# MSMS 301 - Time Series

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#### 1 Moving Average Process

Suppose  $\{Z_t\}$  is a purely random process with mean 0 and variance  $\sigma^2$ . A process  $\{X_t\}$  derived as a weighted sum of present and past  $\mathbf{q}$  white noises is said to be a Moving Average Process of order  $\overline{q}$  (abbreviated to MA(q)).

$$X_t = \beta_0 Z_t + \beta_1 Z_{t-1} + \ldots + \beta_q Z_{t-q}$$
 (1)

where all  $\beta_i$ 's are constants. The Z's are usually scaled so that  $\beta_0 = 1$ .

It immediately follows

- $E(X_t) = 0 \ \forall t \text{ as } E(Z_t) = 0 \ \forall t$
- $Var(X_t) = \sigma^2 \sum_{i=0}^{q} \beta_i^2 \ \forall t \text{ as } Z_t \stackrel{ind}{\sim} \text{variance } = \sigma^2 \ \forall t.$

#### $1.1 \quad MA(1) \text{ Process}$

With  $Z_t \sim$  White Noise  $(0, \sigma^2)$ , the first order moving average process  $\{X_t\}$  is defined as

$$X_t = \beta_0 Z_t + \beta_1 Z_{t-1}; \ \beta_0 = 1 \tag{2}$$

or 
$$X_t = Z_t + \theta Z_{t-1}$$
 (3)

where  $\theta \in \mathbb{R}$  (as the process is finite,  $\theta$  is free to be any real constant).

Clearly  $E(X_t) = 0 \ \forall t \ \text{and} \ Var(X_t) = \sigma^2(1 + \theta^2).$ 

Now

$$\gamma(h) = cov(X_t, X_{t+h}) 
= cov(Z_t + \theta Z_{t-1}, Z_{t+h} + \theta Z_{t+h-1}) 
= cov(Z_t, Z_{t+h}) + \theta \cdot cov(Z_t, Z_{t+h-1}) + \theta \cdot cov(Z_{t-1}, Z_{t+h}) + \theta^2 \cdot cov(Z_{t-1}, Z_{t+h-1}) 
= \begin{cases} \sigma^2(1 + \theta^2), & h = 0 \\ \theta \sigma^2, & h = \pm 1 \\ 0, & h = \pm 2, \pm 3, \pm 4, \dots \end{cases}$$

Then

$$\rho(h) = \frac{\gamma(h)}{\gamma(0)}$$

$$= \begin{cases} 1, & h = 0\\ \frac{\theta}{1 + \theta^2}, & h = \pm 1\\ 0, & h = \pm 2, \pm 3, \pm 4, \dots \end{cases}$$

 $\bigcirc$  So, for MA(1) process, the autocorrelation function vanishes after lag 1. This is an identifier for MA(1) process.

#### MA(q) Process

MA(q) process as in (1) can be written as  $X_t = \sum_{i=0}^{q} \beta_i Z_{t-i}$ .

Then

$$\gamma(h) = cov(X_t, X_{t+h})$$

$$= cov\left(\sum_{i=0}^q \beta_i Z_{t-i}, \sum_{j=0}^q \beta_j Z_{t+h-j}\right)$$

$$= cov\left(\sum_{i=0}^q \beta_i Z_{t-i}, \sum_{s=-h}^{q-h} \beta_{s+h} Z_{t-s}\right) \quad [s = j - h]$$

$$= cov\left(\sum_{i=0}^q \beta_i Z_{t-i}, \sum_{i=-h}^{q-h} \beta_{i+h} Z_{t-i}\right) \quad [\text{runner } s \text{ is just a dummy variable}]$$

$$= \sum_{i=0}^{q-h} \beta_i \beta_{i+h} \cdot cov(Z_{t-i}, Z_{t-i})$$

$$= \sigma^2 \sum_{i=0}^{q-h} \beta_i \beta_{i+h}$$

$$= \begin{cases} \sigma^2 \sum_{i=0}^{q-h} \beta_i \beta_{i+h}, & h = 0, 1, \dots, q \\ 0, & h > q \\ \gamma(-h), & h < 0 \end{cases}$$

Consequently

$$\rho(h) = \frac{\gamma(h)}{\gamma(0)}$$

$$= \begin{cases} \sum_{i=0}^{q-h} \beta_i \beta_{i+h} \\ \sum_{i=0}^{q} \beta_i^2 \\ 0, h > q \\ \rho(-h), h < 0 \end{cases}$$

It can be seen from the above expression that ACF becomes 0 at lag k > q. It shows that ACF of MA process cuts off at lag q which is a special characteristics of MA(q) process.

