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Reg. No.: 20BDS0162 **Date: 27th March 2023**
Slot: L31+L32 **Faculty: Dr. Prakash M.**

Exercise Number – 1

K-Means Clustering

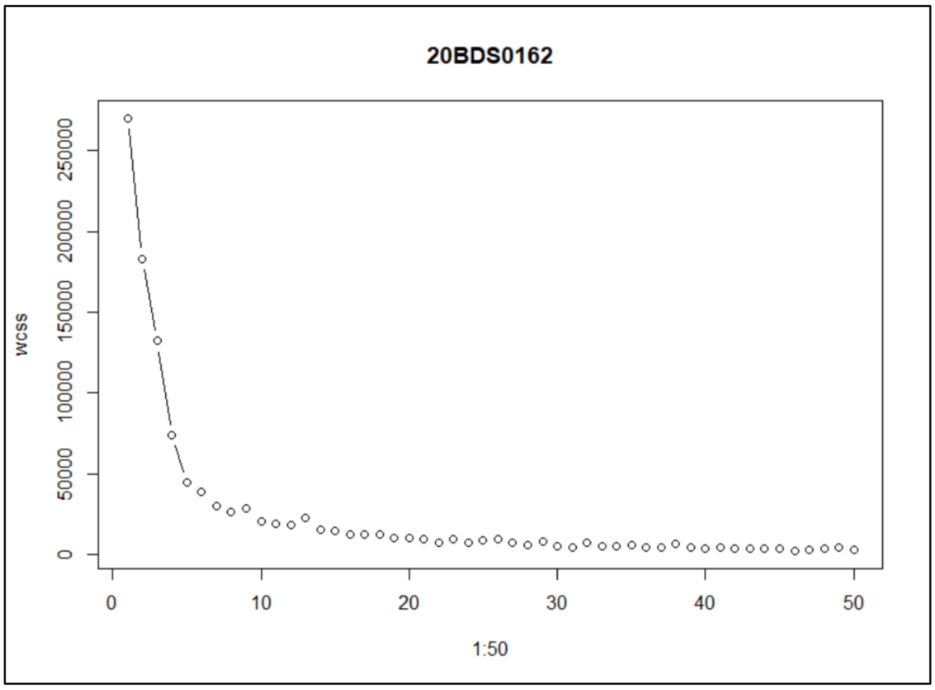
Q1. K-mean Clustering using Mall_Customers dataset.

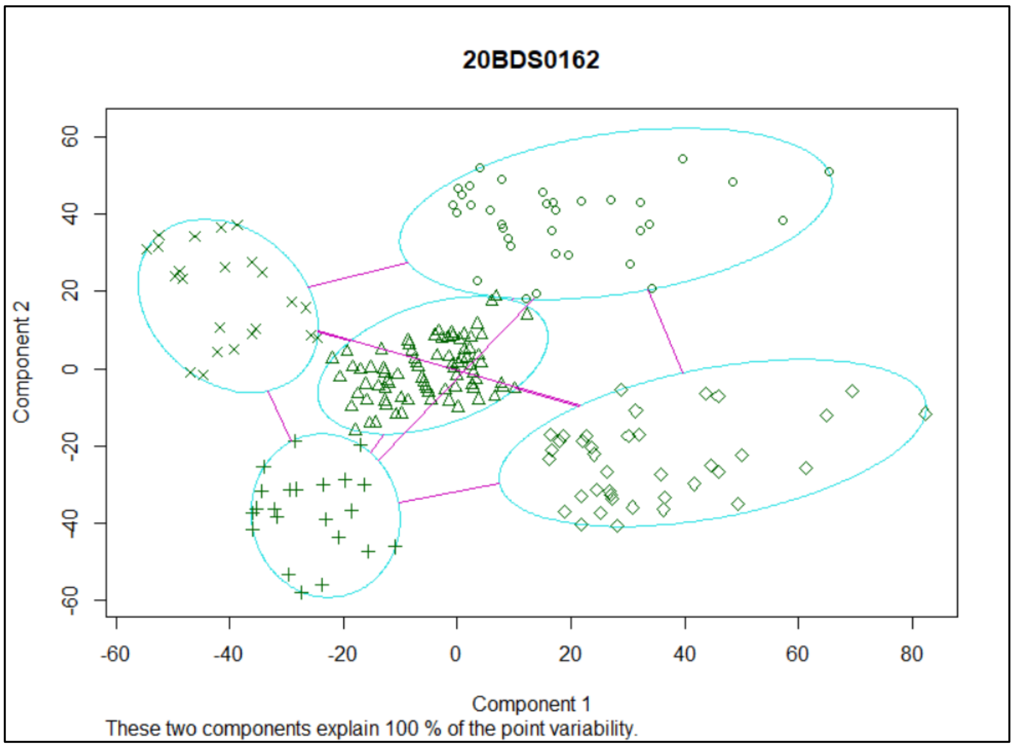
Aim: To use the Mall_Customers dataset with the K-Means Clustering Algorithm and visualise the clusters

Code:

```
library(arules)

library(dplyr)


#k means clustering

df2 = read.csv("D:\\Sem6\\DVP\\ELA\\Assessment4\\Mall_Customers.csv")

df2 = df2[4:5]

df2


library(cluster)


set.seed(5000)

wcss = vector()

wcss


for(i in 1:50)

  wcss[i] = sum(kmeans(df2, i)$withinss)


plot(1:50, wcss, type = 'b') #5 cluster reqd


kmeans = kmeans(x = df2, centers = 5)


y_kmeans = kmeans$cluster

z=clusplot(df2, y_kmeans,main = "20BDS0162")

z
```

Output:





Result:

K-Means Clustering for the dataset Mall Customers was completed successfully. Based on the Annual Income column, I had first put the cluster centroid at 5000. (4th). I used the algorithm to produce five clusters. Following that, all the clusters are shown, and it is also indicated which data points belong to particular clusters and how far away they are from each other.

