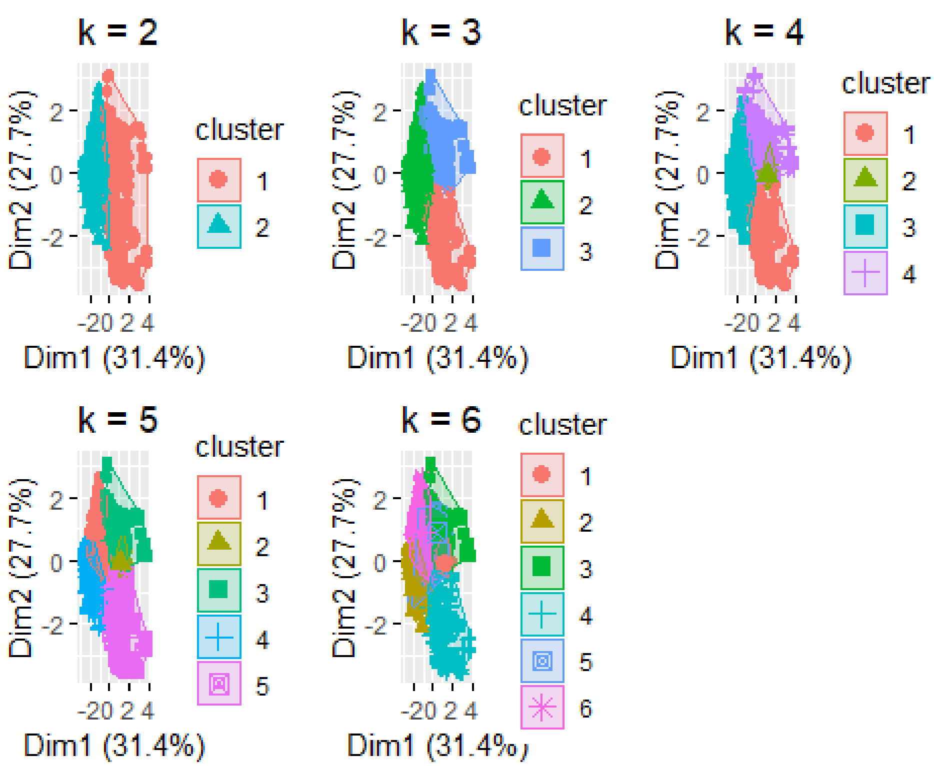
```
#install.packages("VIM")
library(VIM)

## Warning: package 'VIM' was built under R version 3.5.3

## Loading required package: colorspace

## Loading required package: grid

## Loading required package: data.table

## VIM is ready to use.
##  Since version 4.0.0 the GUI is in its own package VIMGUI.
##
##           Please use the package to use the new (and old) GUI.
```

```
## Suggestions and bug-reports can be submitted at:
https://github.com/alexkowa/VIM/issues

##
## Attaching package: 'VIM'

## The following object is masked from 'package:datasets':
##
##     sleep

#install.packages("tidyverse")
library(tidyverse)  # data manipulation

## Warning: package 'tidyverse' was built under R version 3.5.3

## -- Attaching packages ---------------------------------------------------
------- tidyverse 1.2.1 --

## v ggplot2 3.1.1       v purrr   0.3.0
## v tibble  2.0.1       v dplyr   0.8.0.1
## v tidyr   0.8.3       v stringr 1.3.1
## v readr   1.3.1       v forcats 0.3.0

## Warning: package 'ggplot2' was built under R version 3.5.3

## Warning: package 'tidyr' was built under R version 3.5.3

## -- 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()

#install.packages("cluster")
library(cluster)    # clustering algorithms
#install.packages("factoextra")
library(factoextra)

## Warning: package 'factoextra' was built under R version 3.5.3

## Welcome! Related Books: `Practical Guide To Cluster Analysis in R` at
https://goo.gl/13EFCZ

p1 <- fviz_cluster(kmeans2.cluster, geom = "point", data = cluster) +
ggtitle("k = 2")
p2 <- fviz_cluster(kmeans3.cluster, geom = "point",  data = cluster) +
ggtitle("k = 3")
p3 <- fviz_cluster(kmeans4.cluster, geom = "point",  data = cluster) +
ggtitle("k = 4")
p4 <- fviz_cluster(kmeans5.cluster, geom = "point",  data = cluster) +
```

```r
ggtitle("k = 5")
p5 <- fviz_cluster(kmeans6.cluster, geom = "point",  data = cluster) +
ggtitle("k = 6")
```

