Apple company revenue 2005-2020

Time series analysis stat 454

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Introduction

This action research study examines Apple quarterly revenue history and growth rate from 2006 to 2020 Apple Inc. is engaged in designing, manufacturing, and marketing mobile communication and media

devices, personal computers, and portable digital music players. The Company's products and services include iPhone, iPad, Mac, iPod, Apple TV, a portfolio of consumer and professional software applications, the iOS and Mac OS X operating systems, iCloud, and a range of accessory, service and support offerings. It sells its products worldwide through its online stores, its retail stores, its direct sales force, third-party wholesalers, and resellers.

Research goal

our goal is to Forecast Apple's revenue in the coming years to strive for determining whether goals are being met and make adjustments operational for excellence and gain a competitive advantage

Data

Description of the data

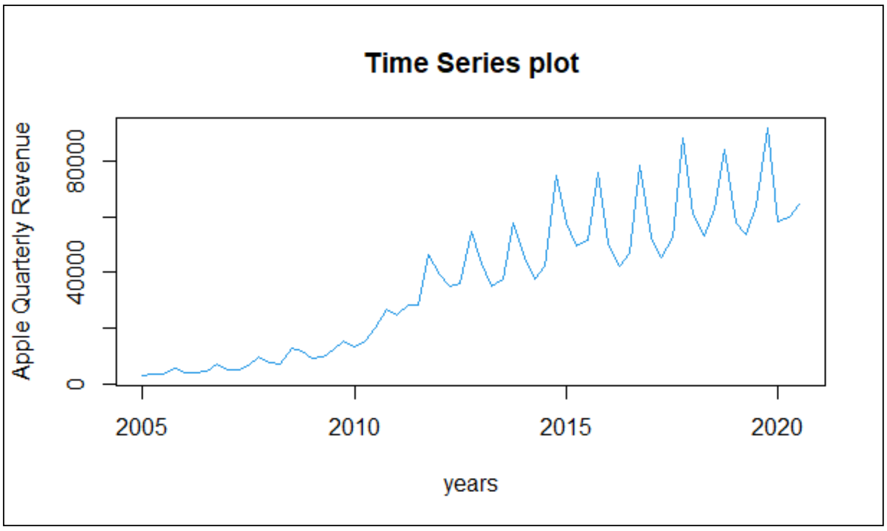
This dataset is Apple quarterly revenue history and growth rate from 2005 to 2020. Revenue can be defined as the amount of money a company receives from its customers in exchange for the sales of goods or services

Data

This table shows Apple's quarterly revenue (in millions of US dollars)

	Months			
Years	**3**	**6**	**9**	**12**
2005	3243	3520	3678	5749
2006	4359	4370	4837	7115
2007	5264	5410	6789	9608
2008	7512	7464	12907	11880
2009	9084	9734	12207	15683
2010	13499	15700	20343	26741
2011	24667	28571	28270	46333
2012	39186	35023	35966	54512
2013	43603	35323	37472	57594
2014	45646	37432	42123	74599
2015	58010	49605	51501	78351
2016	50557	42358	46852	88293
2017	52896	45408	52579	84310
2018	61137	53265	62900	84310
2019	58015	53809	64040	91819
2020	58313	59685	64698	

data analysis



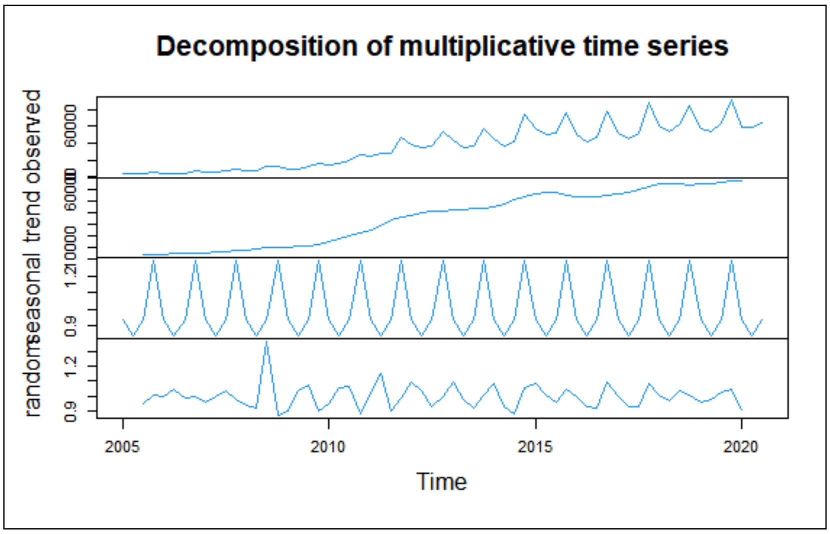
Time series plot:

features of the plot: There is a positive trend,

seasonal variation increases as we move across time.

