
AUTOREGRESSIVE MODELS OF DIFFERENT ORDERS

Practical 5
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INTRODUCTION:

An autoregressive (AR) model predicts future behavior based on past behavior. It's used for forecasting when there is some correlation between values in a time series and the values that precede and succeed them.

In an AR model, the value of the outcome variable (Y) at some point t in time is — like “regular” linear regression — directly related to the predictor variable (X). Where simple linear regression and AR models differ is that Y is dependent on X and previous values for Y.

An AR (p) model is an autoregressive model where specific lagged values of y_t are used as predictor variables.

OBJECTIVES:

The main objectives of this practical are:

1. Generate AR (1) processes of size 500 with $\phi = -0.8, -0.5, -0.3, 0.3, 0.7, 0.8$.
2. Compare the behavior of ACF plots and time series plots in each of the above simulation.
3. Discuss the behavior of ACF plots of AR (1) process with $\phi = 0.3$ and 0.9 and $n = 10000$.

PROCEDURE:

- Generating AR (1) processes of size 500 with ϕ values $-0.8, -0.5, -0.3, 0.3, 0.7, 0.8$ as sim1, sim2, sim3, sim4, sim5 and sim6 respectively.

```
sim1<-arima.sim(list(ar=c(-0.8)),n=500)
sim2<-arima.sim(list(ar=c(-0.5)),n=500)
sim3<-arima.sim(list(ar=c(-0.3)),n=500)
sim4<-arima.sim(list(ar=c(0.3)),n=500)
sim5<-arima.sim(list(ar=c(0.7)),n=500)
sim6<-arima.sim(list(ar=c(0.8)),n=500)
```

- Plotting Time series plots of the simulated AR (1) processes sim1, sim2, sim3, sim4, sim5 and sim6 respectively.

```
par(mfrow=c(3,2))
ts.plot(sim1)
ts.plot(sim2)
ts.plot(sim3)
ts.plot(sim4)
ts.plot(sim5)
ts.plot(sim6)
```

