**# Perform the below given activities:**

**# a. Take Apple Stock Prices from Yahoo Finance for last 90 days**

**# b. Predict the Stock closing prices for next 15 days.**

**# c. Submit your accuracy**

**# d. After 15 days again collect the data and compare with your forecast**

getwd()

setwd("E:\\R\\Assignment\\Assignment 23")

**# import Apple stock price data**

df <- read.csv("E:/R/Assignment/Assignment 23/AAPL.csv")

head(df)

str(df)

View(df)

df$Date <- as.Date(df$Date)

data = ts(df$Close)

test = data[62:73]

data = data[1:61]

plot(data, main= "Daily Close Price")

data = ts(df$Close, frequency = 365)

plot(data, main = "Daily Close Price")

decompose(data)

decompose(data, type = "multi")

par(mfrow=c(1,2))

plot(decompose(data, type = "multi"))

**# creating seasonal forecast**

library(forecast)

par(mfrow=c(1.1))

seasonplot(data)

**# lags**

lag(data,10)

lag.plot(data)

**# Partial auto correlation**

pac <- pacf(data)

pac$acf

**# Auto correlation**

ac <- acf(data)

ac$acf

**# looking at ACF and PACF graph it is clear that the time series is not stationary**

model <- lm(data ~ c(1:length(data)))

summary(model)

plot(resid(model), type = 'l')

accuracy(model)

**# deseasonlise the time series**

tbl <- stl(data, 'periodic')

stab <- seasadj(tbl)

seasonplot(stab, 12)

**# unit root for stationarity**

**# The Augmented Dicky Fuller Test**

library(tseries)

adf.test(data)

**# P value is greater than 0.05 , hence we fail to reject the null hypo**

**# there is unit root in time series hence the time series is not stationary**

**# Automatic ARIMA Model**

model2 <- auto.arima(data)

model2

plot(forecast(model2, h=12))

accuracy(model2)

**# running model on diff data**

**# difference method to smoothen the data with lag = 5**

adf.test(diff(data, lag = 5))

plot(diff(data, lag = 5))

model3 <- auto.arima(diff(data, lag = 5))

accuracy(model3)

acf(diff(data, lag = 5))

pacf(diff(data, lag = 5))

**# taking random order**

model4 <- Arima(diff(data, lag = 5), order = c(4,0,5))

model4

accuracy(model4)

plot(forecast(model4, h=12))

**# taking random order**

model5 <- Arima(diff(data, lag = 5), order = c(4,0,4))

model5

accuracy(model5)

plot(forecast(model5, h=12))

**# taking random order**

model6 <- Arima(diff(data, lag = 5), order = c(3,0,5))

model6

accuracy(model6)

plot(forecast(model6, h=12))

**# taking random order**

model7 <- Arima(diff(data, lag = 5), order = c(0,0,1))

model7

accuracy(model7)

plot(forecast(model7, h=12))

**# taking random order**

model8 <- Arima(diff(data, lag = 5), order = c(1,0,0))

model8

accuracy(model8)

plot(forecast(model8, h=12))

**# Holt Winters Exponential Smoothing Model**

model9 <- HoltWinters(data, gamma = F)

summary(model9)

plot(forecast(model9, h=12))

accuracy(forecast(model9, h=12))

**# ETS**

model10 <- ets(data)

summary(model10)

plot(forecast(model10, h=12))

accuracy(forecast(model10, h=12))

**# model2 ( Automatic ARIMA) is most accurate with MAPE**

**# Making predictions for next 15 days**

predicted <- forecast(model2, 15)

**# comparing data with forecast**

predicted$residuals[62:73]