Exercise Number - 2

Market Basket Analysis

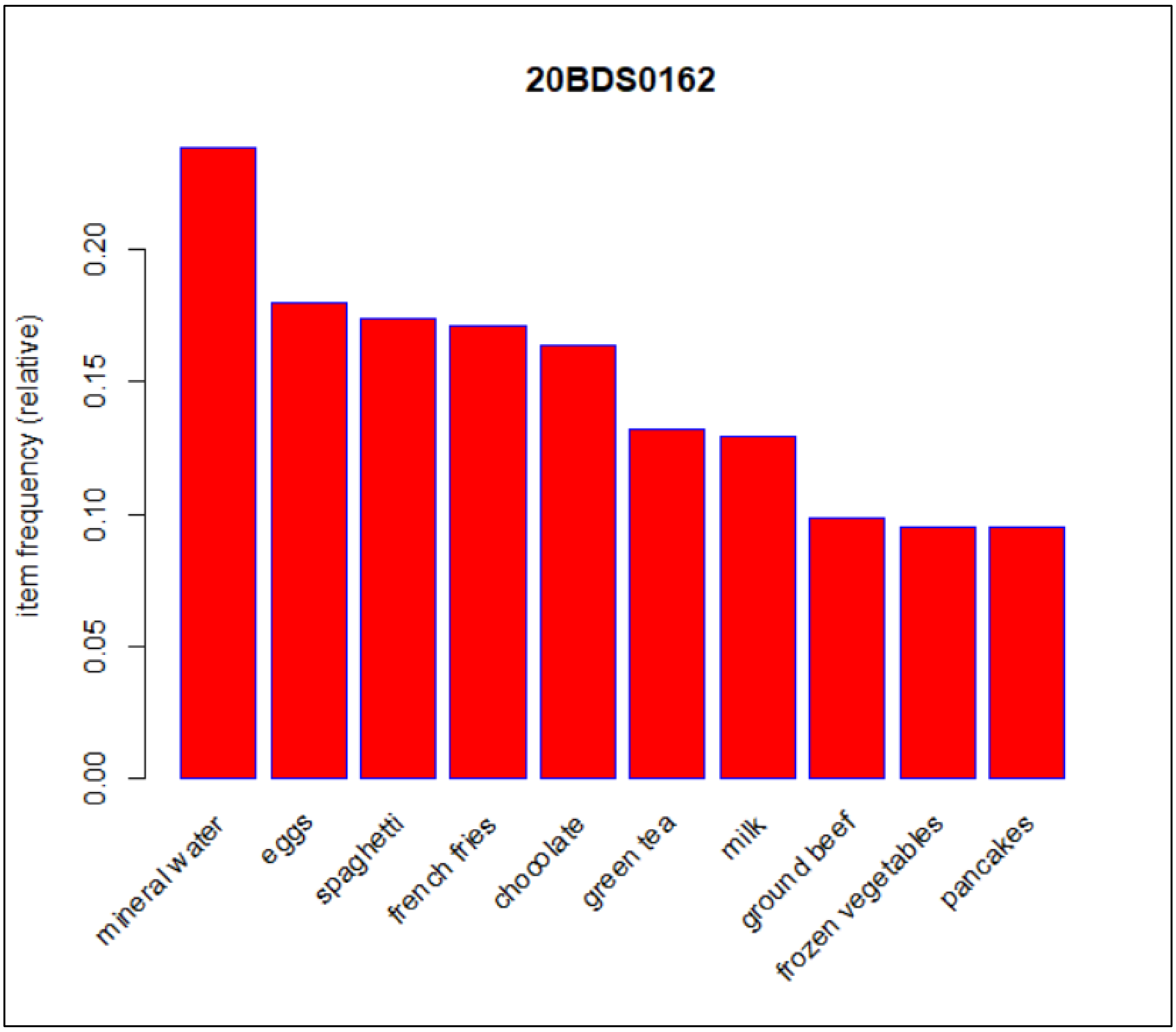
Q1. Market-Basket Data analysis Visualization

Aim: To perform Market-Basket-Data-Analysis Visualization using Apriori Algorithm and visualize the results

Code:

```
install.packages("dplyr")

install.packages("arules")


library(arules)

library(dplyr)


df1 = read.csv("D:\\Sem6\\DVP\\ELA\\Assessment4\\Market_Basket_Optimisation.csv", header =
FALSE)


summary(df1)

dim(df1)

str(df1)


#sparse matrix

df1 = read.transactions(file =
"D:\\Sem6\\DVP\\ELA\\Assessment4\\Market_Basket_Optimisation.csv",

                 sep = ",",

                 rm.duplicates = T)


summary(df1)


itemFrequencyPlot(x = df1, topN = 10,main = "20BDS0162",col = "red", border = "blue")


#apriori algo

rules = apriori(data = df1,

           parameter = list(support = 0.004,
                                confidence = 0.2))
#visualizing
inspect(sort(rules, by = 'lift')[1:10])
```

Output:



Result:

Calculated the necessary support and confidence that properly suit the provided dataset in order to successfully use the Apriori algorithm and visualize the results. According to the findings, one can predict what a person would purchase in total while visiting the market based on the things they initially choose.

Exercise Number – 3

Text Analytics

Q3. Text Analytics on Shakespeare's plays.

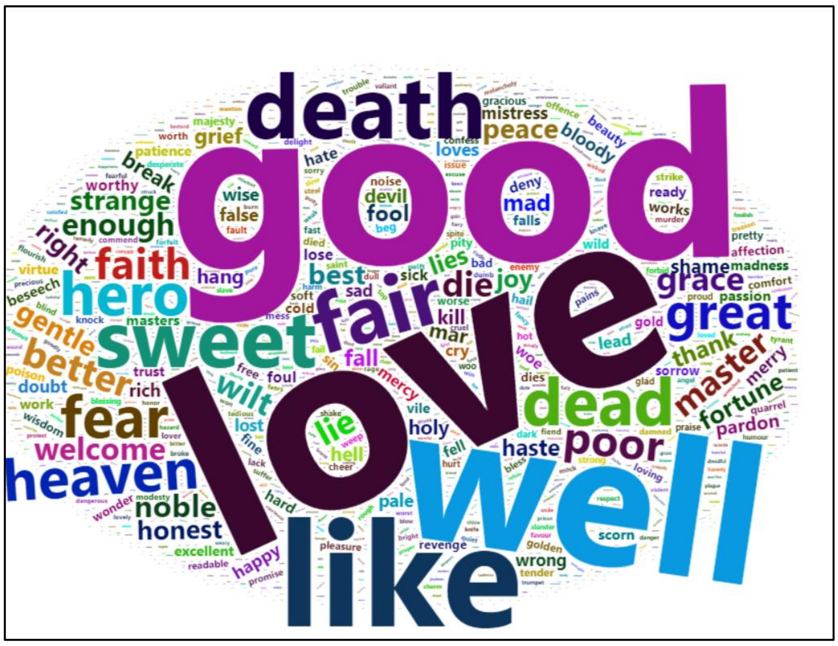
Aim: To perform text analytics for the given shakespeare.rda file using R

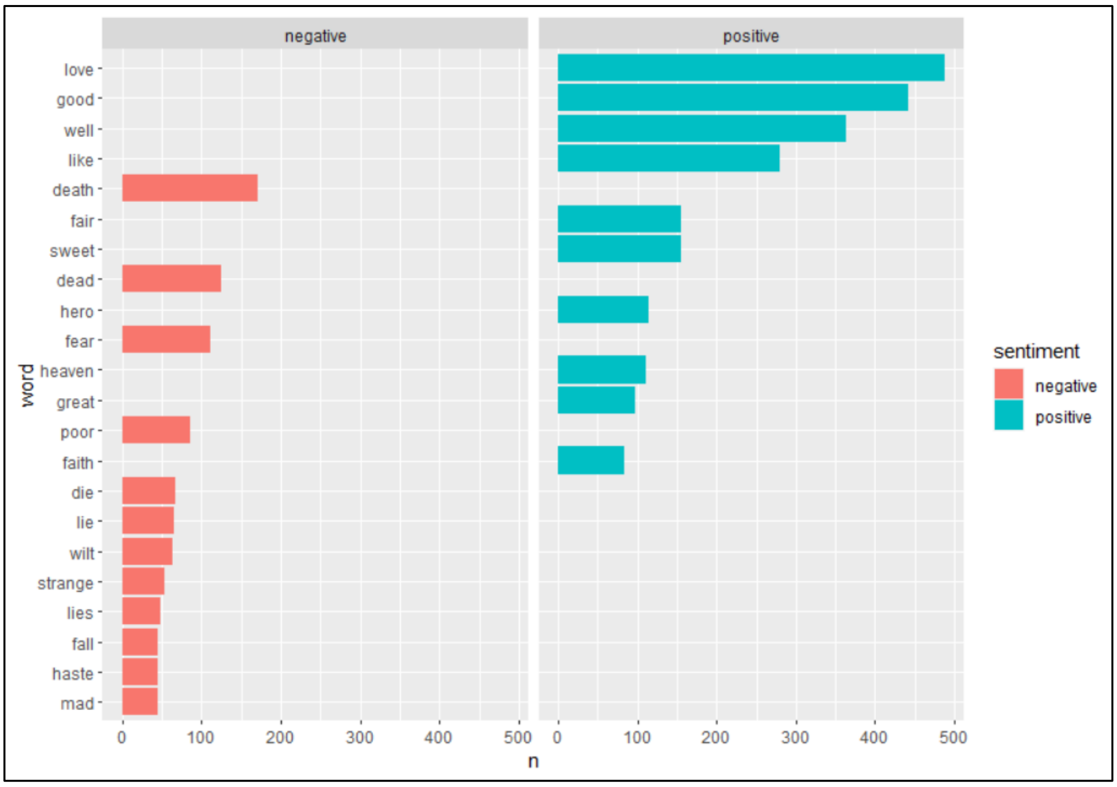
Code:

