

Assignment-2

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MN12B035

$$1) \quad a) \quad x[k] = \phi_1 x[k-1] + e[k] \quad (1)$$

$$\text{corr}(x[k], x[k-L]) = \frac{\sigma_{x[k], x[k-L]}}{\sqrt{\sigma_{x[k], x[k]} \sigma_{x[k-L], x[k-L]}}}$$

$$\sigma_{x[k], x[k-L]} = E[x[k]x[k-L]] - E[x[k]]E[x[k-L]]$$

$$x[k-L] = \phi_1 x[k-L-1] + e[k-L]$$

$$x[k] = \phi_1 x[k-1] + e[k]$$

$$x[k-1] = \phi_1 x[k-2] + e[k-1]$$

$$\therefore x[k] = (\phi_1)^L x[k-L] + \sum_{n=0}^{L-1} \phi_1^n e[k-n]$$

$$\therefore E[x[k]] = (\phi_1)^L E[x[k-L]]$$

$$E[x[k]x[k-L]] = (\phi_1)^L E[x^2[k-L]]$$

$$E[x[k]]E[x[k-L]] = (\phi_1)^L E[x[k-L]]$$

$$\begin{aligned} \therefore \sigma_{x[k], x[k-L]} &= (\phi_1)^L \left[E[x^2[k-L]] - E^2[x[k-L]] \right] \\ &= (\phi_1)^L \sigma_{x[k-L]}^2 = (\phi_1)^L \text{Var}(x[k-L]) \end{aligned}$$

$$\text{corr}(x[k], x[k-L]) = \frac{(\phi_1)^L \text{Var}(x[k-L])}{(\text{Var}(x[k]) \text{Var}(x[k-L]))^{1/2}} = (\phi_1)^L \left[\frac{\text{Var}(x[k-L])}{\text{Var}(x[k])} \right]^{1/2}$$

$$\therefore \text{Corr}(x[k], x[k-l]) = \phi_1^l \left[\frac{\text{Var}(x[k-l])}{\text{Var}(x[k])} \right]^{1/2} \quad (2)$$

Since $E[x[k]] \neq E[x[k-l]]$, $x[k]$ is not stationary.

$$a) \quad x[k] = (\phi_1)^l x[k-l] + \sum_{n=0}^{l-1} \phi_1^n x[k-n]$$

$$\Rightarrow \sum_{n=0}^{\infty} (\phi_1)^n x[k-n]$$

$$\text{as } l \rightarrow \infty \quad (\phi_1)^l \rightarrow 0 \quad (|\phi_1| < 1)$$

$$\therefore \lim_{l \rightarrow \infty} x[k] = \lim_{l \rightarrow \infty} (\phi_1)^l x[k-l] + \sum_{n=0}^{l-1} \phi_1^n x[k-n]$$

$$= 0 + \sum_{n=0}^{\infty} \phi_1^n x[k-n]$$

c) It is not initially stationary as the terms depend on $x[k]$ which is constant process.

d) The $x[0]$ should be constant so the process is stationary preferably be equal to 1 so it can be easily scaled.

2) a) MA(z) process

(3)

$$v[k] = e[k] + a_1 e[k-1] + a_2 e[k-2]$$

$$H(q^{-1}) = 1 + c_1 q^{-1} + c_2 q^{-2}$$

$$H(q) = 1 + c_1 q + c_2 q^2$$

$$g_{\sigma}(q^{-1}) = \sigma_{ee} H(q) H(q^{-1}) = \sum_{l=-\infty}^{\infty} \sigma_w[l] q^{-l}$$

$$\therefore g_{\sigma}(z^{-1}) = \sigma_{ee}^2 (H(z))(H(z^{-1}))$$

$$\therefore g_{\sigma}(z^{-1}) = \sigma_w[2] z^{-2} + \sigma_w[1] z^{-1} + \sigma_w[0] + \sigma_w[-1] z + \sigma_w[2] z^2$$

$$= \sigma_w[2] + \sigma_w[1] z^{-1} + \sigma_w[0] z^2$$

$$= \sigma_{ee}^2 [1 + c_1 z^{-1} + c_2 z^{-2}] [1 + c_1 z + c_2 z^2]$$

$$= \sigma_{ee}^2 [(1 + c_1^2 + c_2^2) + c_1(1 + c_2) z^{-1} + c_2 z^{-2} + c_1(1 + c_2) z + c_2 z^2]$$

$$\therefore \begin{cases} \sigma_w[2] = c_2 = \sigma_w[-2] \\ \sigma_w[1] = c_1(1 + c_2) = \sigma_w[-1] \\ \sigma_w[0] = 1 + c_1^2 + c_2^2 \end{cases}$$

$$k) : p_{vv}[l] \leq 1$$

(4)

$$p_{vv}[0] = 1$$

$$p_{vv}[l] < 1 \quad |x| \neq 0$$

$$\therefore p_{vv}[1] = \frac{c_1(1+c_1)}{1+c_1^2+c_2^2} < 1$$

$$p_{vv}[2] = \frac{c_2}{1+c_1^2+c_2^2} < 1$$

$$\therefore (c_1^2+c_2^2+1) p_{vv}[1] - c_1 - c_1 c_2 = 0$$

$$(c_1^2+c_2^2+1) p_{vv}[2] - c_2 = 0$$

$$\therefore c_1^2 p_{vv}^2[2] = c_2 - (c_2^2+1) p_{vv}^2[2]$$

$$\Rightarrow c_1 = \sqrt{\frac{c_2}{p_{vv}[2]} - (c_2^2+1)}$$

$$\frac{c_2}{p_{vv}[2]} > 1+c_2^2$$

$$\Rightarrow \frac{c_2}{p_{vv}[2]} - c_2^2 > 1$$

$$\Rightarrow \frac{c_2^2}{p_{vv}^2[2]} - c_2^2 > 1$$

causal holds only when

$$|c_1| < 1 \text{ and } |c_2| < 2$$

c) ~~Find~~ $H(q^{-1}) = \frac{1}{1 - 1.3q^{-1} + 0.4q^{-2}}$

(5)

