

MTH442 Assignment 4

Name - Kaushik Raj V Nadar

Roll no - 208160499

Email - nkaushik20@iitk.ac.in

Date - 30/10/2024

1) Given IMA (1,1) model

$$X_t = X_{t-1} + W_t - \lambda W_{t-1}$$

Consider $Y_t = X_t - X_{t-1}$ \therefore model becomes,

$$Y_t = W_t - \lambda W_{t-1}$$

The MA polynomial here is,

$$\theta(z) = 1 - \lambda z$$

 $z_1 = \frac{1}{\lambda}$ is the root of the above polynomial

$$\text{Given } |\lambda| < 1 \Rightarrow |z_1| = \frac{1}{|\lambda|} > 1$$

 \therefore The above model is invertible.

Now,

$$Y_t = (1 - \lambda B) W_t$$

where B is the Backward shift operator.

$$W_t = (1 - \lambda B)^{-1} Y_t$$

We expand $(1 - \lambda B)^{-1}$ as a geometric series:

$$W_t = (1 + \lambda B + (\lambda B)^2 + \dots) Y_t$$

$$W_t = \sum_{j=0}^{\infty} \lambda^j B^j Y_t$$

$$W_t = \sum_{j=0}^{\infty} \lambda^j Y_{t-j}$$

$$\Rightarrow W_t = \sum_{j=0}^{\infty} \lambda^j (X_{t-j} - X_{t-1-j})$$

Rearranging,

$$\begin{aligned} W_t &= X_t + (\lambda - 1) X_{t-1} + (\lambda^2 - \lambda) X_{t-2} \\ &\quad + (\lambda^3 - \lambda^2) X_{t-3} + \dots \\ &= \cancel{X_t} - \sum_{j=0}^{\infty} (1 - \lambda) \lambda^{j-1} X_{t-j} \end{aligned}$$

$$\Rightarrow X_t = \sum_{j=1}^{\infty} (1 - \lambda) \lambda^{j-1} X_{t-j} + W_t$$

$$\begin{aligned} Y_{T+2}^T &= \delta + \phi \delta + \phi^2 Y_T \\ &= \delta (1 + \phi) \end{aligned}$$

$$Y_{T+3}^T = \delta + \phi / \delta (1 + \phi)$$

2) (a) Given ARIMA (1,1,0) model:

$$(1-\phi B)(1-B)X_t = \delta + W_t$$

$$\Rightarrow X_t - X_{t-1} - \phi(X_{t-1} - X_{t-2}) = \delta + W_t$$

$$\text{Also, } Y_t = \nabla X_t = X_t - X_{t-1}$$

\therefore We have,

$$Y_t - \phi Y_{t-1} = \delta + W_t$$

$$\Rightarrow Y_t = \phi Y_{t-1} + \delta + W_t$$

\therefore This is an AR(1) model.

Formulate the predictor \hat{Y}_{T+1} , (linear)

$$\hat{Y}_{T+1} = a + b Y_T \quad \left[\text{coeffs for lags } \geq 1 \text{ are zero assuming AR(1) model} \right]$$

where a and b are constants.

Minimize the mean square error,

$$\text{and get the BLP, } E[(Y_{T+1} - \hat{Y}_{T+1})^2]$$

Using the AR(1) model, we have,

$$Y_{T+1} = \delta + \phi Y_T + W_{T+1}$$

$$\begin{aligned} \therefore Y_{T+1} - \hat{Y}_{T+1} &= (\delta + \phi Y_T + W_{T+1}) - (a + b Y_T) \\ &= (\delta - a) + (\phi - b) Y_T + W_{T+1} \end{aligned}$$

To minimize the MSE, we want \hat{Y}_{T+1} to be an unbiased predictor,

$$E[Y_{T+1} - \hat{Y}_{T+1}] = 0$$

$$\Rightarrow (\delta - a) + (\phi - b) E[Y_T] = 0$$

$E[Y_T]$ will be a polynomial in δ since Y_T has a drift.

\therefore on comparing the coefficients on the LHS with RHS we get.

$$a = \delta \text{ and } b = \phi$$

Thus, our linear predictor becomes,

$$Y_{T+1}^T = \delta + \phi Y_T$$

We can also say

$$Y_{T+2}^T = \delta + \phi Y_{T+1}^T = \delta + \phi (\delta + \phi Y_T)$$

$$Y_{T+3}^T = \delta + \phi Y_{T+2}^T, \dots$$

$$\Rightarrow Y_{T+j}^T = \delta + \phi Y_{T+j-1}^T$$

$$Y_{T+j}^T = \delta(1 + \phi + \dots + \phi^{j-1}) + \phi^j Y_T$$

$$\Rightarrow Y_{T+j}^T = \delta \sum_{k=0}^{j-1} \phi^k + \phi^j Y_T$$

$$\Rightarrow Y_{T+j}^T = \delta \left(\frac{1 - \phi^j}{1 - \phi} \right) + \phi^j Y_T$$