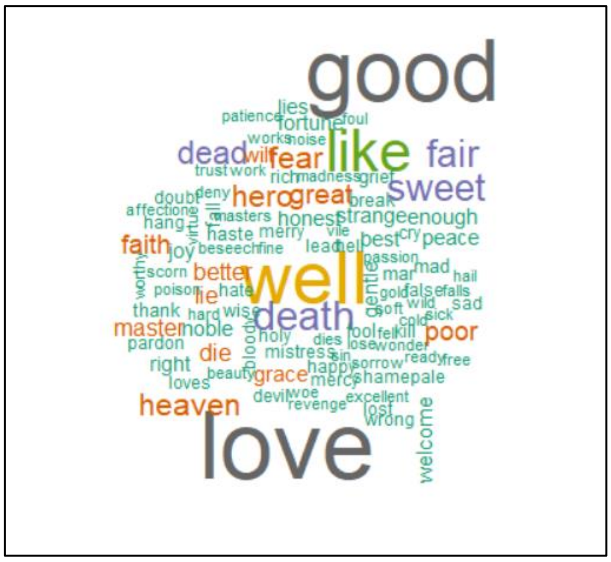
```
#TEXT ALANYTICS ON SHAKESPEARE
#1. load shakespeare.rda into r environment
load("D:\\Sem6\\DVP\\ELA\\Assessment4\\shakespeare.rda")
glimpse(shakespeare)
#2. Pipe the shakespeare data frame to the next line
# Use count to find out how many titles/types there are
shakespeare %>%
  count(title, type)

#3. Load tidytext/ tidyverse
library(tidytext)
library(dplyr)
library(tidyverse)
#4. create an object tidy_shakespeare
# Group by the titles of the plays
# Define a new column line number
# Transform the non-tidy text data to tidy text data
tidy_shakespeare <- shakespeare %>%
  group_by(title) %>%
  mutate(linenumber = row_number()) %>%
  unnest_tokens(word, text) %>%
  ungroup()

#5. Pipe the tidy Shakespeare data frame to the next line
# Use count to find out how many times each word is used
tidy_shakespeare %>%
  count(word, sort = TRUE)

#6. Sentiment analysis of tidy_shakespeare assign to object shakespeare_sentiment
# Implement sentiment analysis with the "bing" lexicon
shakespeare_sentiment <- tidy_shakespeare %>%
  inner_join(get_sentiments("bing"),by="word")
#7. shakespeare_sentiment
# Find how many positive/negative words each play has
shakespeare_sentiment %>%
  count(title, sentiment)

#8. Tragedy or comedy from tidy_shakespeare  assign to sentiment_counts
# Implement sentiment analysis using the "bing" lexicon
# Count the number of words by title, type, and sentiment
sentiment_counts <- tidy_shakespeare %>%
  inner_join(get_sentiments("bing")) %>%
  count(word, title, sentiment)

#9. from sentiment_counts
# Group by the titles of the plays
# Find the total number of words in each play
# Calculate the number of words divided by the total
# Filter the results for only negative sentiment then arrange percentages in ASC order
sentiment_counts %>%
  group_by(title) %>%
  mutate(total = sum(n),
         percent = n / total) %>%
  filter(sentiment == "negative") %>%
  arrange(percent)

#10 Most common positive and negative words and assign to word_could
```

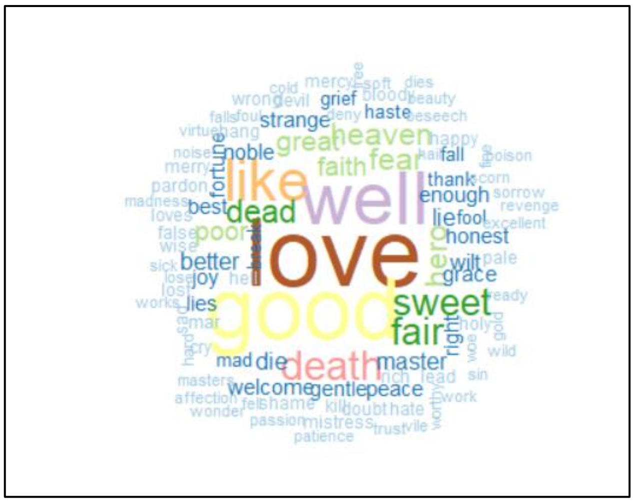
```
# Implement sentiment analysis using the "bing" lexicon
# Count by word and sentiment
word_count <- tidy_shakespeare %>%
  inner_join(get_sentiments("bing"), by = "word") %>%
  count(word, sentiment, sort = TRUE)
word_count1 <- select(word_count,1,3)
word_count1
colnames(word_count1) <- c("word","freq")
#install.packages("wordcloud2")
library(wordcloud2)
wordcloud2(data=word_count1, size=1.4, color='random-dark')



#11. extract the top 10 words from word_counts and assign to top_words
# Group by sentiment
# Take the top 10 for each sentiment and ungroup it
# Make word a factor in order of n
top_words <- word_count %>%
  group_by(sentiment) %>%
  top_n(10, n) %>%
  ungroup() %>%
  mutate(word = factor(word, levels = rev(unique(word))))



#12 Use aes() to put words on the x-axis and n on the y-axis
# Make a bar chart with geom_col()
# facet_wrap for sentiments and apply scales  as free
#Move x to y and y to x
library(ggplot2)
ggplot(top_words, aes(x = n, y = word, fill = sentiment)) +
  geom_col() +
  facet_wrap(vars(sentiment))

install.packages("wordcloud")
library(wordcloud)
top_words
set.seed(100)
top_words <- word_count %>%
  group_by(sentiment) %>%
  top_n(50, n) %>%
  ungroup() %>%
  mutate(word = factor(word, levels = rev(unique(word))))
wordcloud(words = top_words$word, freq = top_words$n, random.order = TRUE,
        colors = brewer.pal(8,"Dark2"))
wordcloud(words = top_words$word, freq = top_words$n, random.order = FALSE,
        colors = brewer.pal(12,"Paired"))
```

Output:




negative
positive
word
love
good
well
like
death
fair
sweet
dead
hero
fear
heaven
great
poor
faith
die
lie
wilt
strange
lies
fall
haste
mad
0
100
200
300
400
500
n
sentiment
negative
positive





Result:

We successfully performed text analytics on Shakespeare's plays using R. Sentiment analysis is performed on the tidy data using the "bing" lexicon. The code also extracts the most common positive and negative words and creates a bar chart and a word cloud for the top words. The final result shows the percentage of negative words in each play and arranges them in ascending order.