@ 03.08.2025, Sunday (Yesss !! On a goddaamn Sunday !!  $\mathfrak{Q}$ )



Random Cosine Curve: Consider a stochastic process  $\{X_t\}$  given by

$$X_t = \cos\left(2\pi\left(\frac{t}{12} + \Phi\right)\right). \ t = 0, \pm 1, \pm 2, \dots$$

where  $\Phi \sim U(0,1)$ . Find  $E(X_t)$  and  $Var(X_t)$ .

#### 2 Autoregressive Process

#### 2.1 AR(1) Process

The first-order autoregressive process  $\{X_t\}$  is defined as

$$X_t = \alpha X_{t-1} + Z_t \ t = 0, \pm 1, \pm 2, \dots$$
 (4)

where  $Z_t$ 's are White Noise with mean 0 and variance  $\sigma^2$ ;  $\alpha \in \mathbb{R}$ , constant.

Notice (4) reduces to a random walk model for  $\alpha = 1$ .

We may write (4) as  $X_t = \alpha B X_t + Z_t$  where B is a backshift operator with  $B X_t = X_{t-1}$ .

Then  $(1 - \alpha B)X_t = Z_t$  so that

$$X_{t} = (1 - \alpha B)^{-1} Z_{t}$$

$$= (1 + \alpha B + \alpha^{2} B^{2} + \alpha^{3} B^{3} + \dots) Z_{t}$$

$$= Z_{t} + \alpha Z_{t-1} + \alpha^{2} Z_{t-2} + \alpha^{3} Z_{t-3} + \dots$$

$$= \sum_{i=0}^{\infty} \alpha^{j} Z_{t-j} \text{ provided the sum exists } i.e. |\alpha| < 1$$
(5)

Using (5),  $E(X_t) = 0$ ,  $t = 0, \pm 1, \pm 2, \dots$ 

And 
$$Var(X_t) = \sigma^2 \sum_{j=0}^{\infty} \alpha^{2j} = \frac{\sigma^2}{1 - \alpha^2}$$
, provided  $|\alpha| < 1$ .

Then

$$\gamma(h) = cov(X_t, X_{t+h})$$

$$= cov\left(\sum_{j=0}^{\infty} \alpha^j Z_{t-j}, \sum_{j=0}^{\infty} \alpha^j Z_{t+h-j}\right)$$

$$= cov\left(\sum_{j=0}^{\infty} \alpha^j Z_{t-j}, \sum_{k=-h}^{\infty} \alpha^{k+h} Z_{t-k}\right), \text{ taking } k = j - h$$

$$= \sigma^2 \sum_{j=0}^{\infty} \alpha^j \alpha^{j+h}$$

$$= \sigma^2 \alpha^h \sum_{j=0}^{\infty} \alpha^{2j}$$

$$= \frac{\sigma^2 \alpha^h}{1 - \alpha^2} \text{ provided } |\alpha| < 1, h \ge 0$$

Note that  $\gamma(h)$  does not depend on t. So AR(1) model is weak stationary only if  $|\alpha| < 1$ .

Consequently

$$\rho(h) = \frac{\gamma(h)}{\gamma(0)}$$

$$= \begin{cases} 1, & h = 0 \\ \alpha^h, & h = 1, 2, \dots \\ \rho(-h), & h = -1, -2, \dots \end{cases}$$

$$= \alpha^{|h|}, & h = \pm 1, \pm 2, \dots$$

Multiplying  $X_{t-k}$  on both sides of (4) and taking expectation we get

$$E(X_t \cdot X_{t-h}) = \alpha E(X_{t-1} \cdot X_{t-h}) + E(Z_t \cdot X_{t-h}),$$
  

$$\Rightarrow \gamma(h) = \alpha \gamma(h-1)$$
(6)

Remember  $Z_t$ ,  $X_{t-h}$  are independent and  $E(X_t) = 0 \ \forall t$ . Also, using (5),  $cov(Z_t, X_{t-h}) = 0$ .