there is no obvious outliers

because as shown in the time series plot seasonal variation increases as we move across time we use multiplicative Decompositions



the graph shows that the data have

,upward trend

,seasonal fluctuations

.and random residuals

After we see the multiplicative Decompositions plot we estimate the trend by using the moving average and after at we de-trend the series after de trend the series we use kruskal Wallis test to test if seasonality exist or not

kruskal Wallis test

H_0: Seasonality doesn't exist H_1: Seasonality exist

Test used: Kruskall Wallis

Test statistic: 43.43 P-value: 1.995826e-09

Reject the null hypotheses ,the Seasonality exist

After we check seasonality exist now we find seasonal factor

Qtr1	Qtr2	Qtr3	Qtr4
0.94	0.84	0.93	1.29
Decreasing seasonal	Decreasing seasonal	Decreasing seasonal	Increasing seasonal

Stationary test

We use acf plot and Augmented Dickey-Fuller Test (adf) to test if our data is Stationary our not

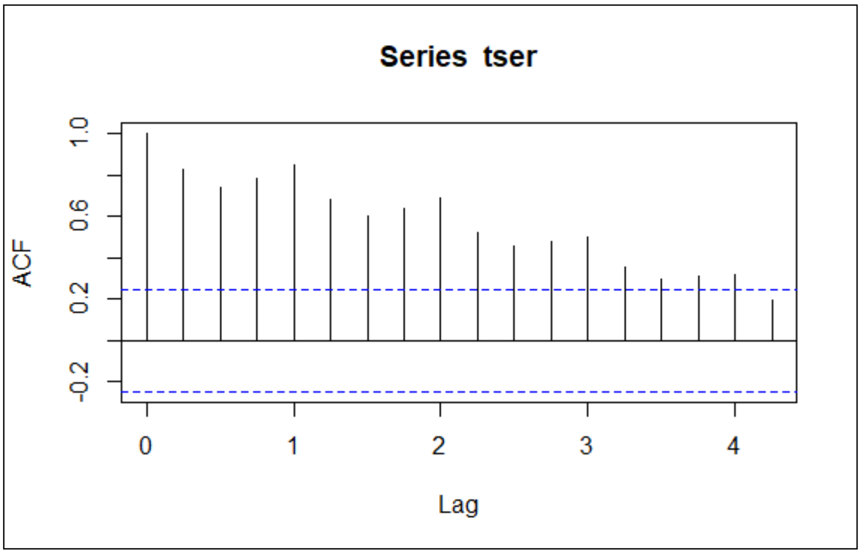
Augmented Dickey-Fuller Test (adf):

$$H_0\text{:}non\text{–}Stationary\ series \quad H_1\text{:Stationary}series$$

Test used: Augmented Dickey-Fuller Test

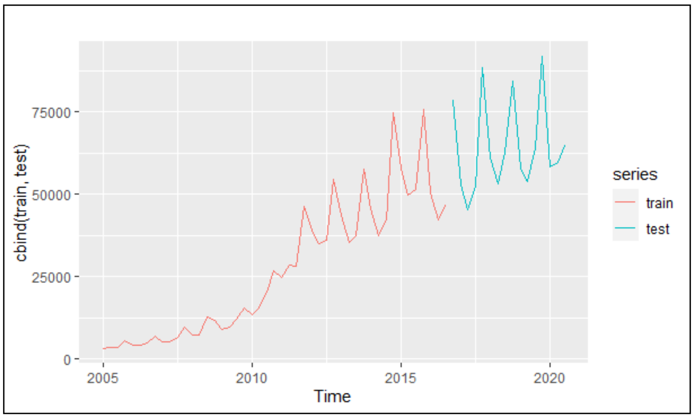
Dickey-Fuller = -1.029 P-value: 0.9263 > 0.05

Don't Reject the null hypotheses ,the series is non-Stationary series



Ass we see in the acf plot to test Stationary ACF is decreasing, very slowly, and remains above the significance range This is indicative of a non-stationary series

Because our time series is not stationary series we use differences method to Transform our time series to stationary time series we use first deferent and deferent in lag 4 because our data is quarterly.