$$V[k] = -d_1 V[k-1] - d_2 V[k-2] + e[k]$$

$$\boxed{-d_2 = 0.4}$$

$$\phi_{p+1, p+1} = \frac{e[p+1] - \sum_{j=1}^p \phi_{p,j} e[p+1-j]}{1 - \sum_{j=1}^p \phi_{p,j} e[j]}$$

$$p=1$$

$$\Rightarrow \phi_{2,2} = \frac{e[2] - \phi_{1,1} e[1]}{1 - \phi_{1,1} e[1]} = 0.4$$

$$\phi_{p+1,i} = \phi_{p,i} - \phi_{p+1,p+1} \phi_{p,p-i+1}$$

$$\Rightarrow \phi_{2,1} = \phi_{1,1} [1 - \phi_{2,2}] = \boxed{e[1](0.8)}$$

$$\sigma_{vv}[0] = -d_1 \sigma_{vv}[1] - d_2 \sigma_{vv}[2] + \sigma_{ee}[0]$$

$$\Rightarrow \sigma_{vv}[0] + d_1 \sigma_{vv}[1] + d_2 \sigma_{vv}[2] = \sigma_e^2$$

Similarly,

$$\sigma_{vv}[1] + d_1 \sigma_{vv}[2] + d_2 \sigma_{vv}[3] = 0$$

$$\sigma_{vv}[2] + d_1 \sigma_{vv}[3] + d_2 \sigma_{vv}[4] = 0$$

$$\begin{bmatrix} 1 & d_1 & d_2 \\ 0 & 1+d_2 & d_1 \\ d_2 & d_1 & 1 \end{bmatrix} \begin{bmatrix} \sigma[0] \\ \sigma[1] \\ \sigma[2] \end{bmatrix} = \begin{bmatrix} \sigma_{\epsilon^2} \\ 0 \\ 0 \end{bmatrix}$$

↓
D

$$|D| = (1+d_2-d_1^2) - d_1[-d_1d_2] + d_2[-d_2(1+d_2)]$$

$$= 1+d_2-d_1^2 + d_1^2d_2 - d_2^2 - d_2^3$$

$$d_2 = -0.4$$

$$|D| = 0.6 + d_1^2[-1.4] - 0.16 - 0.064$$

$$= -1.4d_1^2 + 0.6 - 0.224$$

$$= -1.4d_1^2 + 0.376$$

$$D^{-1} = \frac{1}{|D|} \begin{bmatrix} 1+d_2-d_1^2 & d_1d_2-d_1 & d_1^2-1-d_2 \\ d_1d_2 & 1-d_2^2 & -d_1 \\ -d_2-d_2^2 & d_1d_2-d_1 & 1+d_2 \end{bmatrix}$$

$$\therefore \begin{bmatrix} \sigma[0] \\ \sigma[1] \\ \sigma[2] \end{bmatrix} = \frac{1}{|D|} \begin{bmatrix} (1+d_2-d_1^2)\sigma_{\epsilon^2} \\ d_1d_2\sigma_{\epsilon^2} \\ (-d_2-d_2^2)\sigma_{\epsilon^2} \end{bmatrix}$$

$$\therefore \rho[2] = \frac{-[d_2+d_2^2]}{1+d_2-d_1^2} = -d_2$$

$$\Rightarrow d_1=0 \quad \therefore V[k] = 0.4 V[k-2] + \epsilon[k]$$

2) acf_v <- ARMAacf(ar=c(0,0.4),lag.max=30)

$$3) a) y[k] = A \sin(2\pi f_0 k) + e[k] \quad (7)$$

$$E[y[k]] = A E[\sin(2\pi f_0 k)] + 0$$

= not constant

\therefore not stationary

$$b) R_{yy}[l] = \frac{1}{N} \sum_{k=l+1}^N (y[k] - \bar{y})(y[k-l] - \bar{y})$$

$$= E[y[k] y[k-l]] \quad \text{since } \bar{y} = 0 \text{ for large } N$$

$$= E[A^2 \sin(2\pi f_0 k) \sin(2\pi f_0 (k-l))]$$

$$= A^2 E[\sin(2\pi f_0 k) \sin(2\pi f_0 (k-l))]$$

$$\frac{\sin(A-B) - \sin(A+B)}{2} = \sin A \sin B$$

$$\therefore = \frac{A^2}{2} E[\cos(2\pi f_0 l) - \cos(2\pi f_0 (2k-l))]$$

$$= \frac{A^2}{2} \left[E[\cos(2\pi f_0 l)] - E[\cos(2\pi f_0 (2k-l))] \right]$$

\therefore frequency of f_0

c) Based on ACF, we can tell if it is stationary or not and also if it is an MA or AR model

```
3d) k=c(1:1000)
```

```
t=sin(2*pi*0.2*k)
```

```
sigt=var(t)
```