(b) We now have,

$$Y_{T+j}^T = \frac{\delta(1-\phi^j)}{(1-\phi)} + \phi^j Y_T$$

$$\begin{aligned} \text{(i)} \sum_{j=1}^M Y_{T+j}^T &= \sum_{j=1}^M (X_{T+j}^T - X_{T+j-1}^T) \\ &= (X_{T+1}^T - X_T^T) + (X_{T+2}^T - X_{T+1}^T) \\ &\quad + \dots + (X_{T+M}^T - X_{T+M-1}^T) \end{aligned}$$

This forms a telescopic series and only 2 terms remain.

$$\begin{aligned} \therefore \sum_{T=1}^M Y_{T+j}^T &= X_{T+M}^T - X_T^T \\ &= X_{T+M}^T - X_T \end{aligned}$$

$$\begin{aligned} \text{(ii)} \sum_{j=1}^M \frac{\delta(1-\phi^j)}{(1-\phi)} &= \frac{\delta}{(1-\phi)} \left[M - \sum_{j=1}^M \phi^j \right] \\ &= \frac{\delta}{1-\phi} \left[M - \phi \frac{(1-\phi^M)}{(1-\phi)} \right] \end{aligned}$$

$$\begin{aligned} \text{(iii)} \sum_{j=1}^M \phi^j Y_T &= Y_T \sum_{j=1}^M \phi^j \\ &= Y_T \phi \frac{(1-\phi^M)}{(1-\phi)} \end{aligned}$$

Now,

$$\begin{aligned} Y_{T+j}^T &= \frac{\delta(1-\phi^j)}{(1-\phi)} + \phi^j Y_T \\ \Rightarrow \sum_{j=1}^M Y_{T+j}^T &= \frac{\delta}{(1-\phi)} \sum_{j=1}^M 1 + \sum_{j=1}^M \phi^j Y_T \end{aligned}$$

From (i), (ii) and (iii), we have,

$$X_{T+M}^T - X_T = \frac{\delta}{(1-\phi)} \left[\frac{M - \phi(1-\phi^M)}{(1-\phi)} \right] + Y_T \frac{\phi(1-\phi^M)}{(1-\phi)}$$

$$\Rightarrow X_{T+M}^T = X_T + \frac{\delta}{(1-\phi)} \left[\frac{M - \phi(1-\phi^M)}{(1-\phi)} \right] + (X_T - X_{T-1}) \frac{\phi(1-\phi^M)}{(1-\phi)}$$

(c) To get the ψ^* coefficients, we need to solve,

$$\psi^*(z) (1 - \phi z)$$

$$\psi^*(z) \phi(z) = \theta(z)$$

where

$$\psi^*(z) = \psi_0^* + \psi_1^* z + \psi_2^* z^2 + \dots$$

$$\phi(z) = (1 - \phi z)(1 - z)$$

$$\theta(z) = 1$$

\therefore Equation becomes,

$$(\psi_0^* + \psi_1^* z + \psi_2^* z^2 + \dots)(1 - (1+\phi)z + \phi z^2) = 1$$

Comparing the coeffs of z^0 , we get,

$$\psi_0^* = 1$$

Comparing the coefficients of z^1 ,

$$\psi_1^* - \psi_0^*(1+\phi) = 0$$

$$\Rightarrow \psi_1^* = (1+\phi)$$

Comparing the coeffs of z^2 ,

$$\psi_2^* - \psi_1^*(1+\phi) + \phi \psi_0^* = 0$$

Comparing the coeffs of z^j , we have
 $\psi_j^* - \psi_{j-1}^* (1+\phi) + \phi \psi_{j-2}^* = 0 \quad j \geq 2$

Claim: $\psi_j^* = (1-\phi)^{-1} (1-\phi^{j+1}) \quad j \geq 1$

Proof:

Use induction,

(i) For $j=1$,

$$\psi_1^* = (1-\phi)^{-1} (1-\phi^2)$$

$$\psi_1^* = (1+\phi)$$

which is true

(ii) ~~Assume~~ Assume $\psi_j^* = \frac{(1-\phi^{j+1})}{(1-\phi)}$

is true for $j=k$ and $k \geq 1$, $k \geq 2$

(iii) Show $\psi_{k+1}^* = \frac{(1-\phi^{k+2})}{(1-\phi)}$ based on the

above assumption.

$$\begin{aligned} \text{We know, } \psi_{k+1}^* - \psi_k^* (1+\phi) + \phi \psi_{k-1}^* &= 0 \\ \Rightarrow \psi_{k+1}^* &= \frac{(1-\phi^{k+1})(1+\phi)}{(1-\phi)} - \phi \frac{(1-\phi^k)}{(1-\phi)} \\ &= \frac{1}{1-\phi} \left[1-\phi^{k+1} + \phi - \phi^{k+2} - \phi + \phi^{k+1} \right] \\ \Rightarrow \psi_{k+1}^* &= \frac{(1-\phi^{k+2})}{(1-\phi)} \end{aligned}$$

Hence, Proved.

$$\text{Thus, } \psi_j^* = \frac{(1-\phi^{j+1})}{(1-\phi)}$$