Multivariate Time Series Analysis of Growth of Money Supply

Name: Devendra Sanjay Patil

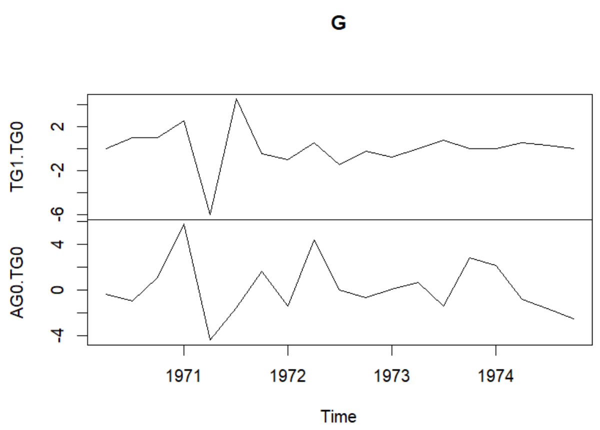
Introduction:

A multivariate quarterly time series from 1970(2) to 1974(4) with variables
TG1.TG0:difference of current and preceding target for the growth rate of the money supply,
AG0.TG0:difference of actual growth rate and target growth rate for the preceding period.

Source:

The data was originally studied by Hetzel (1981), the data set is given in Krämer and Sonnberger (1986). Below we replicate a few examples from their book. Some of these results differ more or less seriously and are sometimes parameterized differently.

Data Visulazation:



In Growth of money data has two variables one TG1.TG0 and AG0.TG0.

Stationarity:

```
> adf.test(G[,1])
        Augmented Dickey-Fuller Test
data:  G[, 1]
Dickey-Fuller = -2.8962, Lag order = 2, p-va
lue = 0.231
alternative hypothesis: stationary
> adf.test(G[,2])
Augmented Dickey-Fuller Test
data:  G[, 2]
Dickey-Fuller = -2.7852, Lag order = 2, p-va
lue = 0.2733
alternative hypothesis: stationary
```

both the variables are non-stationary so we have to make differencing on both variables by using adf.test() function,

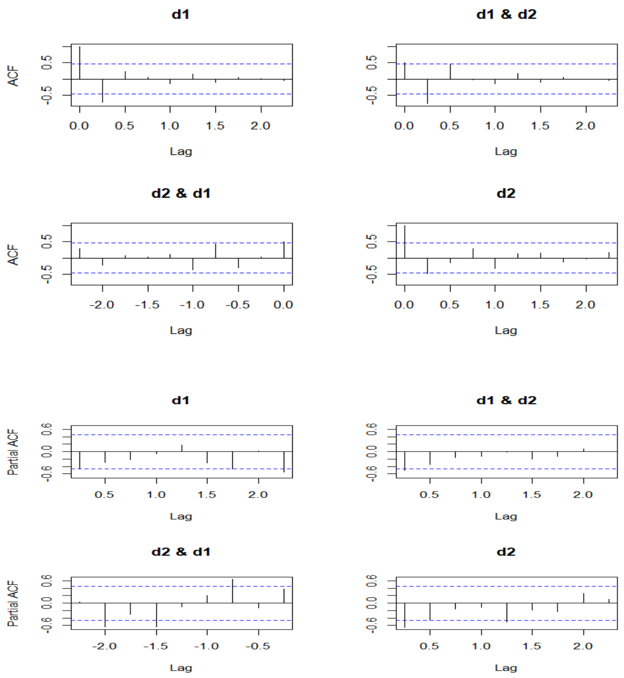
```
> adf.test(d1)

        Augmented Dickey-Fuller Test
data:  d1
Dickey-Fuller = -5.5087, Lag order = 2,
p-value = 0.01
alternative hypothesis: stationary
> adf.test(d2)

        Augmented Dickey-Fuller Test
data:  d2
Dickey-Fuller = -3.3916, Lag order = 2,
p-value = 0.01
alternative hypothesis: stationary
```

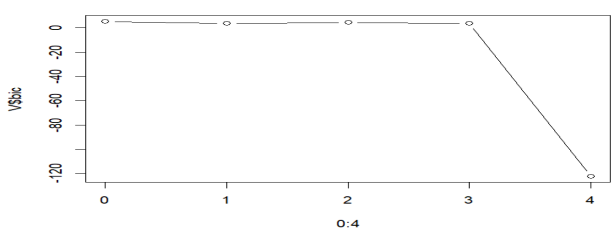
Now our data is get stationary.