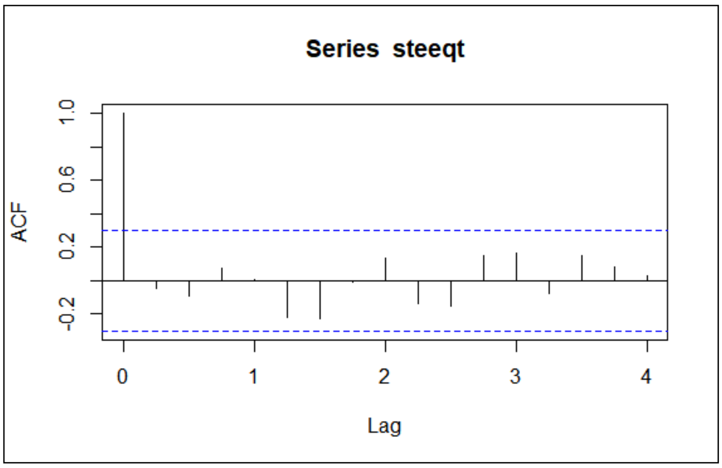


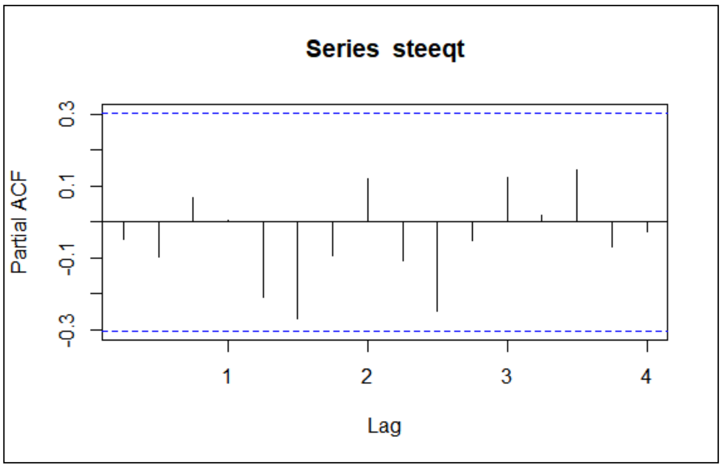
Splitting the data into training and testing