Exercise Number – 4

Time Series Analysis

Q4. Time Series Analysis on the AirPassengers dataset

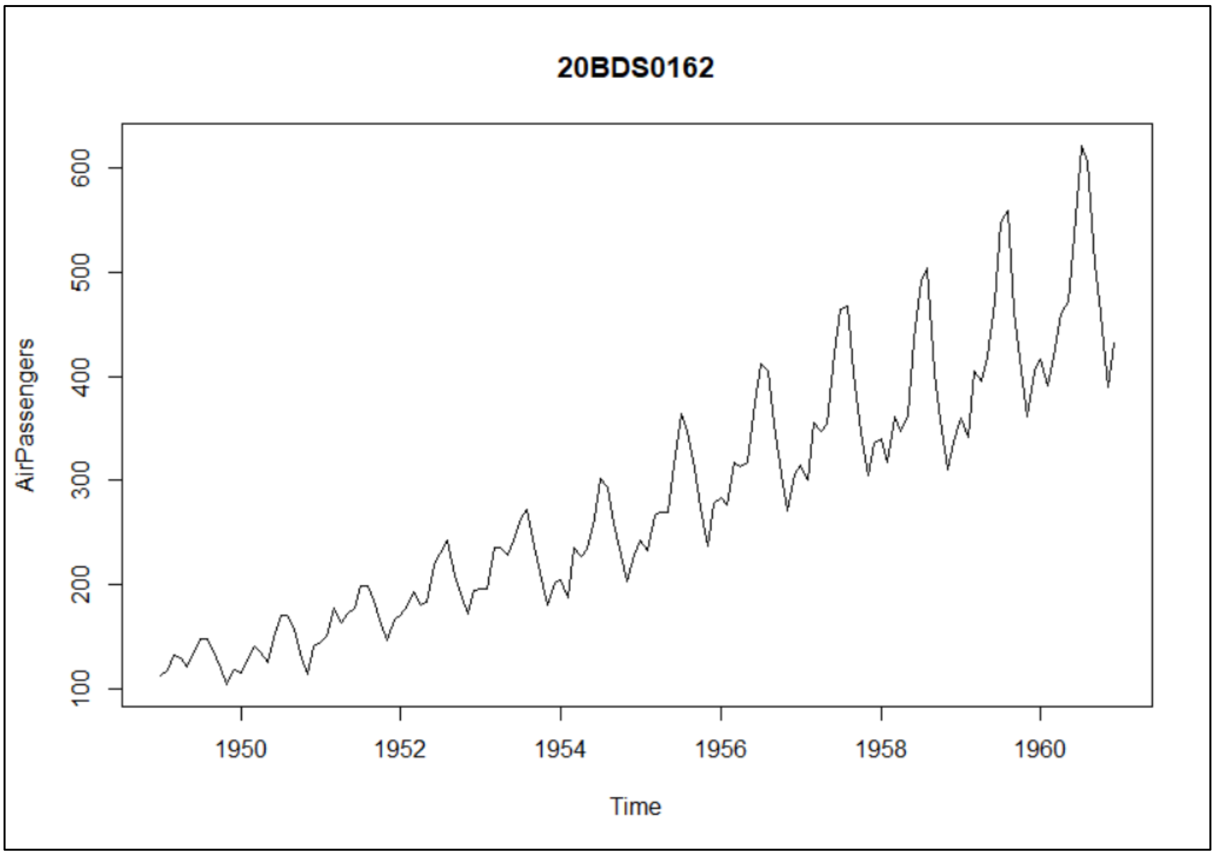
Aim: To perform time series analysis for AirPassengers dataset in R and predict the values for the next 10 years

Code:

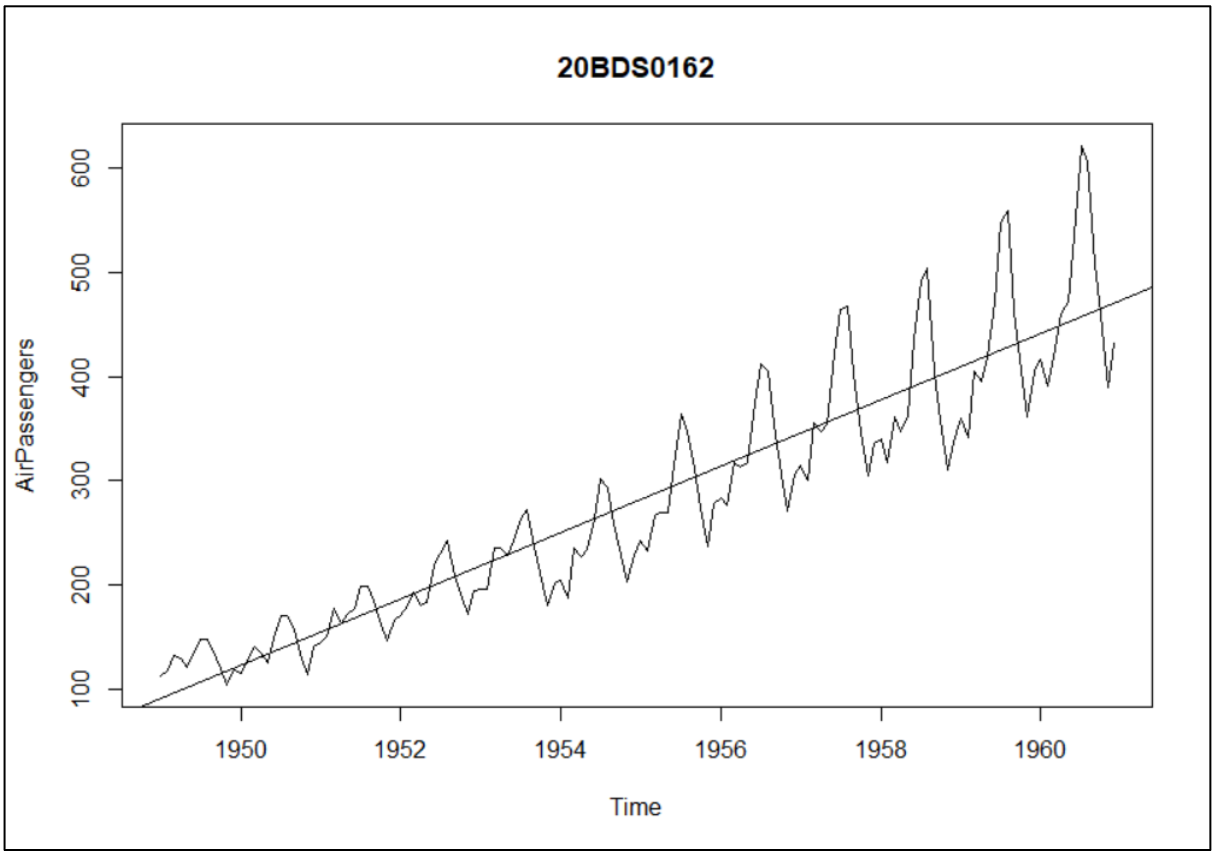
```
data("AirPassengers")
AirPassengers

str(AirPassengers)
class(AirPassengers)
sum(is.na(AirPassengers))

start(AirPassengers)
end(AirPassengers)

frequency(AirPassengers)

summary(AirPassengers)

plot.ts(AirPassengers, main = "20BDS0162")
abline(reg =
    lm(AirPassengers~time(AirPassengers)), main = "20BDS0162")
cycle(AirPassengers)

#Make the data is Stationary
#1. Mean should be constant to time
#2. Var should be equal
#3. Cor should be equal

par(mfrow=c(3,3))
```

```
plot(AirPassengers)

plot(log(AirPassengers)) #var to be equal

plot(diff(log(AirPassengers))) #Check for Mean - Constant


#Trend

plot(aggregate(AirPassengers, FUN=mean))

boxplot(AirPassengers~cycle(AirPassengers))

plot(decompose(AirPassengers))


#Model Identification and Estimation

# AR I MA

# p  d  q

acf(AirPassengers, main = "Series AirPassenegers 20BDS0162")

acf(log(AirPassengers),main = "Series log(AirPassengers) 20BDS0162")

acf(diff(log(AirPassengers)), main = "Series diff(log(AirPassengers)) 20BDS0162")#q=1

pacf(diff(log(AirPassengers)), main = "Series diff(log(AirPassengers)) 20BDS0162")#p=0

#d = 1


fit <- arima(log(AirPassengers),

        order = c(0, 1, 1),

        seasonal = list(order = c(0, 1, 1),

                  period = 12))

fit

pred<- predict(fit, n.ahead = 10*12)

pred1<-round(2.718^pred$pred,0)

ts.plot(AirPassengers, pred1,   log="y", lty=c(1,3), main = "Predicted Values 20BDS0162")
```