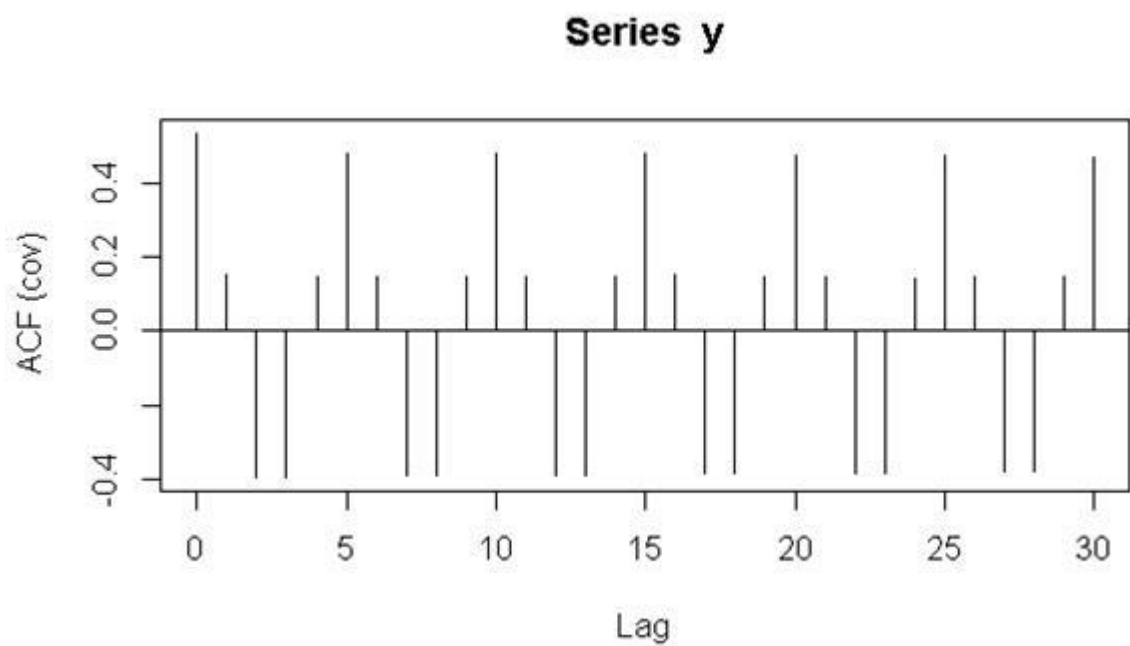
```
sige=sigt/10
```

```
e=rnorm(1000,0,sqrt(sige))
```

```
y=sin(2*pi*0.2*k)+e
```

```
acf(y,lag.max=NULL,type="covariance",plot=TRUE)
```

in the plot we can see that the graph repeats at lags of 5 which implies the frequency is 0.2



$$4 \quad a) (i) x_1[k] = 0.7x[k-1] - 0.12x[k-2] + e[k] \quad (1)$$

$$(ii) x_2[k] = e[k] + 0.4e[k-1]$$

$$(i) \text{ACVF}(\ell) = E[x_1[k] x_1[k-\ell]]$$

$$= E[(0.7x[k-1] - 0.12x[k-2] + e[k]) x[k-1]]$$

$$= 0.7 E[x[k-1] x[k-1]] - 0.12 E[x[k-2] x[k-1]] + E[e[k] x[k-1]]$$

$$\text{ACVF}[0] = 0.7 \sigma_{xx}^2[1] - 0.12 \sigma_{xx}^2[2] + \sigma_{ee}^2$$

$$\sigma_{xx}^2[0] = 0.7 \sigma_{xx}^2[1] - 0.12 \sigma_{xx}^2[2] + \sigma_{ee}^2$$

$$\sigma_{xx}^2[1] = 0.7 \sigma_{xx}^2[2] - 0.12 \sigma_{xx}^2[1]$$

$$\Rightarrow \sigma_{xx}^2[1] = \frac{0.7}{1.12} \sigma_{xx}^2[0]$$

$$\sigma_{xx}^2[2] = 0.7 \sigma_{xx}^2[1] - 0.12 \sigma_{xx}^2[0]$$

$$= \left[\frac{0.49}{1.12} - 0.12 \right] \sigma_{xx}^2[0]$$

$$\therefore \rho_{xx}[1] = \frac{70}{112} = 0.625$$

$$\rho_{xx}[2] = \left[\frac{0.49 - 0.12(1.12)}{1.12} \right] = 0.3175$$

$$\text{II) } x_2[k] = x[k] + 0.4x[k-1] \quad (9)$$

$$\sigma_{xx}[l] = E[x[k] x[k-l]]$$

$$= \sigma_{xx}[l] + 0.4\sigma_{xx}[l-1]$$

$$= E[x[k](x[k-l] + 0.4x[k-l-1])]$$

$$+ 0.4 E[x[k-1](x[k-l] + 0.4x[k-l-1])]$$

$$= \sigma_x^2[l] + 0.4\sigma_x^2[l+1] + 0.4\sigma_{xx}[l-1] + 0.16\sigma_x^2[l]$$

$$\sigma_{xx}[0] = 1.16\sigma_x^2$$

$$\sigma_{xx}[1] = 0.4\sigma_x^2$$

$$\sigma_{xx}[2] = 0$$

$$\therefore \rho_{xx}[1] = \frac{0.4}{1.16} = \frac{10}{29}$$

$$\rho_{xx}[2] = 0$$

$$\therefore \boxed{\phi_{xx}[1] = \frac{10}{29}}$$

4a)

```
acf_x1 <- ARMAacf(ar=c(0.7,-0.12),lag.max=4,pacf= TRUE)
```

```
acf_x2 <- ARMAacf(ma=c(0.4),lag.max=4,pacf = TRUE)
```

```
pacf_x1_1=acf_x1[1]# pacf at lag 1 for x1
```

```
pacf_x1_2=acf_x1[2]# pacf at lag 2 for x1
```

```
pacf_x2_1=acf_x2[1]# pacf at lag 1 for x2
```

```
pacf_x2_2=acf_x2[2]# pacf at lag 2 for x2
```

4b)

```
SMI=EuStockMarkets[,3]
```

```
mag=quakes[,4]
```

```
not=nottem
```

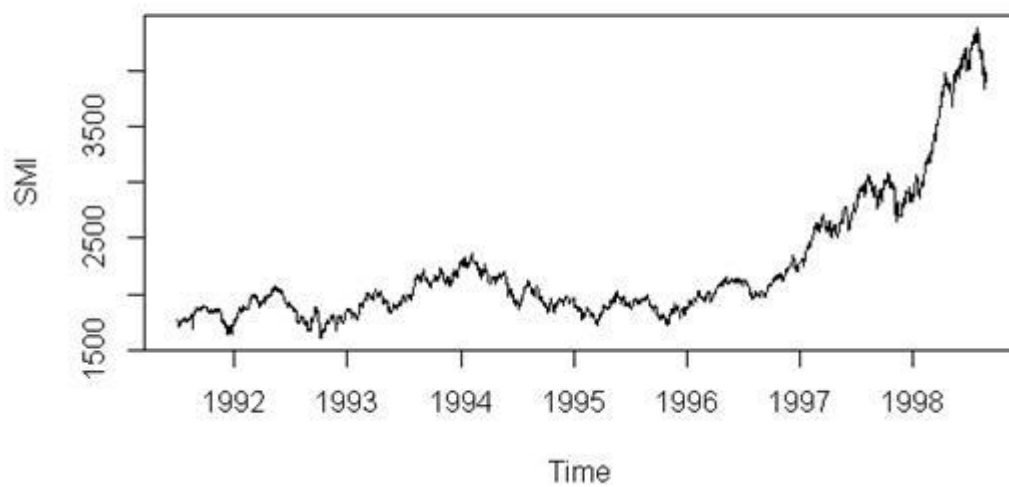
```
k=c(1:1000)
```

```
e=rnorm(1000,0,1)
```

