ARMA Model

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Introduction

An ARMA model, or Autoregressive Moving Average model, is used to describe weakly stationary stochastic time series in terms of two polynomials.
The first of these polynomials is for autoregression, the second for the moving average

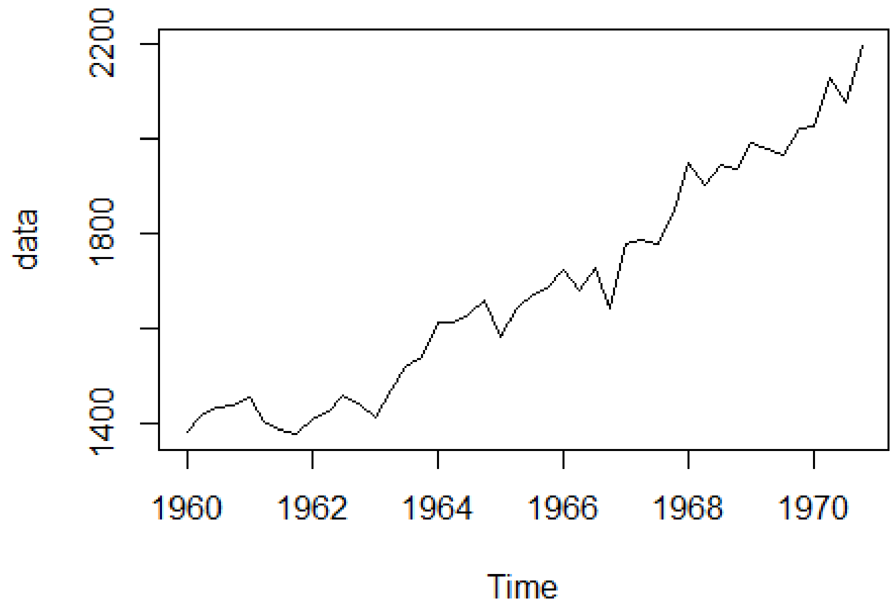
Data Description

The dataset describes Quarterly U.K. imports: goods and services (Pound millions) from 1960 – 1970.

```
library(readxl)
UK <- read_excel("C:/Users/Srikar/Desktop/SS/R/Sem 6/Practical 
7/UKimport.xlsx")
head(UK)
```

```
##   Value
##   <dbl>
## 1  1382
## 2  1417
## 3  1432
## 4  1438
## 5  1457
## 6  1403
```

```
data=ts(UK,start=(1960),frequency=4)
ts.plot(data)
```



Objective

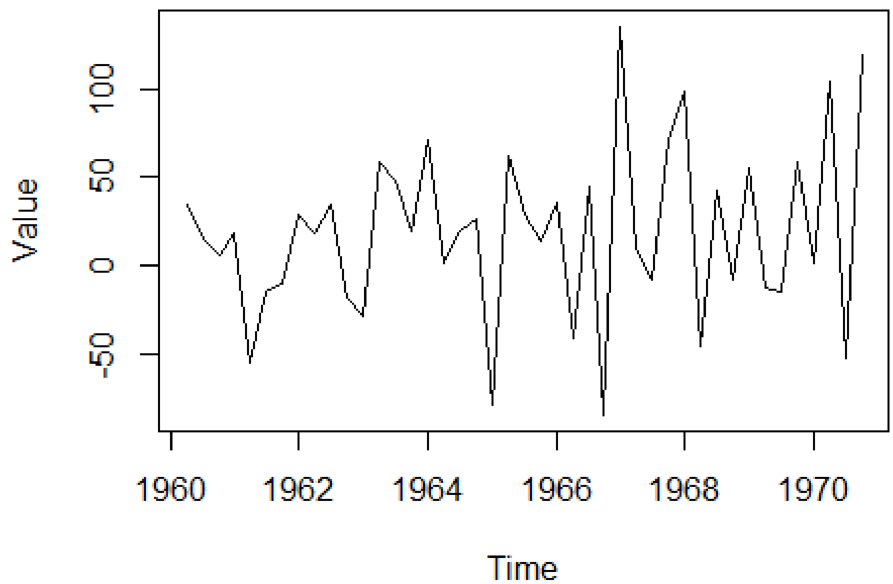
1 To fit a suitable ARIMA model for describing the patterns in the model
2. To find a suitable model while examining the ACF and PACF plot of the stationary data

Analysis

Objective 1

#1) Using first difference to make it stationary

```
diffdata=diff(data)

plot(diffdata)

#We observe that data is stationary after looking at the plot.

#2) Checking for stationarity
library(tseries)
```

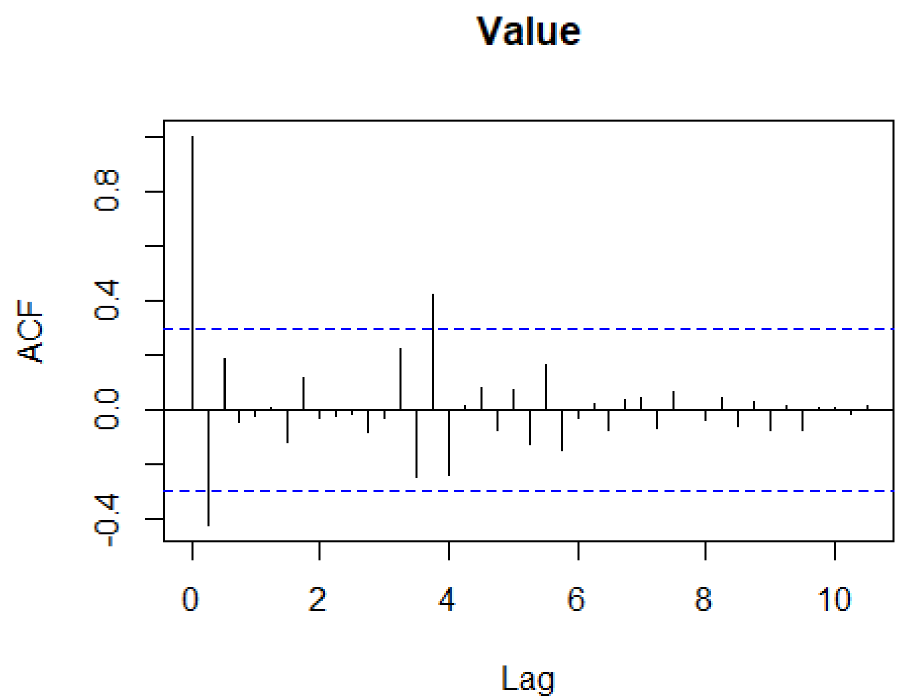



```
adf.test(diffdata)

##
##  Augmented Dickey-Fuller Test
##
## data:  diffdata
## Dickey-Fuller = -3.8136, Lag order = 3, p-value = 0.02772
## alternative hypothesis: stationary
```