75% training =47 observation

25% testing =16 observation

Transform the training data into Stationary time series using first difference





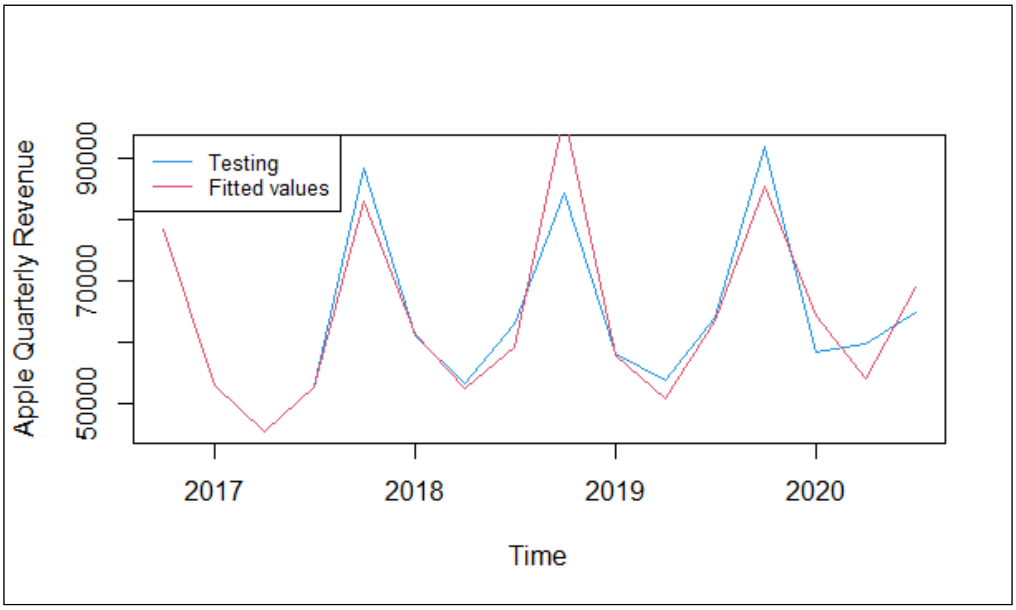
The bast model using ARIMA

Series : train							
ARIMA(1,0,0)(0,1,0)[4]							
Coefficients :							
	Ar1						
	0.8330						
S.e.	0.0771						
sigma^2	estimated as	15665764: log	likelihood=-417.29				
AIC=838.58	AICc=838.88	BIC=842.1					
Training	**set error**	**measures:**					
	ME	RMSE	MAR	MPE	MAPE	MASE	ACF1
Training set	616.2358	3741.55	2370.915	3.294642	8.998999	0.4255923	0.0228843

From the results in the table The bast model is ARIMA $(1,0,0)(0,1,0)_4$:

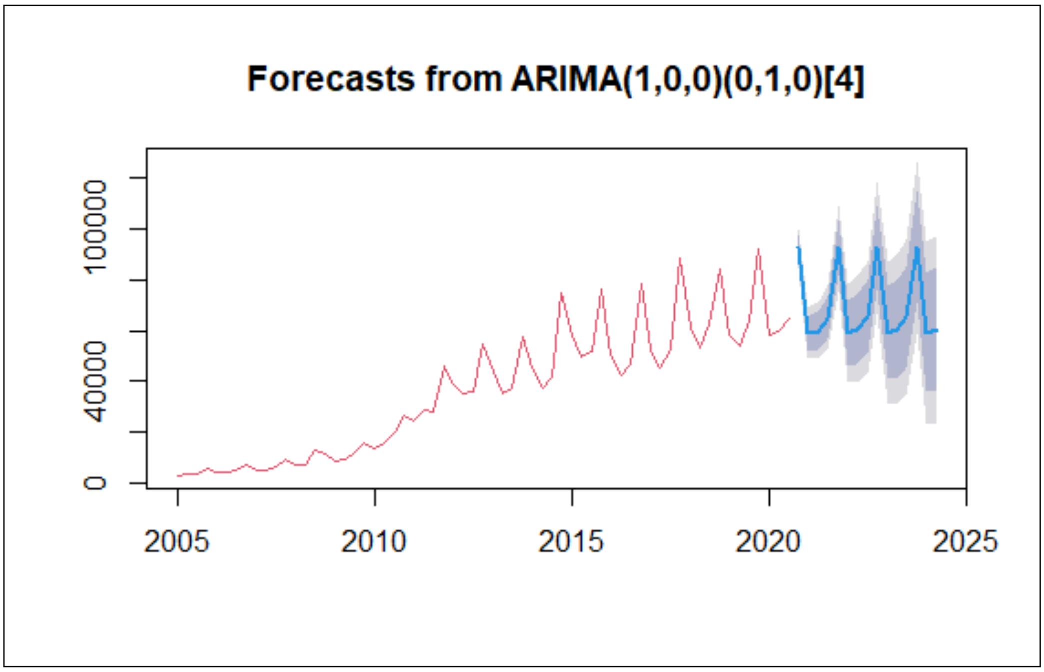
$$\phi_0(B^s)\varnothing_1(B)(1-B)^0(1-B^4)^3 x_t = \theta_0(B)\theta_0(B^4)\varepsilon_t$$

Model Validation using testing data to test the optimal statistical model:



The fitted value is very close to the test data, which means the model is suitable