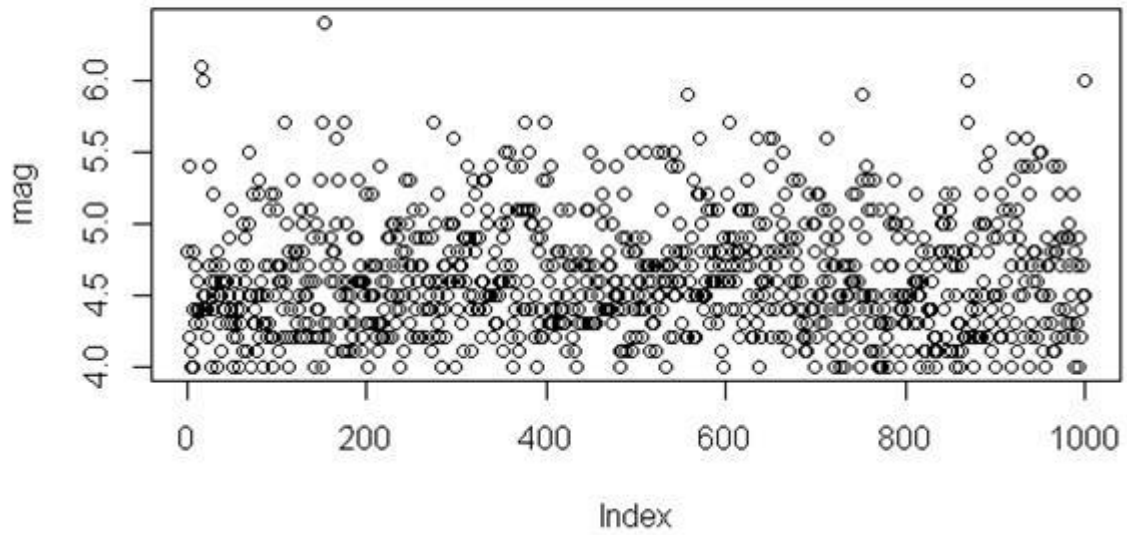
```
x=0.01*k + e
```

```
#time series
```

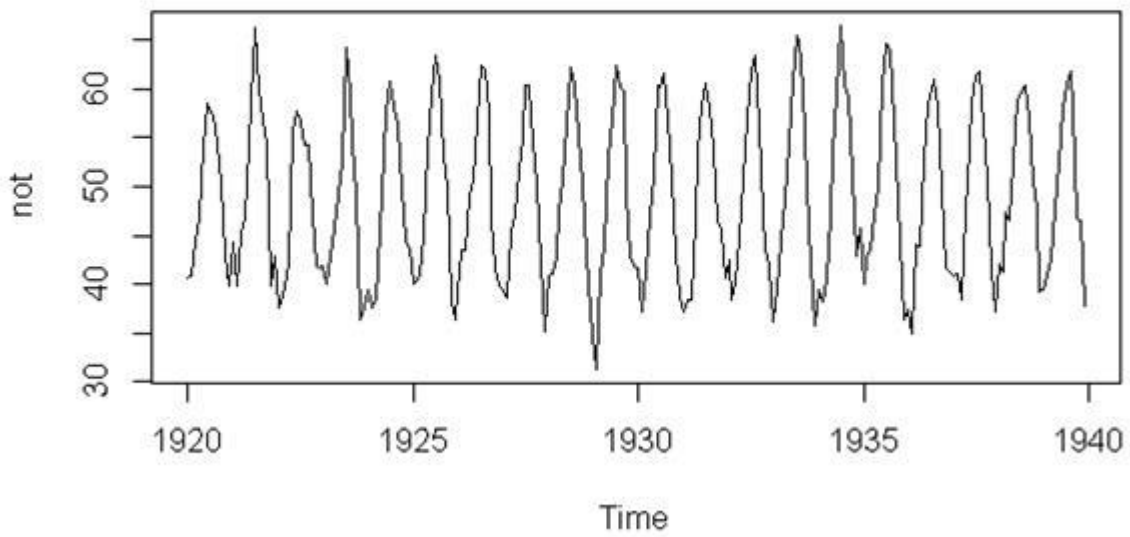
```
plot(SMI)
```



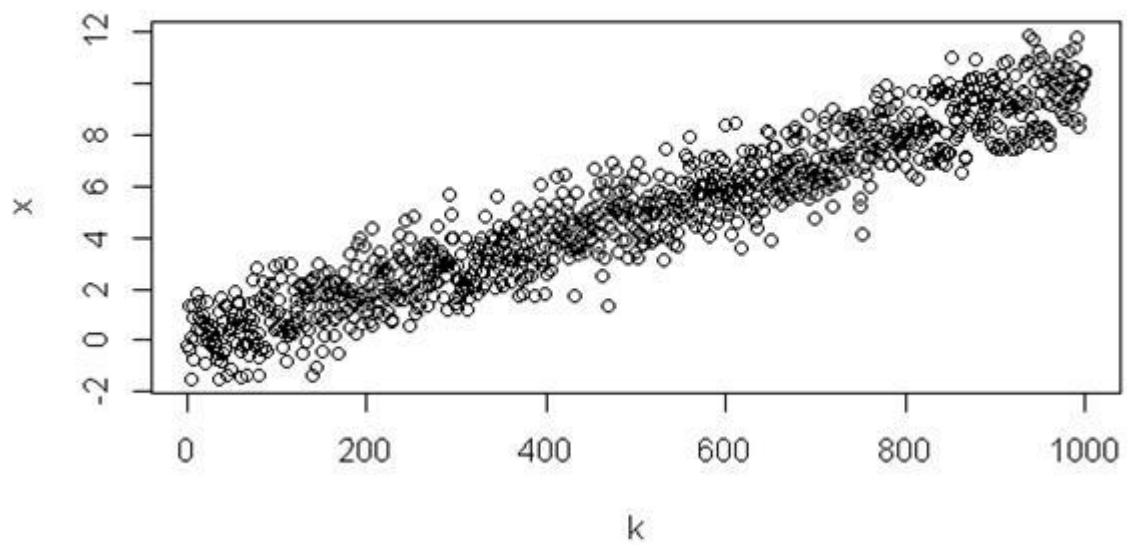
plot(mag)



plot(not)