Following (6) we have

$$\gamma(1) = \alpha \gamma(0)$$

$$\gamma(2) = \alpha^2 \gamma(0)$$

$$\vdots$$

$$\gamma(h) = \alpha^h \gamma(0)$$
(7)

On dividing both sides of (7) by  $\gamma(0)$ , we get

$$\rho(h) = \alpha^{|h|}, \ h = 0, \pm 1, \pm 2, \dots$$



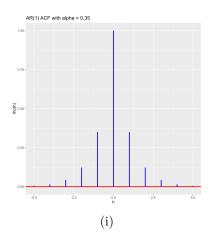
- (i)  $X_t = 0.35 X_{t-1} + Z_t$
- (ii)  $X_t = 0.85 X_{t-1} + Z_t$
- (iii)  $X_t = -0.35 X_{t-1} + Z_t$

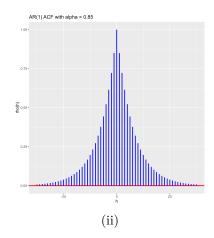
The ACVFs and ACFs are as follows.

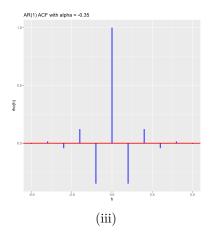
(i) 
$$\gamma(h) = 0.8775 \cdot \sigma^2 \, 0.35^{|h|}, \, \rho(h) = 0.35^{|h|} \, \forall h = 0, \pm 1, \pm 2, \dots$$

(ii) 
$$\gamma(h) = 0.2775 \cdot \sigma^2 \, 0.85^{|h|}, \, \rho(h) = 0.85^{|h|} \, \forall h = 0, \pm 1, \pm 2, \dots$$

(iii) 
$$\gamma(h) = 0.8775 \cdot \sigma^2 (-0.35)^{|h|}, \ \rho(h) = (-0.35)^{|h|} \ \forall h = 0, \pm 1, \pm 2, \dots$$







#### 2.2 AR(2) Process

The second-order autoregressive process  $\{X_t\}$  is defined as

$$X_t = \alpha_1 X_{t-1} + \alpha_2 X_{t-2} + Z_t \ t = 0, \pm 1, \pm 2, \dots$$
 (8)

where  $Z_t$ 's are White Noise with mean 0 and variance  $\sigma^2$ ;  $\alpha_1, \alpha_2 \in \mathbb{R}$ , constants.

The AR(2) process in (8) can be written in terms of backshift operator B as follows.

$$X_t = \alpha_1 B X_t + \alpha_2 B^2 X_t + Z_t$$

$$(1 - \alpha_1 B - \alpha_2 B^2) X_t = Z_t$$

$$X_t = (1 - \alpha_1 B - \alpha_2 B^2)^{-1} Z_t$$

$$= (\alpha(B))^{-1} Z_t$$

$$= \psi(B) Z_t$$

where  $\alpha(z) = 1 - \alpha_1 z - \alpha_2 z^2$  and  $\psi(z) = 1 + \psi_1 z + \psi_2 z^2 + \ldots = \sum_{j=0}^{\infty} \psi_j z^j$  with  $\psi_0 = 1$ .

$$\therefore X_t = \sum_{j=0}^{\infty} \psi_j B^j Z_t$$

$$= \sum_{j=0}^{\infty} \psi_j Z_{t-j} \text{ with } \psi_0 = 1$$
(9)

Using (9),  $E(X_t) = 0$ ,  $t = 0, \pm 1, \pm 2, \dots$ 

And  $\gamma(0) = Var(X_t) = \sigma^2 \sum_{j=0}^{\infty} \psi_j^2$ , provided the sum exists.

Then

$$\forall h > 0, \ \gamma(h) = cov(X_t, X_{t+h})$$

$$= cov\left(\sum_{j=0}^{\infty} \psi_j Z_{t-j}, \sum_{j=0}^{\infty} \psi_j Z_{t+h-j}\right)$$

$$= cov\left(\sum_{j=0}^{\infty} \psi_j Z_{t-j}, \sum_{k=-h}^{\infty} \psi_{k+h} Z_{t-k}\right), \text{ taking } k = j - h$$

$$= \sigma^2 \sum_{j=0}^{\infty} \psi_j \psi_{j+h} \text{ provided the sum exists}$$

Thus

$$\gamma(h) = \begin{cases} \sigma^2 \sum_{j=0}^{\infty} \psi_j \psi_{j+h}, \ h = 1, 2, 3, \dots \\ \sigma^2 \sum_{j=0}^{\infty} \psi_j^2, \ h = 0 \\ \rho(-h), \ h = -1, -2, -3, \dots \text{ provided all the sums exist} \end{cases}$$

Consequently

$$\rho(h) = \begin{cases} \sum_{j=0}^{\infty} \psi_j \psi_{j+h} \\ \sum_{j=0}^{\infty} \psi_j^2 \\ \rho(-h), \ h = -1, -2, -3, \dots \text{ provided all the sums exist} \end{cases}$$