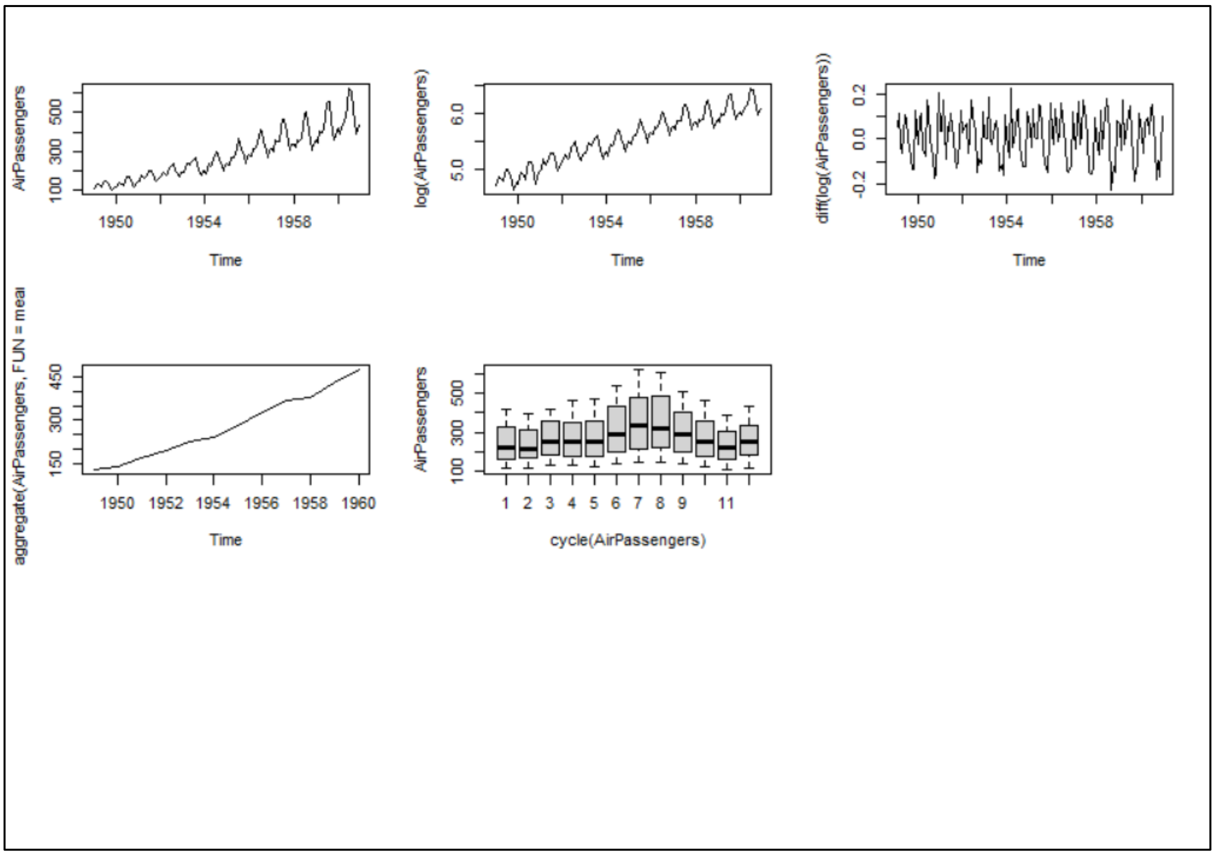
Output:



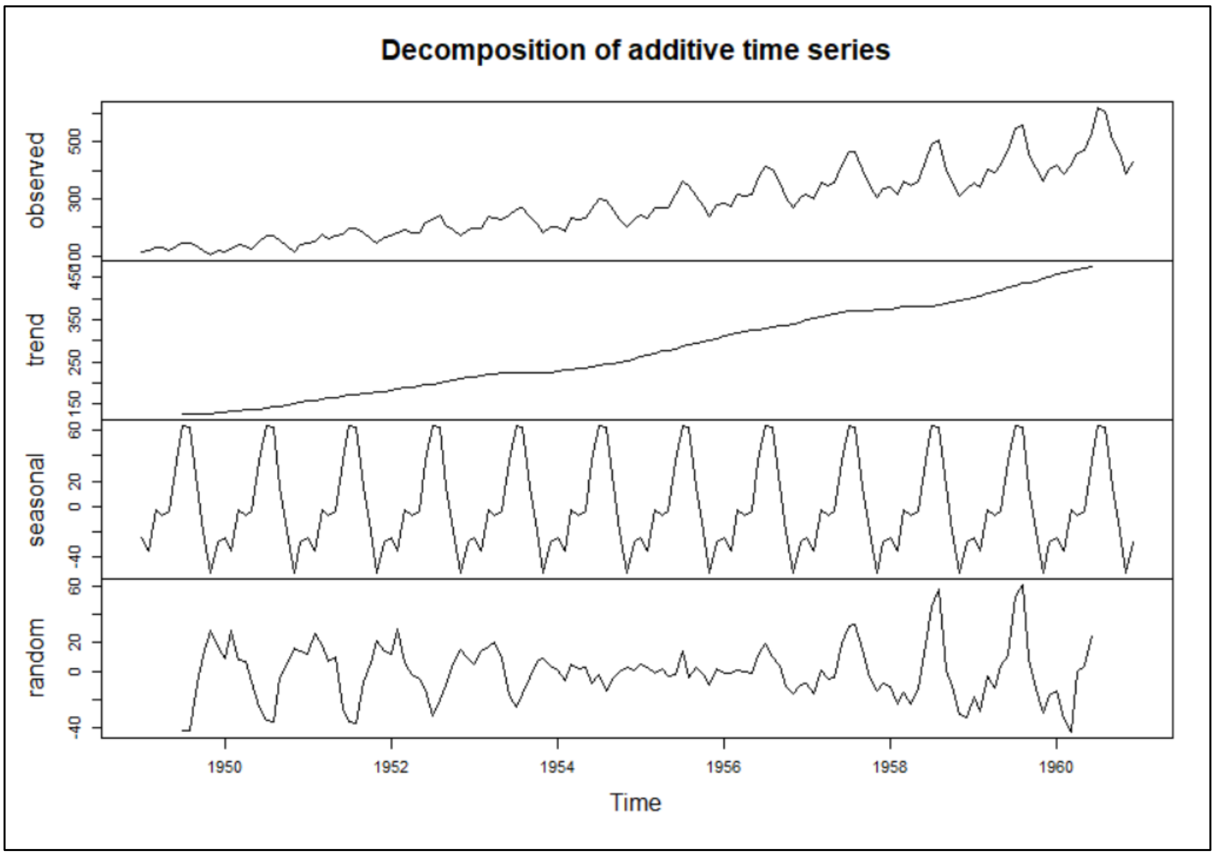
20BDS0162
AirPassengers
100
200
300
400
500
600
1950
1952
1954
1956
1958
1960
Time