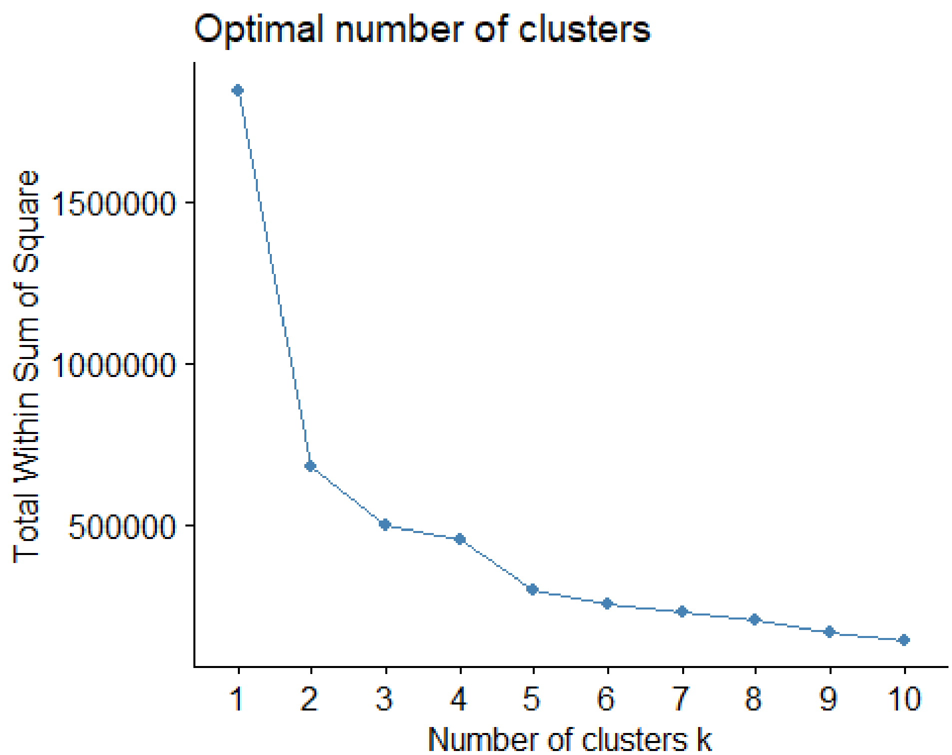
Grid plot

```r
library(gridExtra)

## Warning: package 'gridExtra' was built under R version 3.5.3

##
## Attaching package: 'gridExtra'

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

grid.arrange(p1, p2, p3, p4,p5, nrow = 2)
```



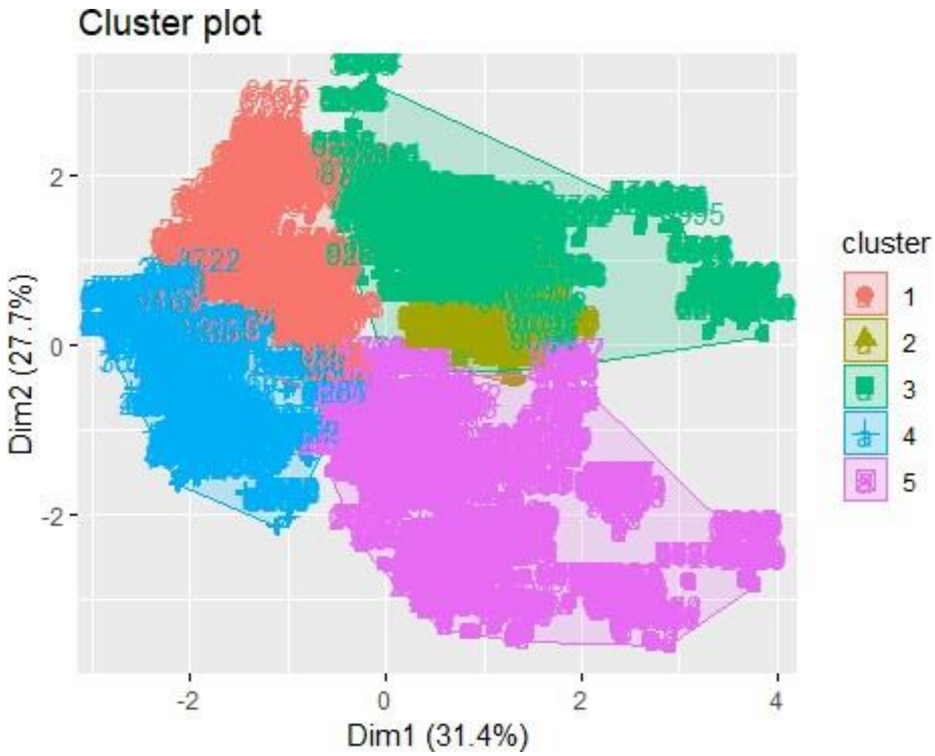
Determining Optimal Clusters

```r
set.seed(123)
fviz_nbclust(cluster, kmeans, method = "wss")
```

