

Problem Set #3

[1]

(a)

Recall that in lecture we have derived the following result:

$$\gamma(1) = E[AR(1)AR(t-1)] = E[AR(t-1)][b \times AR(t-1) + e(t)] = b \times \gamma(0) = b$$

Recall from above that  $AR(t-1)$  did not depend upon  $e(t)$  so that the covariance of  $AR(t-1)$  and  $e(t)$  is zero. Similarly, the autocovariance at lag two is:

$$\gamma(2) = E[AR(t)AR(t-2)] = E[AR(t-2)][b \times AR(t-1) + e(t)] = b \times \gamma(1) = b^2$$

and the autocorrelation function at lag two is  $b^2$ ,

and in general:

$$\gamma(u) = b^u$$

Thus,

$$\rho(0) = 1$$

$$\rho(1) = 0.5$$

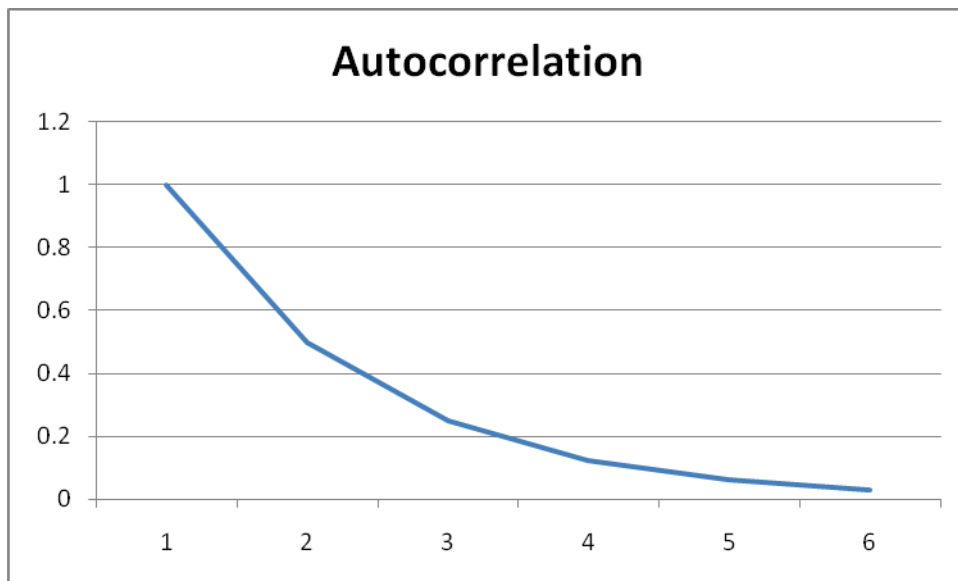
$$\rho(2) = 0.25$$

$$\rho(3) = 0.125$$

$$\rho(4) = 0.0625$$

$$\rho(5) = 0.03125$$

Plotting this we get:



(b)

We have the following formula:

$$x(t) = b_1 x(t-1) + e(t), \text{ where } b_1 \text{ in our case is } 0.5$$

The partial autocorrelation function,  $p(\tau)$ , is just the coefficient of  $y_{t-\tau}$  in a population linear regression of  $y_t$  on  $y_{t-1}, \dots, y_{t-\tau}$

At lag(0)  $p(0)$  is simply  $x(t)$  (Since Zeroth derivative of  $x(t)$  is  $x(t)$ )