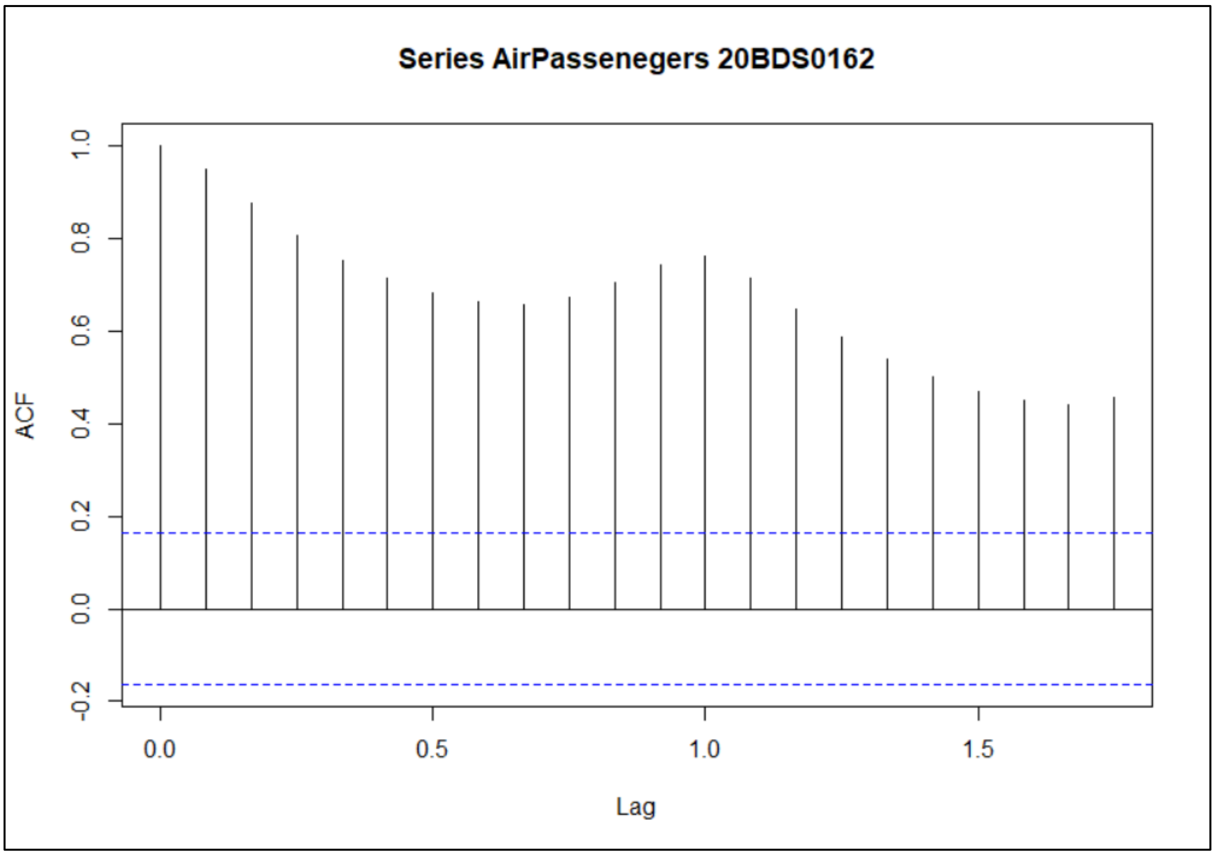
20BDS0162
AirPassengers
100
200
300
400
500
600
1950
1952
1954
1956
1958
1960
Time