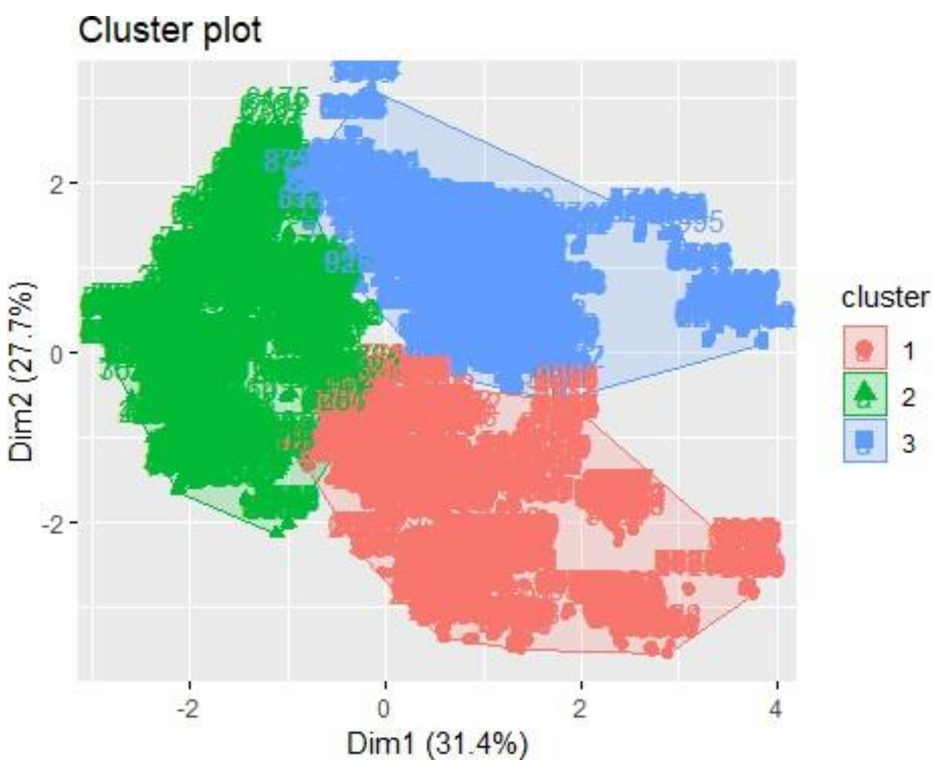


K=5 seems optimal number of clusters

```
fviz_cluster(kmeans5.cluster, data = cluster)
```




```
fviz_cluster(kmeans3.cluster, data = cluster)
```