Now, at lag(1),

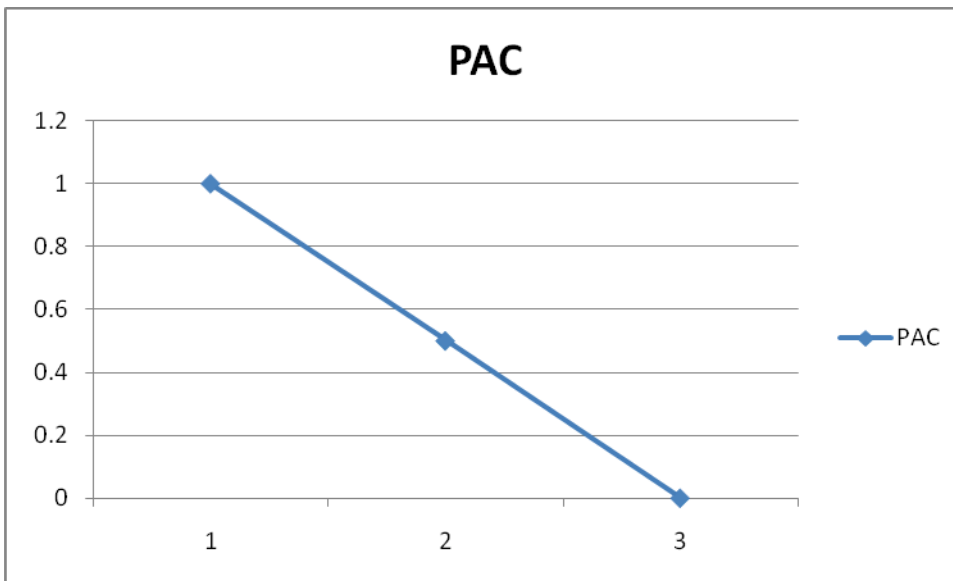
The change in the process for a change one period ago is:

$$\partial x(t) / \partial x(t-1) = b_1 = 0.5,$$

And from the Yule-Kendall equation for an AR(1) the estimate for  $b_1$  is:

$$b_1 = p(1),$$

Now applying the same strategy for partial auto-correlations we get 0. (i.e. the number of non-zero terms in our partial correlation function will actually determine the degree of AR!)



(2)

(a) Again, we have derived the autocorrelation function for an AR(2) in Problem Set #2.

From ideas above we can, for example, show that autocovariance at lag one is:

$$\begin{aligned} \gamma(t, 1) &= E(x(t)x(t-1)) = E[b_1x(t-1)^2 + b_2x(t-2)x(t-1) + \overbrace{e(t)x(t-1)}^{E.V.=0}] \\ &= b_1\gamma(0) + b_2\gamma(1) \end{aligned}$$

Similarly, we derive the autocovariance function at lag two:

$$\gamma(2) = E(x(t)x(t-2)) = E[b_1x(t-1)x(t-2) + b_2x(t-2)^2 + \overbrace{e(t)x(t-2)}^{E.V.=0}] = b_1\gamma(1) + b_2\gamma(0)$$

And finally, by recognizing recursion, we can derive autocovariance of lag three:

$$\begin{aligned} \gamma(3) &= E(x(t)x(t-3)) = E[b_1x(t-1)x(t-3) + b_2x(t-2)x(t-3) + \overbrace{e(t)x(t-3)}^{E.V.=0}] \\ &= b_1\gamma(2) + b_2\gamma(1) \end{aligned}$$

Thus, clearly by multiplying by  $\text{ARTWO}(t-3)$  and taking expectations, we obtain a recursive formula for the autocovariance of lag 3 in terms of the autocovariance at lag 2 and the autocovariance at lag 1.

In order to derive  $\rho(3)$  we simply divide by  $\gamma(0)$  to obtain:

$$\frac{\gamma(3)}{\gamma(0)} = \frac{b_1\gamma(2) + b_2\gamma(1)}{\gamma(0)}$$

$$\rho(3) = b_1\rho(2) + b_2\rho(1)$$

We can further derive the Autocorrelation for AR(2) to be:

$$p_{xx(1)} = \frac{b_1}{(1 - b_2)}$$

$$p_{xx(U)} = b_1 p_{xx}(U - 1) + b_2 p_{xx}(U - 2)$$

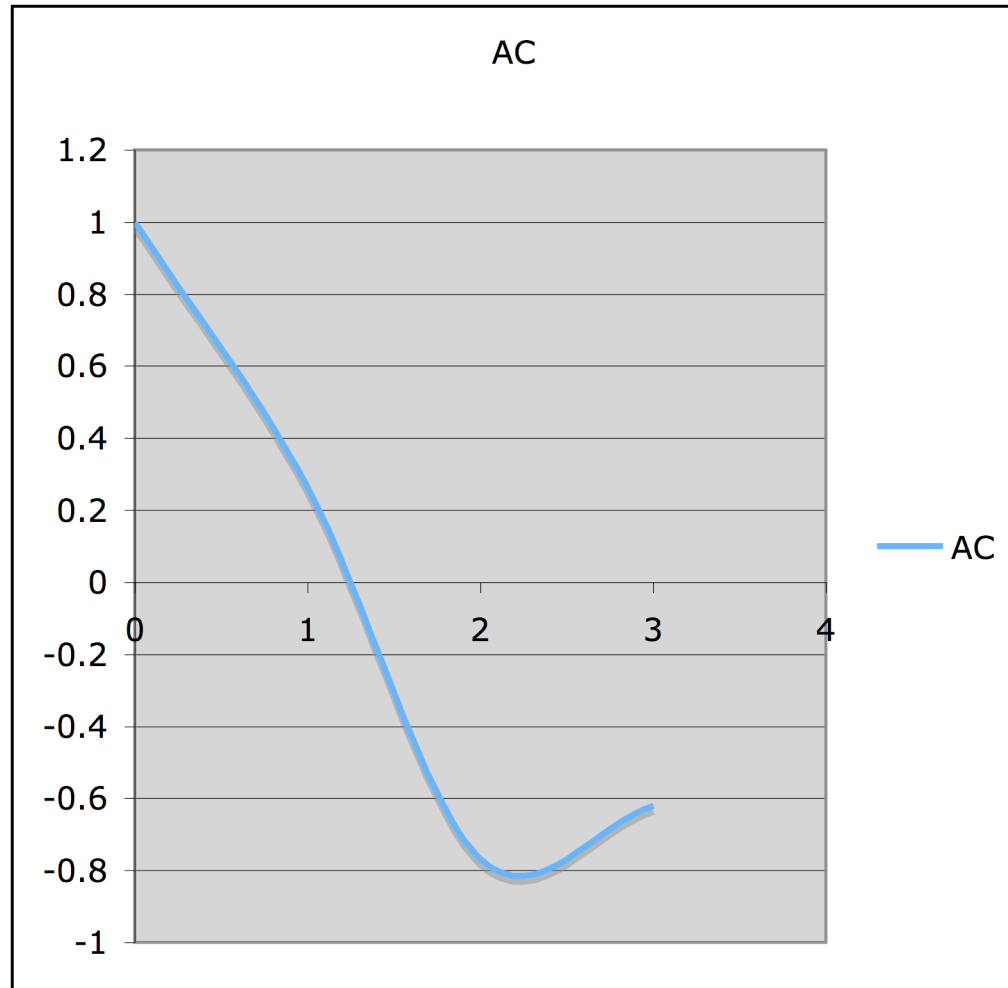
Thus,

$$\rho(0) = 1$$

$$\rho(1) = \frac{0.5}{(1 - (-0.9))} = 0.263$$

$$\rho(2) = 0.5p_{xx}(1) + (-0.9)p_{xx}(0) = -0.7684$$

$$\rho(3) = 0.5p_{xx}(2) + (-0.9)p_{xx}(1) = -0.6209$$



(b)

$$x(t) = b_1x(t-1) + b_2x(t-2) + e(t),$$

the change in the process for a change two periods ago is:

$$\partial x(t)/\partial x(t-2) = b_2,$$

and from the Yule-Kendall equations for an AR(2) the estimate for  $b_2$  is:

$$b_2 = \rho_{x,x}(2) - b_1[\rho_{x,x}(1)]^2,$$

and the estimate for  $b_1$  is:

$$b_1 = \rho_{x,x}(1)(1-b_2),$$

and substituting for  $b_1$  and solving for  $b_2$ , the estimate is:

$$b_2 = \{\rho_{x,x}(2) - [\rho_{x,x}(1)]^2\} / \{1 - [\rho_{x,x}(1)]^2\} = \text{PACF}(2),$$

i.e. the estimate of the partial autocorrelation at lag two. Note that if the time series is an AR(1), then