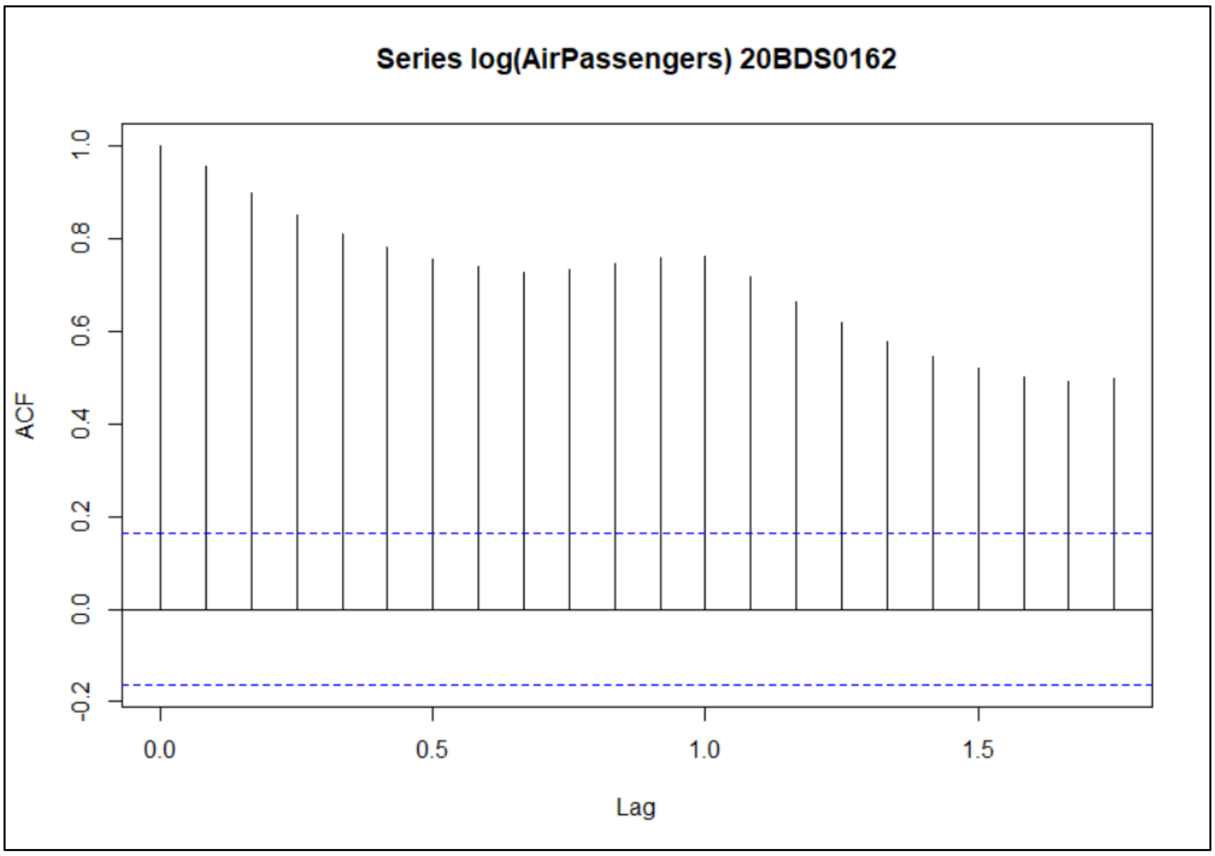


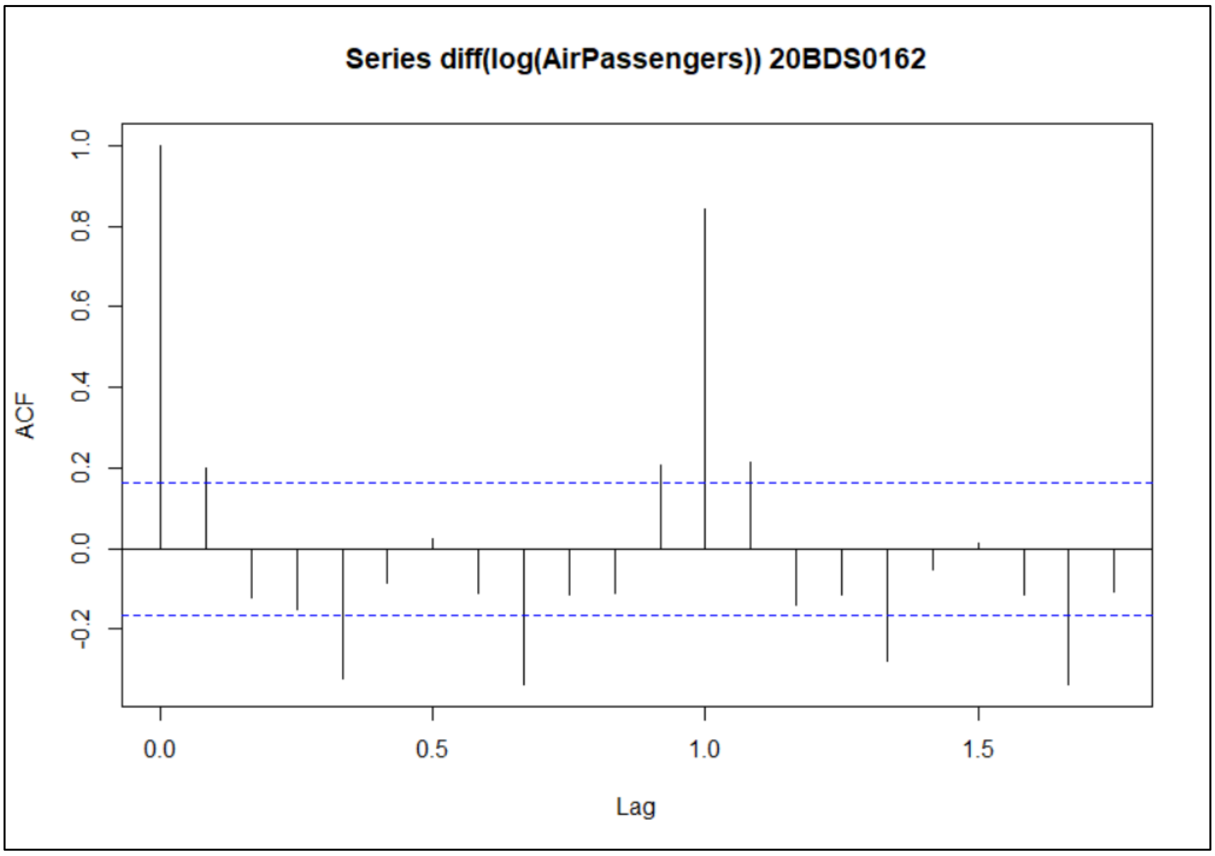
AirPassengers
log(AirPassengers)
diff(log(AirPassengers))
aggregate(AirPassengers, FUN = mean)
AirPassengers
cycle(AirPassengers)
Time

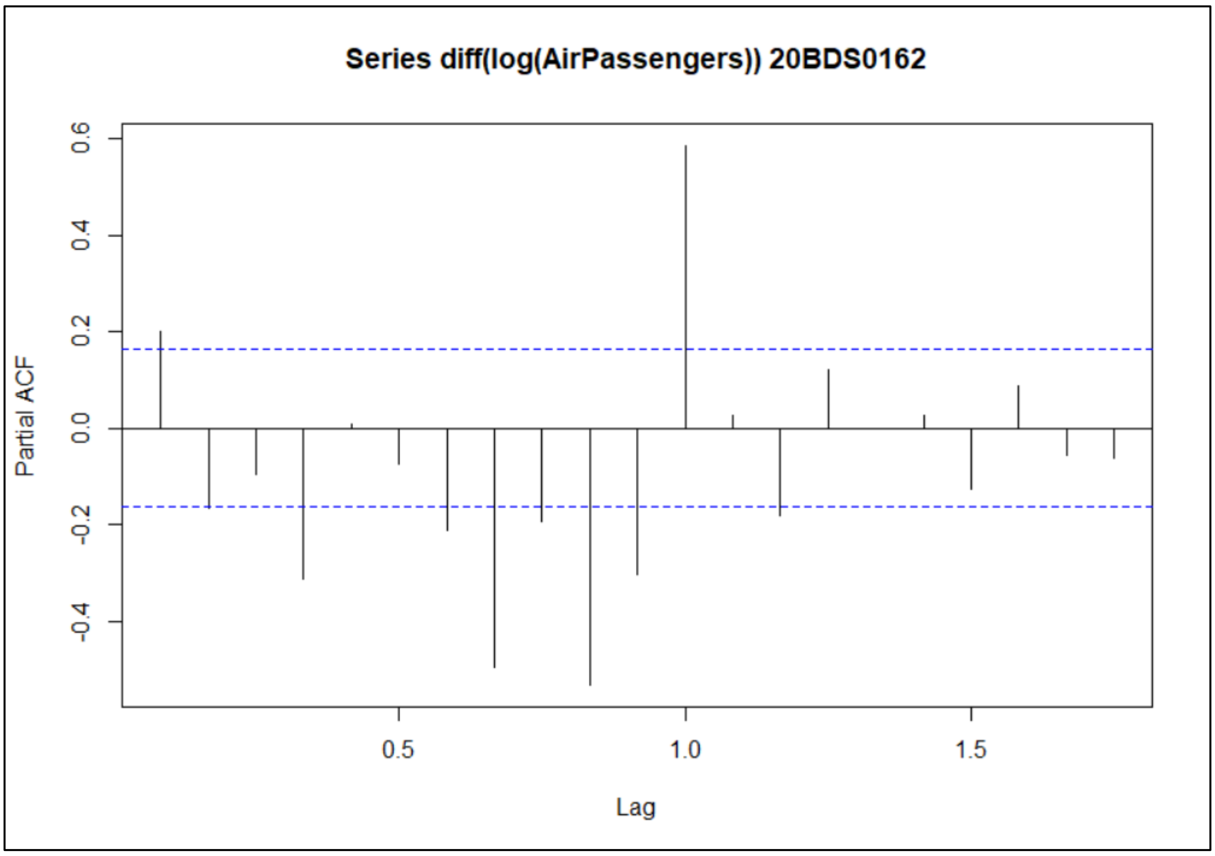


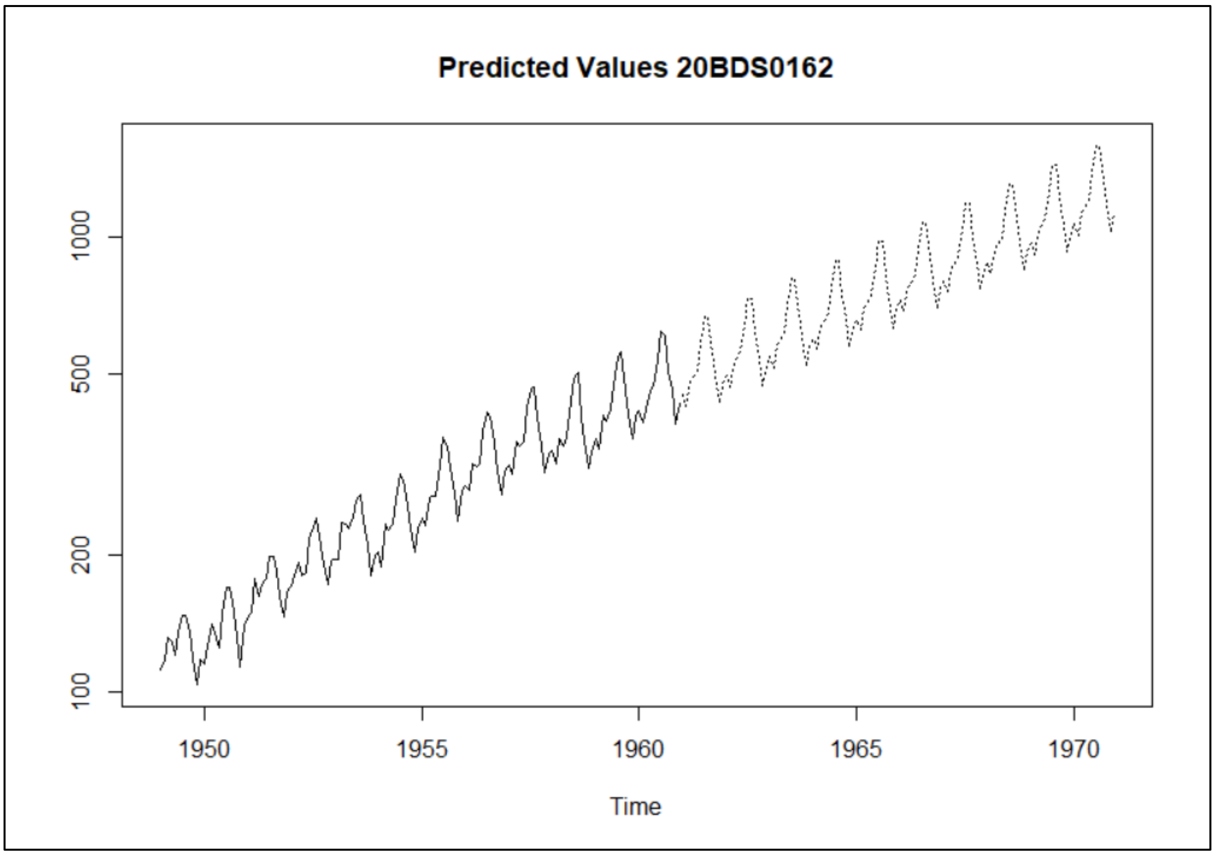
Decomposition of additive time series
observed
trend
seasonal
random
Time