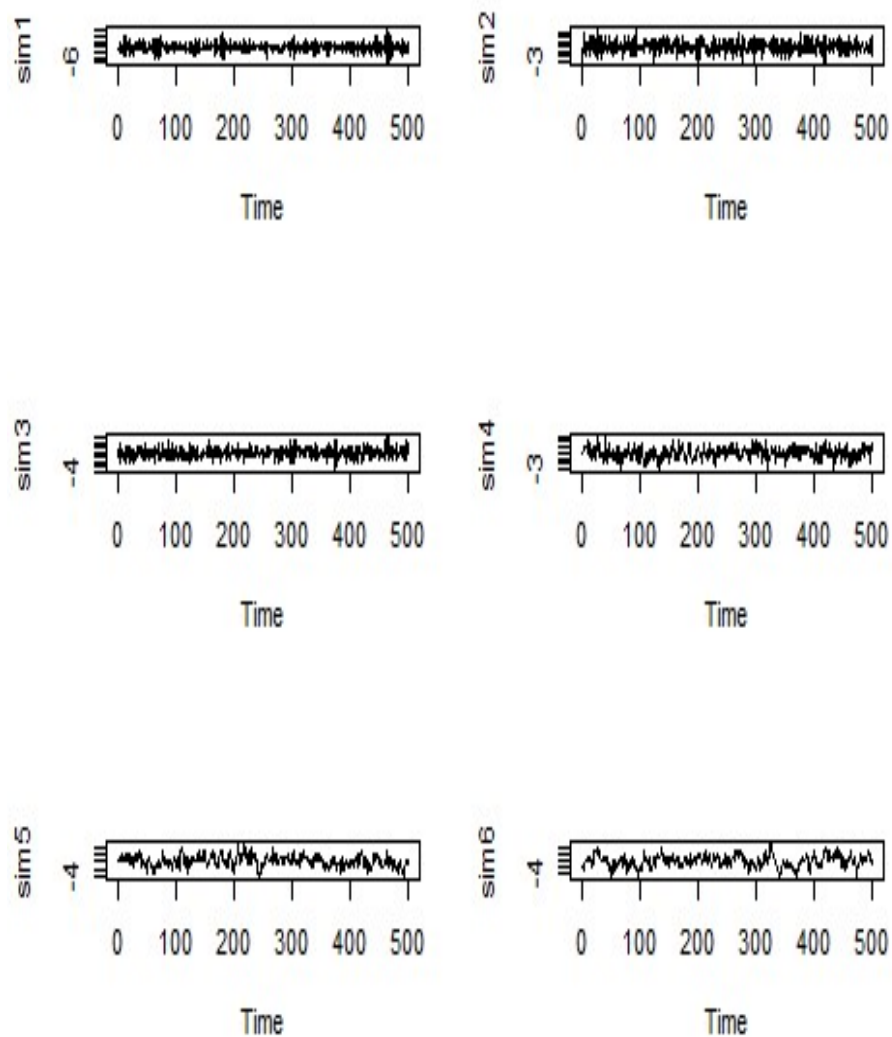


Figure 1: Time series plots of the simulations with different phi values

INFERENCE:

From figure 1, we can say that they all show stationarity. As the ϕ value approaches 1, they tend to become non – stationary.

- Plotting ACF plots of the simulated AR (1) processes sim1, sim2, sim3, sim4, sim5 and sim6 respectively.

```
par(mfrow=c(3,2))  
acf(sim1); acf(sim2); acf(sim3); acf(sim4); acf(sim5); acf(sim6);
```

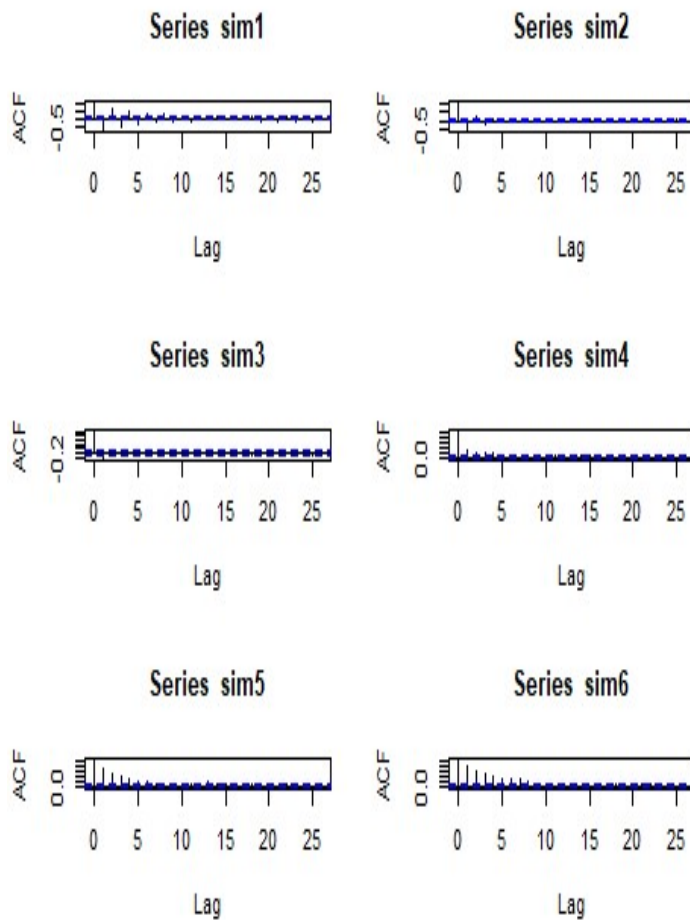


Figure 2: ACF Plots of the simulations with different ϕ values

INFERENCE:

From figure 2, we can conclude that when the ϕ value is negative, the ACF values are oscillating and when they are positive, the ACF values are exponentially decreasing in the ACF plots.

- Plotting PACF plots of the simulated AR (1) processes sim1, sim2, sim3, sim4, sim5 and sim6 respectively.

```
par(mfrow=c(3,2))
pacf(sim1); pacf(sim2); pacf(sim3); pacf(sim4); pacf(sim5); pacf(sim6);
```