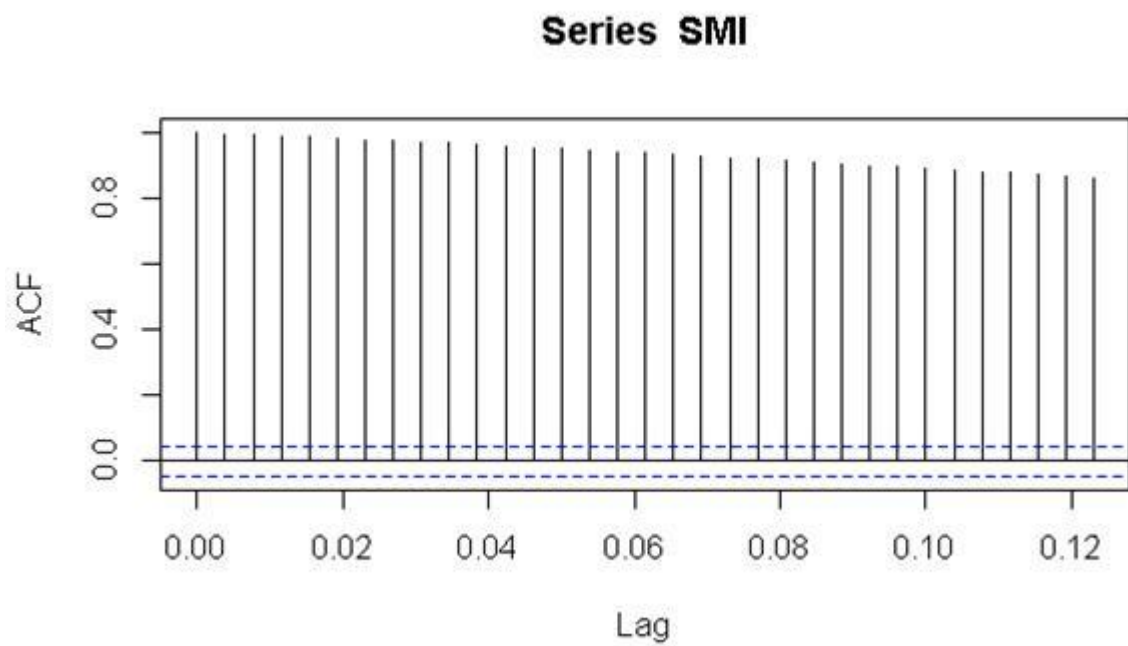


plot(k,x)