Forecasting 15 future value



The value increases as we move across time

Point		Forecast	Lo 80	Hi 80	Lo 95	Hi 95
2020	Q4	92367.08	87294.70	97439.46	84609.54	100124.62
2021	Q1	58769.53	52168.01	65371.04	48673.37	68865.68
2021	Q2	60065.25	52584.27	67546.25	48624.08	71506.45
2021	Q3	65014.74	56979.93	73049.55	52726.56	77302.92
2021	Q4	92630.91	81630.03	103631.79	75806.52	109455.30
2022	Q1	58989.28	46332.56	71646.00	39632.50	78346.06
2022	Q2	60248.31	46559.95	73936.67	39313.77	81182.85
2022	Q3	65167.21	50806.57	79527.85	43204.51	87129.91
2022	Q4	92757.91	75972.98	109542.84	67087.58	118428.24
2023	Q1	59095.07	40816.10	77374.03	31139.81	87050.33

References

- Data

Appendices

R code

```
library(readxl)

aqr <- read_excel("C:/Users/Gh255/OneDrive/المستندات/STAT454/Apple Quarterly
Revenue.xlsx")

View(aqr)

str(aqr)

#data as time series

tser=ts(data=aqr$Revenue,start =c(2005,1),end =c(2020,3) ,frequency = 4);tser

#time series plot

plot.ts(tser,xlab=" Time ",ylab="Apple Quarterly Revenue",main="Time Series
plot",col=4)

#Trend regression model

rl=lm(tser~time(tser));rl

summary(rl)

#Plotting Trend regression line with the fitted line

plot(tser,xlab="Time ",ylab="Apple Quarterly Revenue",main="Trend regression line
```

```
with fitted line",col=3) abline(rl,col=2)

#Residual Analysis

plot(rl$fitted.values,rl$residuals,main="Residual Plot",col=4)

abline(h=0,col=2,lty=1)

#Normal probability plot (Q-Q plot)

qqnorm(rl$residuals,pch=20, col=4)

qqline(rl$residuals)

#Calculate MSE

mse=(sum((rl$residuals)^2)/length(tser));mse

anova(rl)


#Decomposition

de=decompose(tser, type ="multiplicative")

de

plot(de,col=4)

#Moving average smoothing

library(forecast)

movingA=ma(tser, order=4 , centre=TRUE)

movingA

plot(tser,xlab=" Time ",ylab="Apple Quarterly Revenue",col=4)

lines(movingA , lwd=2 , col=3)

legend("topleft",col=c(4,3),legend=c('Time series','Moving average'),lty=1)

# De-trend with moving averages
```

```
ma=rollmean(tser,4);ma

# since the type ="multiplicative"

detrend=tser/ma

detrend

plot(detrend,xlab="Time ",ylab="Apple Quarterly Revenue",main="De-trend

plot",col=4) # Test for seasonality( Kruskall -Wallis Test)

library(seastests)

amsetest=kw(tser)

amsetest

summary(amsetest)

# Seasonal Factor

detser=decompose(tser, type ="multiplicative")

detser

round(detser$seasonal,digits=2)

#stationary test

library("tseries")

adf.test(tser)

acf(tser)

# Stationarize the series using differencing

stationary=diff(diff(tser,1),4);stationary

plot(tser,xlab="Time",ylab="Apple Quarterly Revenue ",col=4 ,ylim=c(1000,65000))
```

```
lines(stationary, lwd=3, col=3) legend("topleft",col=c(4,3),legend=c('non-
stationary','stationary'),lty=1) #stationary plot

stationary=diff(diff(tser,1),4)

plot(stationary,col=3) legend("topleft",col=c(3),legend=c('stationary'),lty=1)

# split the data into 75% training and 25% testing

library(forecast)

train=head(tser,round(length(tser)*0.75));train

h=length(tser) - length(train)

h

test=tail(tser,h);test

autoplot(cbind(train, test))

#Transform the data into Stationary time series using first difference

steeqt=diff(diff(train,1),4)

plot(steeqt,xlab="Time",ylab="Apple Quarterly Revenue",col=7) acf(steeqt)

pacf(steeqt)

#The best Model using ARIMA

u=auto.arima(train);u

#Model Validation

fv=Arima(test,model = u)

w=fv$fitted

w

fv$residuals
```

```
plot(test, xlab="Time",ylab="Apple Quarterly Revenue",col=4) lines(w,col=2)

legend("topleft",col=c(4,2),legend=c('Testing','Fitted values'),lty=1) #Forecasting
Future Values

fv1=Arima(tser,model = u);summary(fv1)

future = forecast(fv1, h = 10) # 10 observation

future

plot(future,col=2)
```