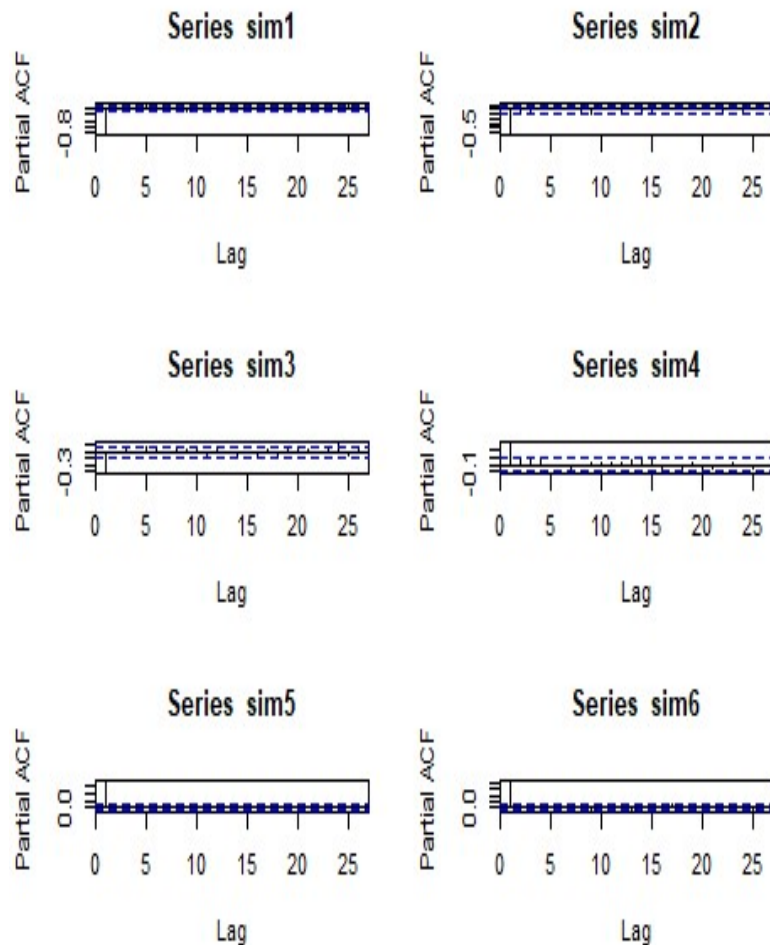


Figure 3: PACF Plots of the simulations with different phi values

INFERENCE:

From figure 3, we can conclude that the values cut off after lag = 1. For the negative phi values, the pcaf value is negative at lag 1 and for positive, it is positive at lag 1.

- Plotting Time series plots of the simulated AR (1) processes sim1, sim2, sim3, sim4, sim5 and sim6 respectively.

```
AR1=arima.sim(model=list(ar = 0.3),n=10000)#simulation of AR(1) with ?? =0.3
acf(AR1)
AR1=arima.sim(model=list(ar = 0.9),n=10000)#simulation of AR(1) with ?? =0.9
acf(AR1)
```

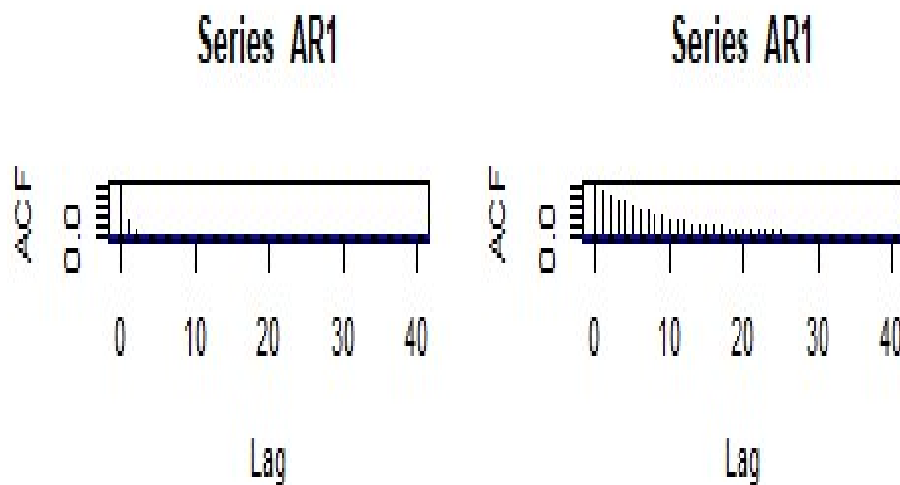


Figure 4: ACF Plots for the simulations with size 10000

CONCLUSION:

We can say that they all show stationarity. As the phi value approaches 1, they tend to become non – stationary. From figure 2, we can conclude that when the phi value is negative, the ACF values are oscillating and when they are positive, the ACF values are exponentially decreasing in the ACF plots.

We can also conclude that the values cut off after lag = 1. For the negative phi values, the PCAF value is negative at lag 1 and for positive, it is positive at lag 1.