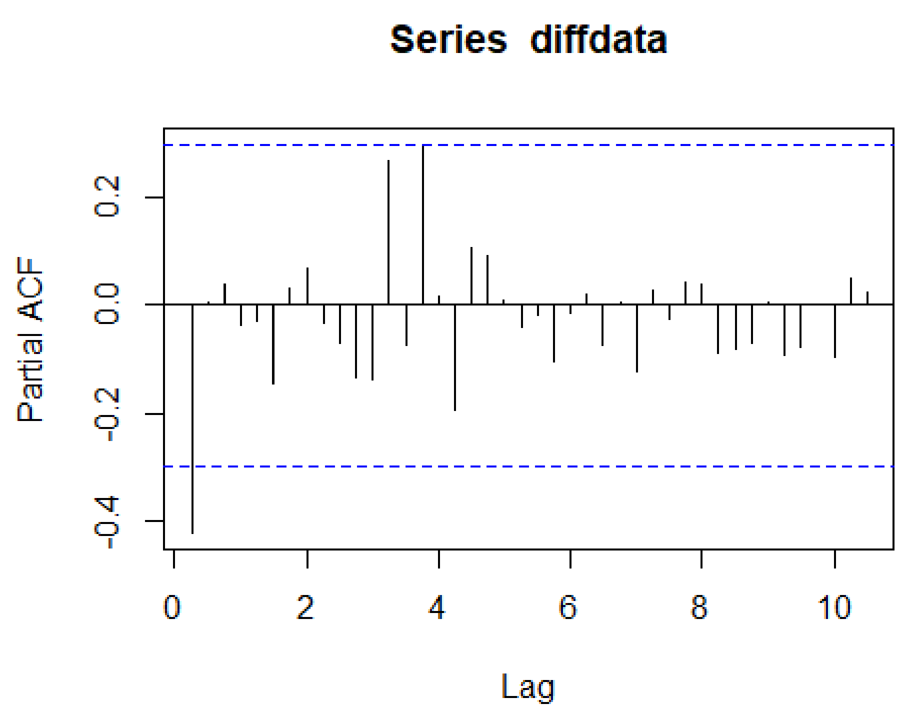
#Since the p-value is less than 0.05, we accept the null hypothesis i.e our model is non-stationary

#3)Checking the ACF and PACF

```
library(forecast)

par=(mfrow=c(1,2))
acf(diffdata, lag=100)
```




```
pacf(diffdata , lag=100)
```



#From the acf and pacf, we can see that both tails off to 0 after certain lags, which is an indication of an ARMA(p,q) model.That is both AR and MA part will be included in the model. But we cannot identify the order p,q of ARMA(p,q) using acf and pacf plots

#5. Fitting ARMA models

```
library(forecast)
fit=auto.arima(diffdata,seasonal="FALSE")
fit
```

```
## Series: diffdata
## ARIMA(1,0,0) with non-zero mean
##
## Coefficients:
##           ar1     mean
##       -0.4602  18.0899
## s.e.   0.1416   4.5349
##
## sigma^2 estimated as 1945:  log likelihood=-222.93
## AIC=451.86   AICc=452.48   BIC=457.15
```

Conclusion

#We get a model Yt= -0.4602(Yt-1)

#Objective 2

#From the ACF and PACF we observe that the plots tend to zero after some lags. However,#we cannot determine the value of p and q. Hence we use different values of p and q. Since#there is a significant ρ value at lag of 15, we suspect that this process has a moving average component of 15 lags. Hence we check for an ARMA(1,15).

```
arima(order=c(1,0,15),UK)
```

```
##
## Call:
## arima(x = UK, order = c(1, 0, 15))
##
## Coefficients:
##          ar1      ma1     ma2     ma3     ma4      ma5      ma6     ma7
ma8
##       0.9748  -0.1836  0.1818  0.1662  0.2280  -0.1407  -0.0408  0.2060
```

```
0.3201
## s.e.  0.0354   0.2158  0.1902  0.2118  0.2197   0.2276   0.2237  0.2087
0.2316
##           ma9    ma10    ma11    ma12    ma13     ma14    ma15  intercept
##       -0.0197  0.1737  0.0018  0.1558  0.4930  -0.1413  0.5522  1850.7859
## s.e.   0.2185  0.2448  0.2001  0.2464  0.2446   0.2199  0.2082   349.0429
##
## sigma^2 estimated as 1133:  log likelihood = -226.19,  aic = 488.39
```

#The AIC of this new tested model is 488.39. This is much greater than the AIC of the fitted model which is 452.48. Hence we can conclude that the fitted model was the best model.

Conclusion

Thus,an ARMA model can be fitted for a time series data.