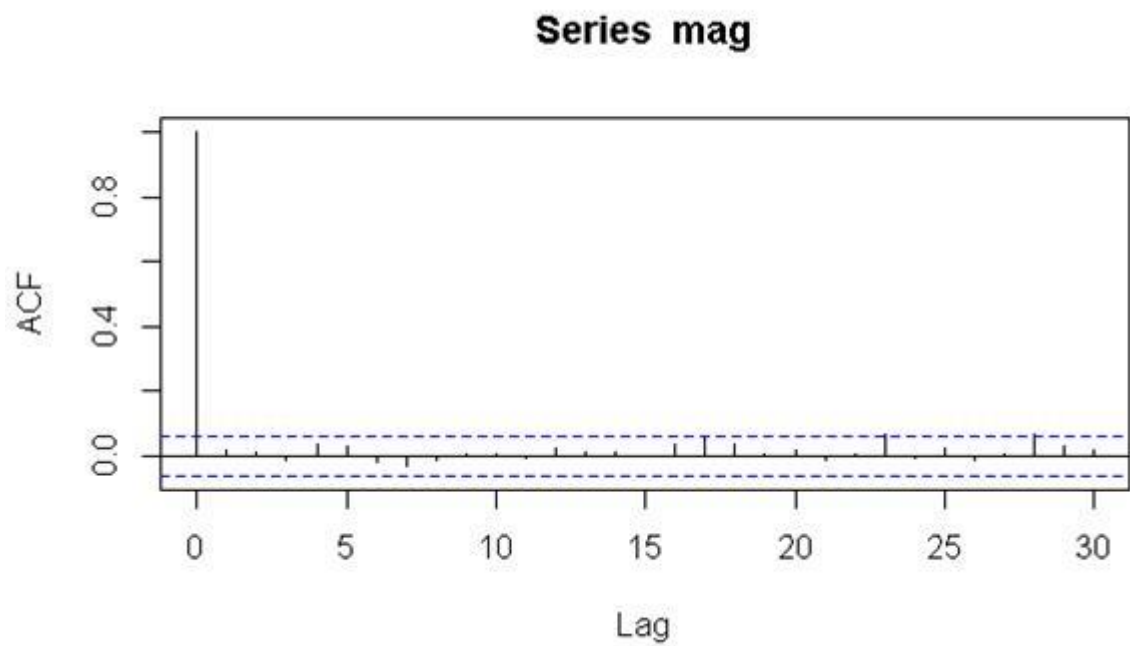


#ACF

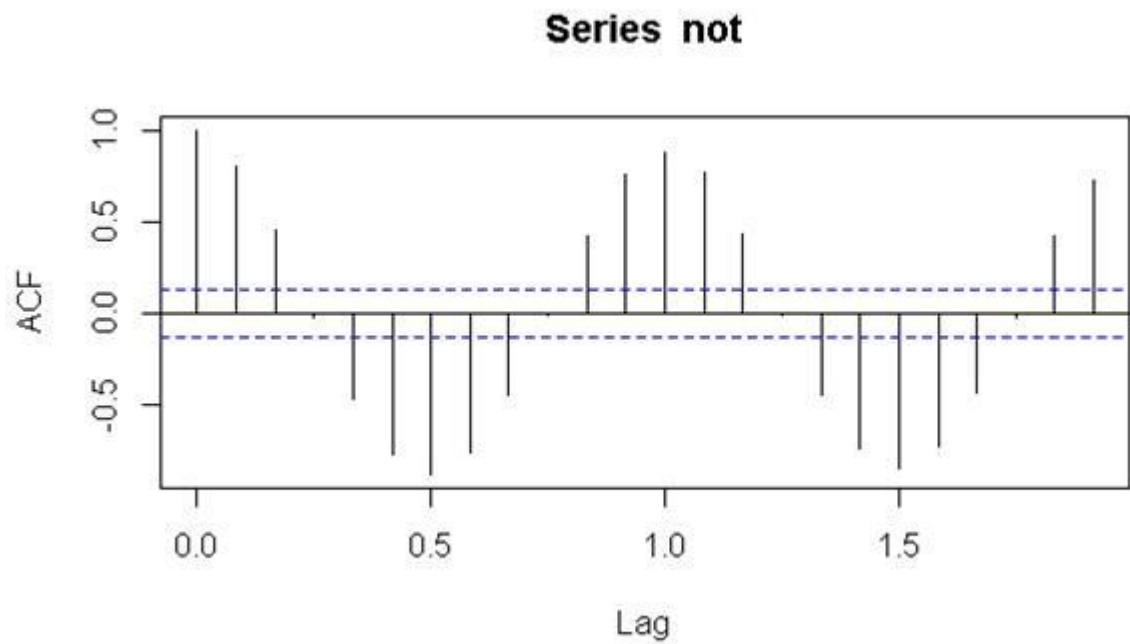
acf(SMI,lag.max=NULL,type="correlation",plot=TRUE)



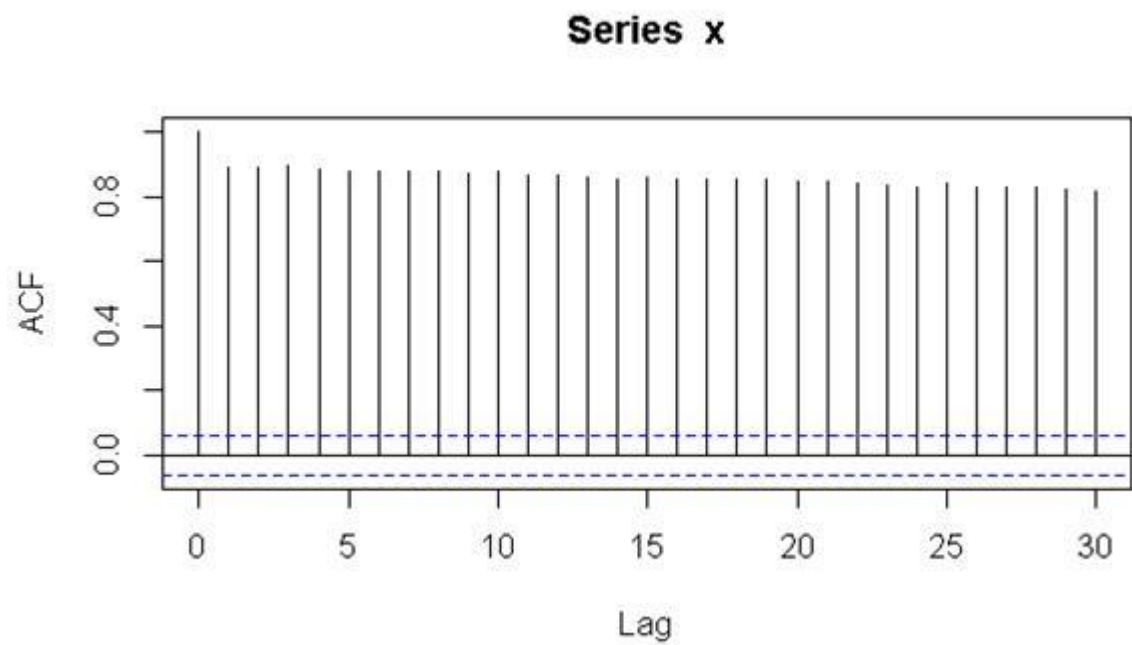
```
acf(mag,lag.max =NULL,type="correlation",plot=TRUE)
```



```
acf(not,lag.max =NULL,type="correlation",plot=TRUE)
```

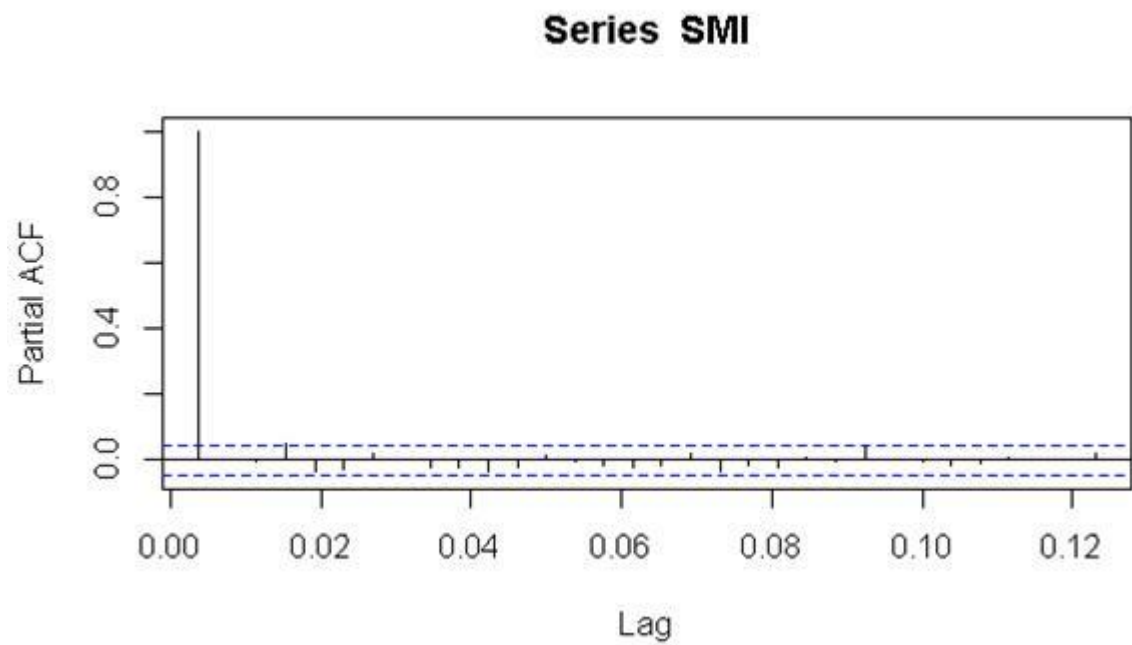


```
acf(x,lag.max =NULL,type="correlation",plot=TRUE)
```