ACF/PACF plot:

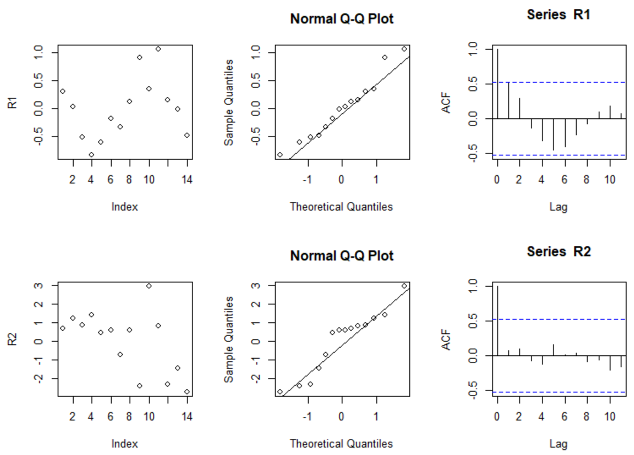


From the acf and pacf plot we can see the correlation between both variable and correlation between the values that variable itself

Model Building: First of all we convert the data into train and test, train data contain 1st 3 quarter and test data contain last quarter, now we finding best lag by using the BIC the following plot BIC shows at lag 4 we have lowest BIC so further model building we gone using the p=4,



Residual Analysis:



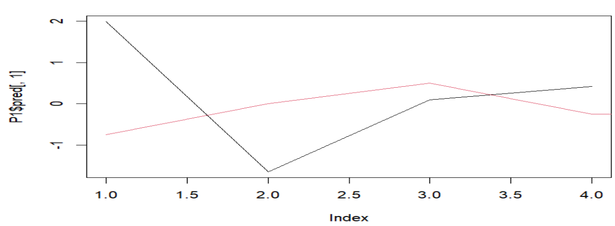
Above plot showing the residual analysis of both variables, both variables satisfying all the assumption.below result shows test for normality and both residuals are normal,

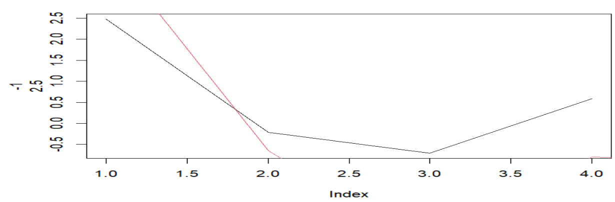
```
> shapiro.test(R1)

        Shapiro-Wilk normality test
data:  R1
W = 0.95639, p-value = 0.6635
> shapiro.test(R2)

        Shapiro-Wilk normality test
data:  R2
W = 0.91141, p-value = 0.1652
```

Forecast Plot:





So from the above plots we can say that the forecasted values for both variables are quit good red line shows the forecasted values and black line shows the test data values

Conclusion: Multivariate time series model with lag 4 is fitted very well on the Growth on money data.

Code:

```
library(readxl)
library(vars)
library(MTS)
library(dplyr)
library(ggplot2)
library(tseries)
G=growthofmoney
G
######## Acf  and  Pacf plot
Acf(G)
Pacf(G)
autoplot(ts(G))
class(G)
#### test for stationarity
adf.test(G[,1])
adf.test(G[,2])

####### Make the data stationary
d1=diff(G[,1])
d2=diff(G[,2])
adf.test(d1)
adf.test(d2)
G1=as.matrix(cbind(d1,d2))

acf(G1)
pacf(G1)

#### split the data into train & test
G2=G1[-(14:18),]

##### model fitting
V=VARorderI(G2,maxp=4)
plot(0:4,V$bic,type="b")
V
V1=VAR(G1,p=4)
summary(V1)
P1=VARpred(V1,h=4)
plot(P1$pred[,1],type="l")
lines(G1[14:18,1],col=2)
plot(P1$pred[,2],type="l",ylab=c(-1,2.5))
lines(G1[14:18,2],col=2)

###### residual analysis
R=(V1$residuals)
R1=R[,1]
R2=R[,2]
par(mfrow=c(2,3))
plot(R1)
qqnorm(R1)
qqline(R1)
acf(R1)

###### test for normality
shapiro.test(R1)
shapiro.test(R2)

plot(R2)
qqnorm(R2)
qqline(R2)
acf(R2)
```