Adding cluster number to the file for each observation-

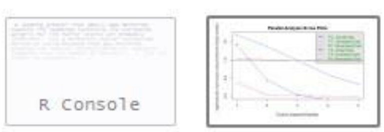
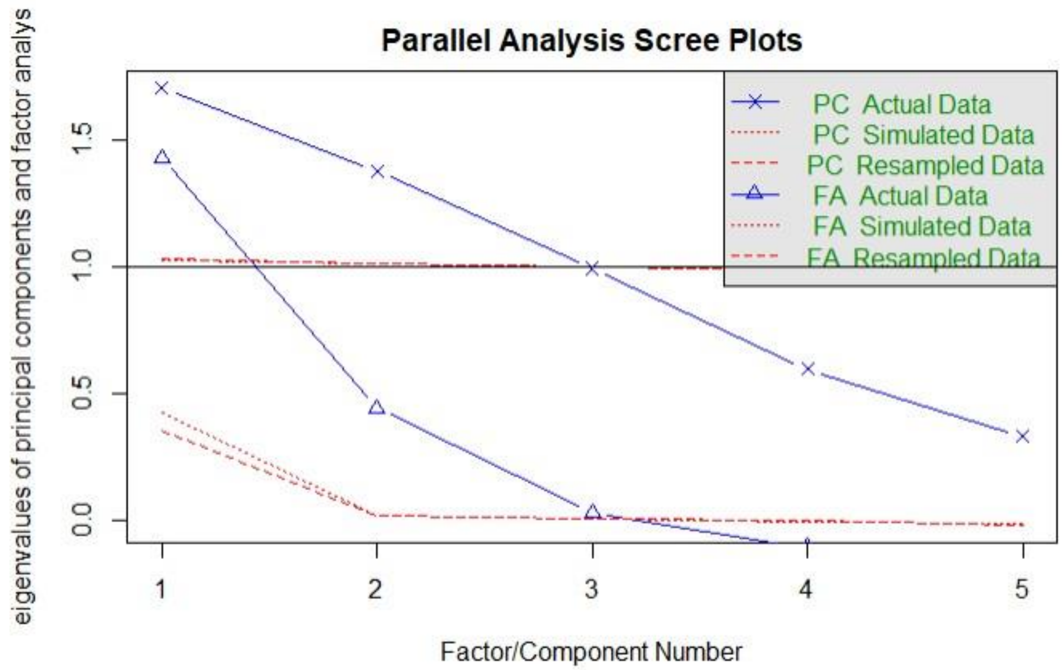
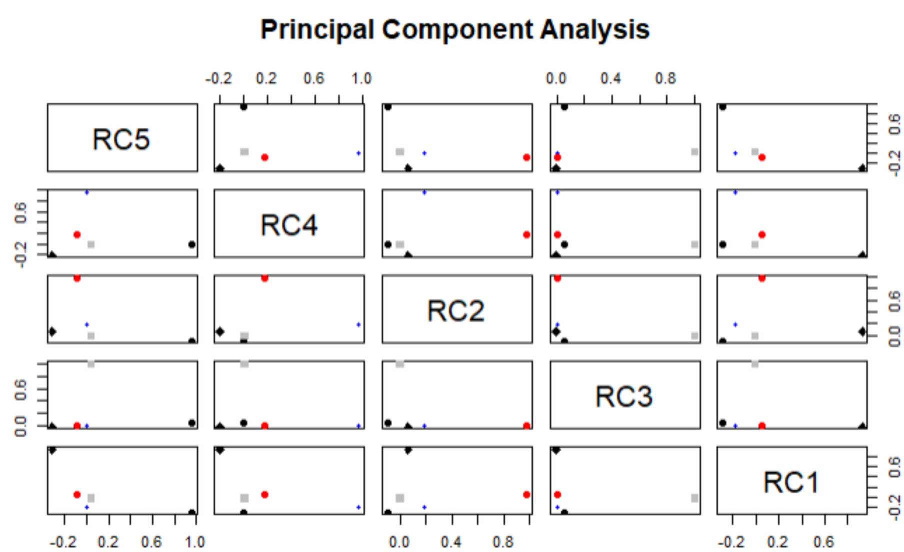
```
clusterFile <- cbind(df, clusterNum = kmeans5.cluster$cluster)
head(clusterFile)

##   clouds pressure rain humidity wind         date_time.x distance
## 1   0.87  1014.39    0     0.92 1.46 2018-11-26 04:34:05 2.168125
## 2   0.86  1014.17    0     0.93 2.57 2018-11-26 05:34:13 2.168125
## 3   0.86  1014.17    0     0.93 2.59 2018-11-26 05:34:58 1.440000
## 4   0.86  1014.17    0     0.93 2.65 2018-11-26 05:36:38 1.360000
## 5   0.86  1014.17    0     0.93 2.65 2018-11-26 05:36:38 1.220000
## 6   0.95  1013.78    0     0.92 2.59 2018-11-26 05:42:57 1.340000
##   surge_multiplier  temp    price    day     time  date_time clusterNum
## 1         1.018365 41.04 16.67376 Monday 04:34:05 2018-11-26          4
## 2         1.018365 40.63 16.67376 Monday 05:34:13 2018-11-26          4
## 3         1.000000 40.63  8.50000 Monday 05:34:58 2018-11-26          4
## 4         1.000000 40.61 16.50000 Monday 05:36:38 2018-11-26          4
## 5         1.000000 40.61 16.67376 Monday 05:36:38 2018-11-26          4
## 6         1.000000 40.72 26.50000 Monday 05:42:57 2018-11-26          4
```

Factor Analysis:

We concluded during Principal Component Analysis that all the variables of our dataset are not highly correlated and all are significant. Hence, we did not apply Factor Analysis on our data.

```
##Factor Analysis

```{r}
library(psych)
install.packages("psych", lib="/Library/Frameworks/R.framework/Versions/3.5/Resources/library")
fit.pc <- principal(x_new, nfactors=5, rotate="varimax")
fit.pc
fa.parallel(x_new) # See factor recommendation
```
```






```
#We see there is small correlation within factors
```{r}
fa.plot(fit.pc) # See Correlations within Factors
```
```



```
# Visualize the relationship
#Here we can see that each variable is assigned to each factor. Hence, we do not proceed with factor analysis on our dataset.
```{r}
fa.diagram(fit.pc)
```
```