Series AirPassenegers 20BDS0162
ACF
Lag
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
0.0
0.5
1.0
1.5


Series log(AirPassengers) 20BDS0162
ACF
Lag
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
0.0
0.5
1.0
1.5


Series diff(log(AirPassengers)) 20BDS0162
ACF
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
0.0
0.5
1.0
1.5
Lag


Series diff(log(AirPassengers)) 20BDS0162
Partial ACF
0.6
0.4
0.2
0.0
-0.2
-0.4
0.5
1.0
1.5
Lag



Result:

We successfully performed time series analysis for the AirPassengers dataset in R. We used the ARIMA model for the prediction and fitted the model to the dataset. The fitted model is used to make predictions for the next 10 years and finally plotted the predicted values graph.

Exercise Number – 5

Dashboard in R

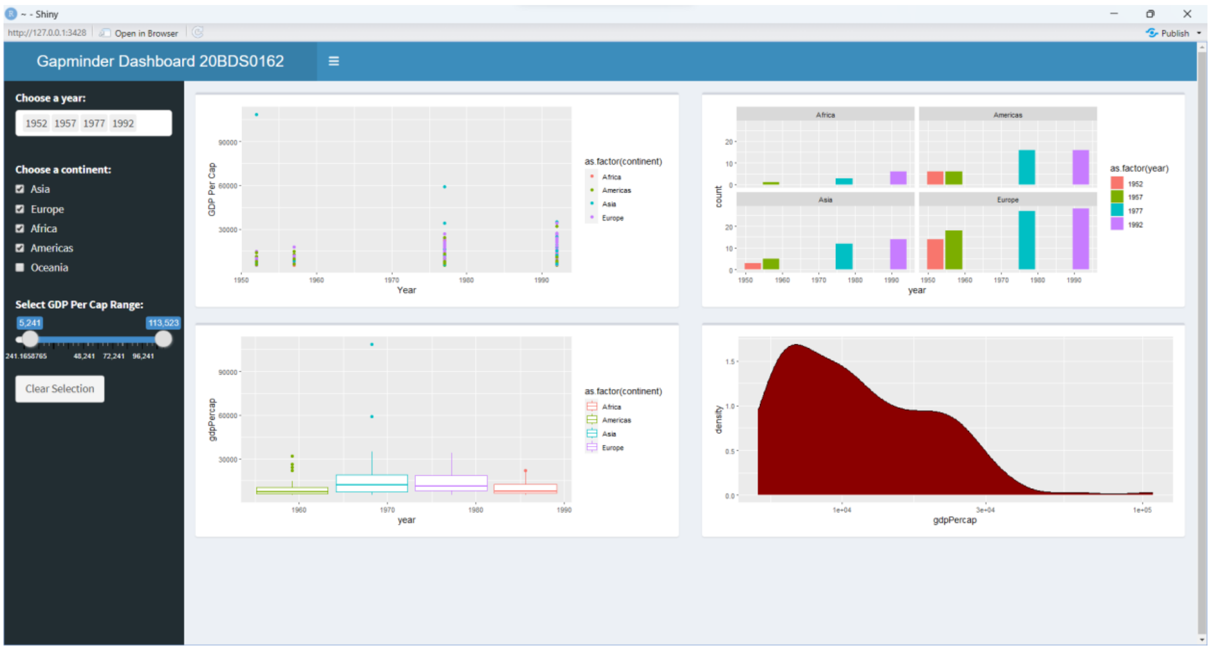
Q5. Create a Simple dashboard using Shiny.

Aim: To create a simple dashboard in R using the Shiny library on the gapminder dataset

Code:

```
library(shiny)

library(shinydashboard)

library(datasets)

library(ggplot2)

library(dplyr)

library(gapminder)


data = gapminder

View(data)


ui <- dashboardPage(
  dashboardHeader(title = "Gapminder Dashboard 20BDS0162",titleWidth = 400),
  dashboardSidebar(
    selectInput("year", "Choose a year:", choices = unique(data$year), multiple = TRUE, selected = "1952"),
    checkboxGroupInput("continent", "Choose a continent:", choices = c(unique(data$continent)),selected = "Asia"),
    sliderInput("gdpPercap", "Select GDP Per Cap Range:", min = min(data$gdpPercap), max = max(data$gdpPercap), value = c(241.1658765,113523)),
    actionButton("clear_button", "Clear Selection")
  ),
  dashboardBody(
    fluidRow(
      box(plotOutput("plot1", height = 250)),
      box(plotOutput("plot2", height = 250)),
      box(plotOutput("plot3", height = 250)),
      box(plotOutput("plot4", height = 250))
    )
  )
)

server <- function(input, output,session) {
  filter_data <- reactive({
    data %>% filter(gdpPercap >= input$gdpPercap[1] & gdpPercap <= input$gdpPercap[2]) %>%
      filter(continent %in% input$continent) %>%
      filter(year %in% input$year)
  })
  output$plot1 <- renderPlot({
    ggplot(filter_data(), aes(
      x = year,
      y = gdpPercap,
      color = as.factor(continent)))+
      geom_point() + labs(x = "Year", y = "GDP Per Cap")
  })
  output$plot2 <- renderPlot({
    ggplot(filter_data(), aes(
      x = year, fill = as.factor(year)))+
      geom_bar() + facet_wrap(~continent) +
     scale_x_log10()
  })
  output$plot3 <- renderPlot({
    ggplot(filter_data(), aes(
      x = year, y = gdpPercap,
      color = as.factor(continent)))+
      geom_boxplot()
  })
  output$plot4 <- renderPlot({
    ggplot(filter_data(), aes(
      x = gdpPercap))+
      geom_density(fill = "darkred")+scale_x_log10()
  })
  observeEvent(input$clear_button, {
    updateSelectInput(session, "year", selected = "1952")
    updateRadioButtons(session, "continent", selected = "Asia")
    updateSliderInput(session, "gdpPercap", value = c(241.1658765,113523))
  })
}
shinyApp(ui, server)
```

Output:



Gapminder Dashboard 20BDS0162

Choose a year: 1952 1957 1977 1992

Choose a continent:
- ☑ Asia
- ☑ Europe
- ☑ Africa
- ☑ Americas
- ☐ Oceania

Select GDP Per Cap Range: 5,241 – 113,523

Clear Selection

Result:

Successfully created a straightforward dashboard in R using the Shiny package on the gapminder dataset. The dashboard gives the option to the user to select multiple years and continents and also the range of GDP Per Cap. Also, a clear selection button is there to reset the values to default. The dashboard has totally 4 graphs.