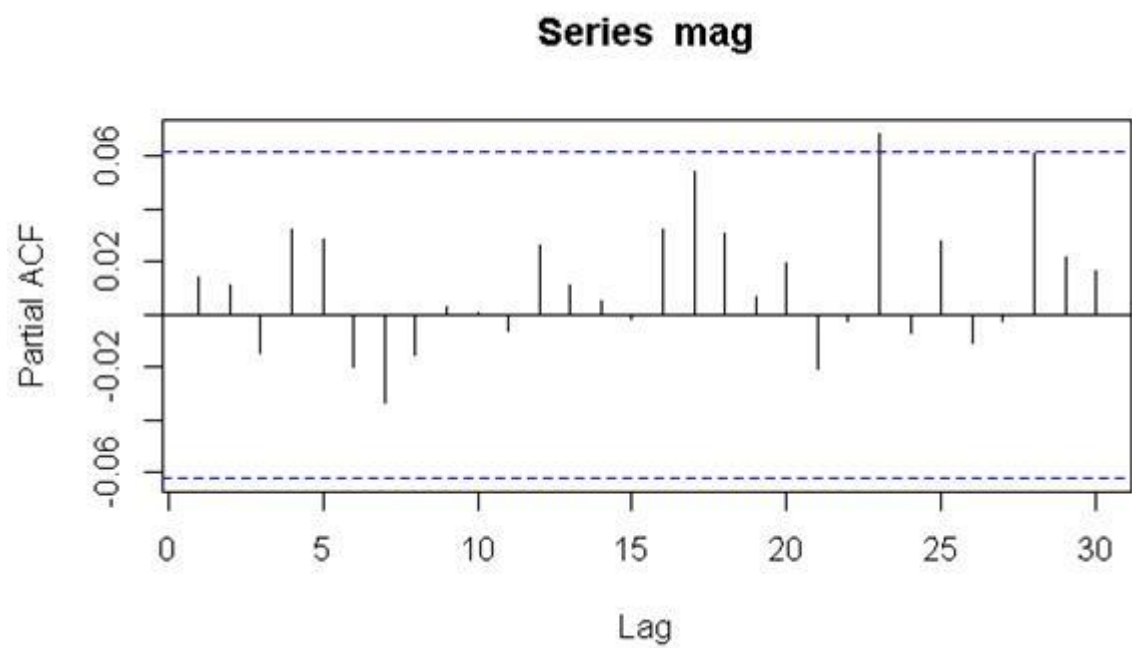


```
#PACF
```

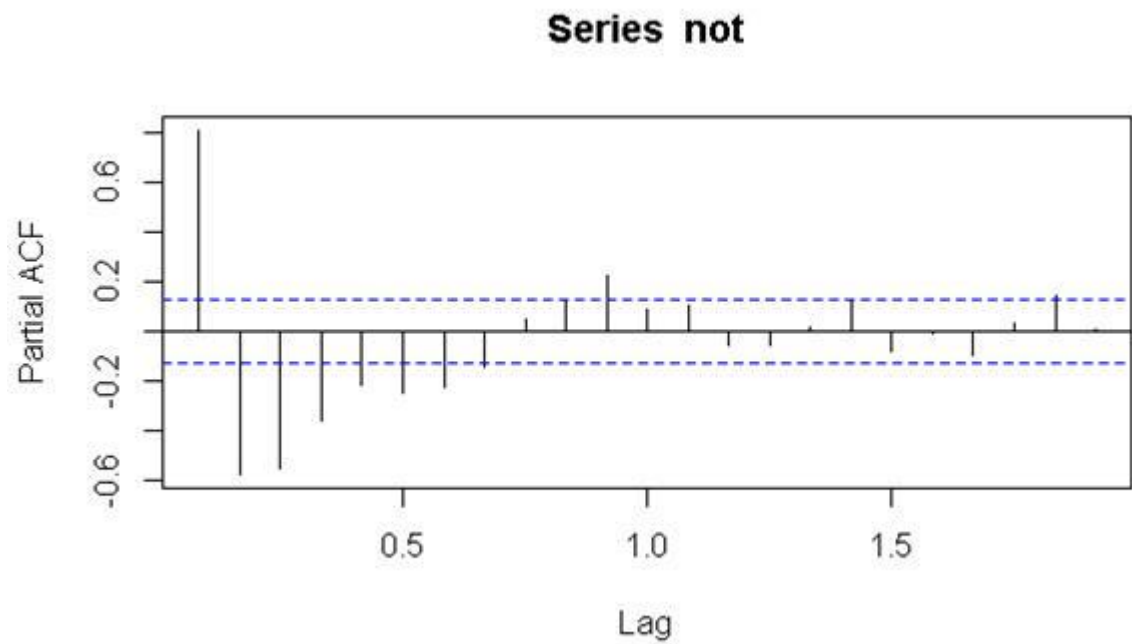
```
pacf(SMI,lag.max =NULL,plot=TRUE)
```



