# 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:\\Acadgild\\Class 12\\Assignment")

# import Apple stock price data

df <- read.csv("E:/Acadgild/Class 12/Assignment/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 for

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 1.15

#---------------------------------------------------------------

# Making predictions for next 15 days

predicted <- forecast(model2, 15)

# comparing data with forecast

predicted$residuals[62:73]

#-------------------------------------------------------------------