$$\rho_{x,x}(2) = [\rho_{x,x}(1)]^2,$$

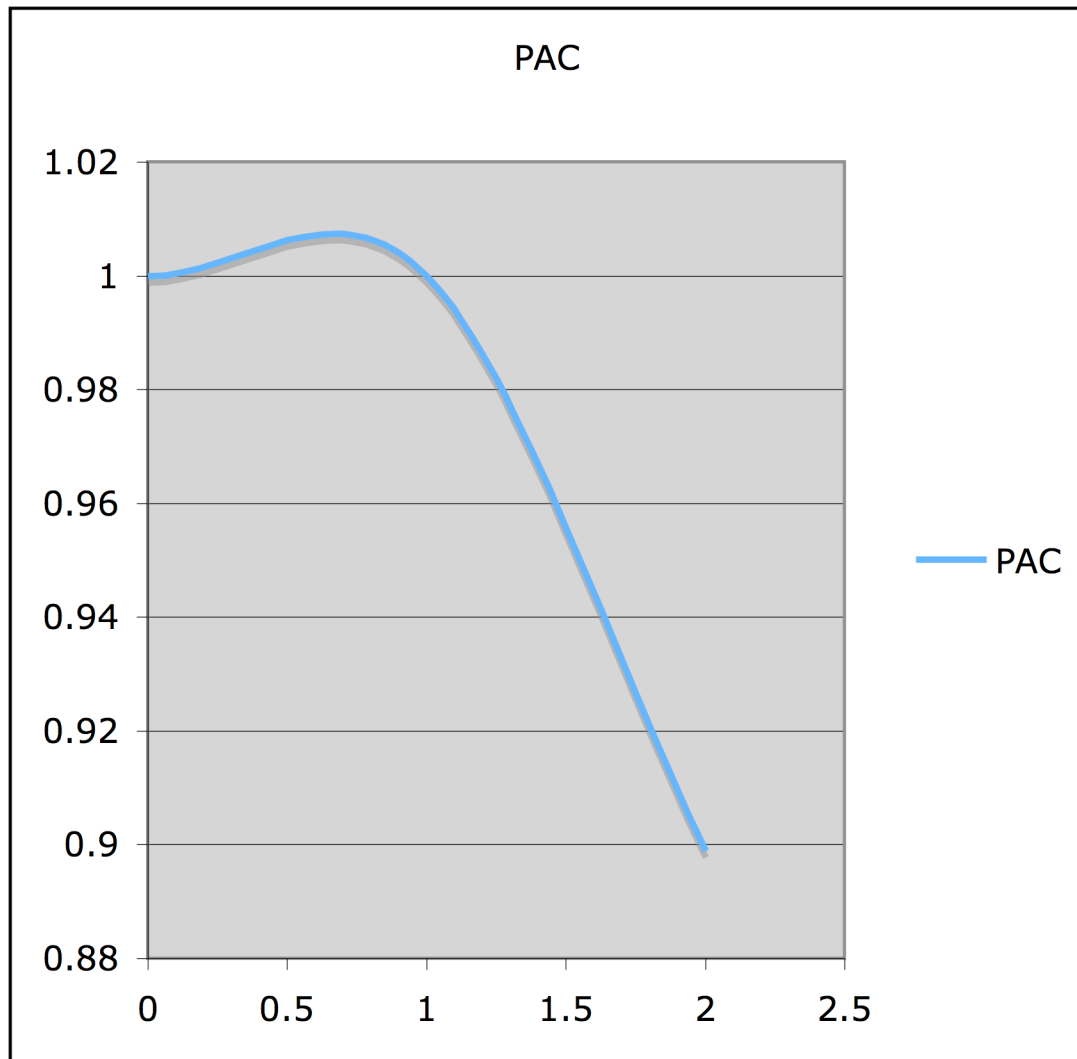
and the partial autocorrelation function at lag two will be zero, so that the number of non-zero estimates of the partial autocorrelation function will indicate the order of the autoregressive process.

$$\text{PACS}(0) = 1$$

$$\text{PACS}(1) = 1$$

$$\text{PACS}(2) = \frac{[\text{ACF}(2) - \text{ACF}(1)^2]}{[1 - \text{ACF}(1)^2]} = \frac{[-0.7684 - 0.263^2]}{[1 - 0.263^2]} =$$

$$= -0.899$$



(3) On the given plot we see that we have a slow decay, with an obvious spike at lag one in our partial autocorrelation. This would suggest that our process is AR(1).

Note\*: Note that the decay starts after a few lags, which would indicate that there is a possibility of a mixed autoregressive model and moving average. In our example we are only provided with choice of AR(1) and AR(2) thus we pick AR(1).