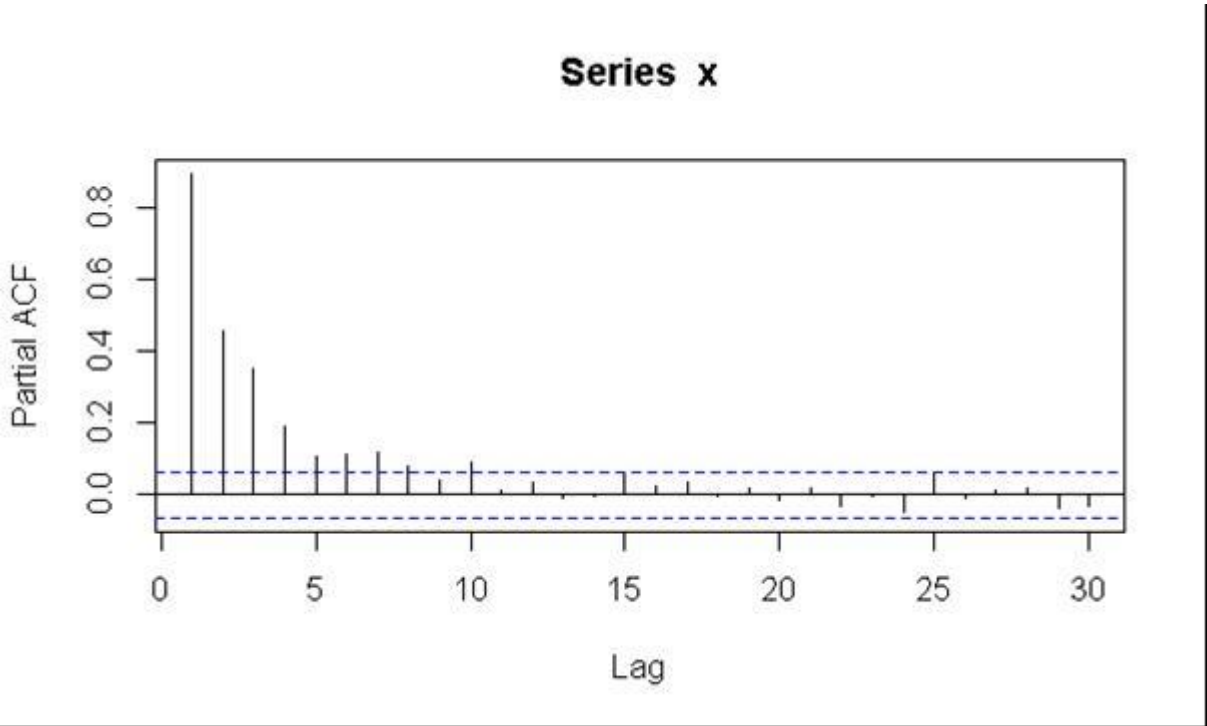

```
pacf(mag,lag.max=NULL,plot=TRUE)
```



```
pacf(not,lag.max=NULL,plot=TRUE)
```



```
pacf(x,lag.max =NULL,plot=TRUE)
```

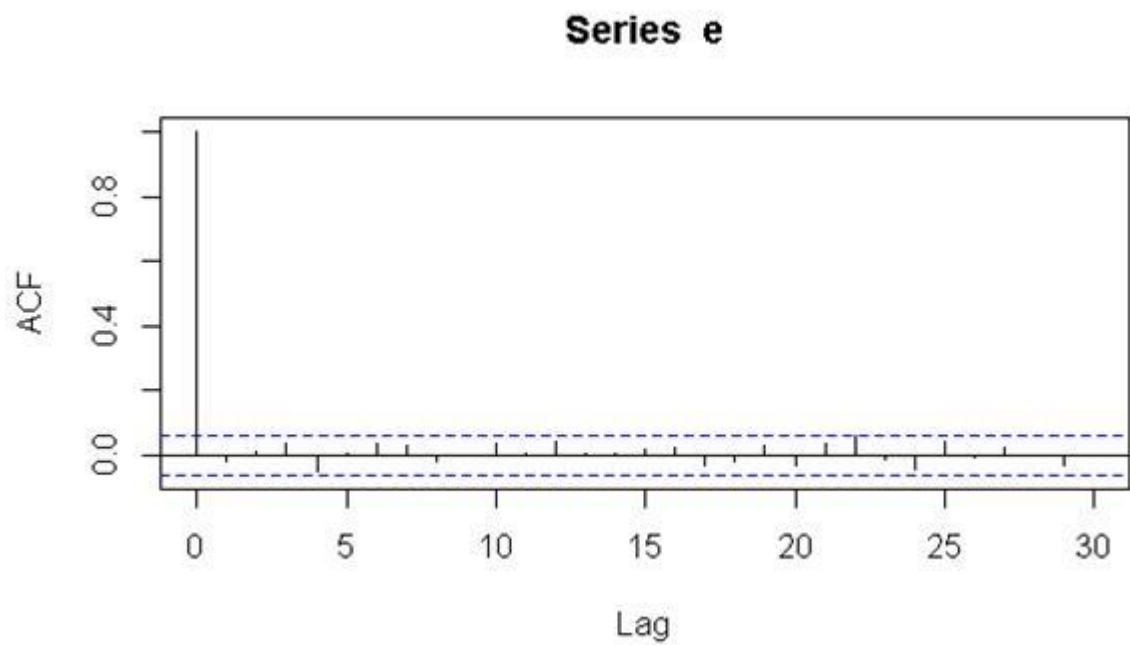


	Stationary	Periodicity
SMI	Yes (AR model)	-
Quakes(mag)	Yes(MA model)	-
nottem	No	Yes(every 5 lags)
x	Yes(AR Model)	-

5)

```
e=rnorm(1000,0,1)
```

```
t=acf(e,lag.max=NULL,type="correlation",plot=TRUE)
```



```
y=t$acf
```

```
z=acf(y,lag.max=20,type="correlation",plot=TRUE)
```

