

# General Autoregressive Process, AR(p)

The General  $p^{\text{th}}$  order AR model is given as

$$y_t = \underline{\delta} + \underline{\phi_1 y_{t-1}} + \underline{\phi_2 y_{t-2}} + \dots + \underline{\phi_p y_{t-p}} + \underline{\varepsilon_t}$$

↓

$B y_t$

↓

$B^2 y_t$

$B^p y_t$  ①

It is regression of  $y_t$  on  $y_{t-1}, y_{t-2}, \dots, y_{t-p}$ .

Now, we can write eq<sup>n</sup> ① in terms of backshift operator as

$$y_t = \delta + \phi_1 B y_t + \phi_2 B^2 y_t + \dots + \phi_p B^p y_t + \varepsilon_t$$

$$[\because B^i y_t = y_{t-i}]$$

$$y_t - \phi_1 B y_t - \phi_2 B^2 y_t - \dots - \phi_p B^p y_t = \delta + \varepsilon_t$$

$$(1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p) y_t = \delta + \varepsilon_t \quad \text{②}$$

$$\Phi(B) y_t = \delta + \varepsilon_t \quad \text{③}$$

or

$$A^{-1} A = I$$

(2)

apply  $\Phi(B)^{-1}$  to both sides, we obtain

$$y_t = \Phi(B)^{-1} \delta + \Phi(B)^{-1} \varepsilon_t$$

or

$$y_t = \mu + \psi(B) \varepsilon_t$$

- (4)

where  $\mu = \Phi(B)^{-1} \delta$

$\psi(B) = \Phi(B)^{-1}$

$$y_t = \mu + \sum_{i=0}^{\infty} \psi_i \varepsilon_{t-i}$$

$$y_t = \mu + \sum_{i=0}^{\infty} \psi_i B^i \varepsilon_t$$

where

$$\mu = \Phi(B)^{-1} \delta$$

- (5)

and

$$\Phi(B)^{-1} = \sum_{i=0}^{\infty} \psi_i B^i = \psi(B)$$

- (6)

Now, we use eqn (6) to obtain the weights in Eqn (4) in terms of  $\phi_1$  and  $\phi_2, \dots, \phi_p$ .

For that, we use

$$\Phi(B) \Psi(B) = 1 \quad \text{--- (7)}$$

~~$$\phi_1(B)$$~~



$$(1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p) \times (\psi_0 + \psi_1 B + \psi_2 B^2 + \dots + \psi_p B^p + \dots) = 1 \quad (8)$$

on RHS of eq<sup>n</sup> (8) there are no ~~parameters~~ backshift operator for

$$\Phi(B) \Psi(B) = 1$$

we need,

$$\psi_j = 0, \quad j < 0$$

$$\psi_0 = 1 \quad \checkmark$$

$$\psi_j - \phi_1 \psi_{j-1} - \phi_2 \psi_{j-2} - \dots - \phi_p \psi_{j-p} = \underline{\underline{0}} \quad (9)$$

for  $j = 1, 2, \dots$

The AR(P) time series  $\{y_t\}$  in eqn (1) is causal and stationary if the roots of the associated polynomial

$$m^P - \phi_1 m^{P-1} - \phi_2 m^{P-2} - \dots - \phi_P = 0$$

AR(2)  $\rightarrow m^2 - \phi_1 m - \phi_2 = 0$  are less than one in absolute value. i.e. (10)

$$|m_1|, |m_2|, \dots, |m_P| < 1$$

then we have  $\sum_{i=0}^{\infty} |\psi_i| < \infty$ .

{ mean of AR(p) process }

we can easily show that, for the stationary AR(p) process.

✓  $E(y_t) = \underline{\mu} = \frac{\delta}{1 - \phi_1 - \phi_2 - \dots - \phi_p}$

(II)

{ Autocovariance and Autocorrelation of Stationary AR(p) process }

from eqn (I)

✓  $\underline{y_t = \delta + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \dots + \phi_p y_{t-p} + \varepsilon_t}$

(I)

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The autocovariance function is

$$\underline{\gamma(k)} = \text{cov}(y_t, y_{t-k})$$

$$\gamma(k) = \text{cov}(y_t, \phi_1 y_{t-1} + \phi_2 y_{t-2} + \dots + \phi_p y_{t-p} + \varepsilon_t, y_{t-k})$$

See AR(p) process  
Autocovariance ✓

$$\gamma(k) = \sum_{i=1}^p \phi_i \text{cov}(y_{t-i}, y_{t-k}) + \text{cov}(\varepsilon_t, y_{t-k})$$

$$\gamma(k) = \sum_{i=1}^p \phi_i \underline{\gamma(k-i)} + \sigma^2 \quad \text{if } \underline{k=0}$$

$$\gamma(k) = \sum_{i=1}^p \phi_i \underline{\gamma(k-i)} + \underline{0} \quad \text{if } \underline{k > 0}$$



Thus for  $k=0$  we have

$$\checkmark \gamma(0) = \sum_{i=1}^p \phi_i \gamma(i) + \sigma^2$$

③

$$\gamma(-i) = \gamma(i)$$

$$\Rightarrow \gamma(0) =$$

$$\Rightarrow \gamma(0) - \sum_{i=1}^p \phi_i \gamma(i) = \sigma^2$$

$$\Rightarrow \underline{\gamma(0)} = \left[ 1 - \sum_{i=1}^p \phi_i \frac{\gamma(i)}{\gamma(0)} \right] = \sigma^2$$

$$\Rightarrow \gamma(0) \left[ 1 - \sum_{i=1}^p \phi_i \rho(i) \right] = \sigma^2$$

④

$$\left[ \because \rho(i) = \frac{\gamma(i)}{\gamma(0)} \right]$$



Now divide eqn (2) by  $\text{Var}(y_t)$  for  $k > 0$ ,

it can be observed that the ACF of an AR(p) process satisfies the Yule-Walker equations

$$\checkmark P(k) = \sum_{i=1}^p \phi_i P(k-i), \quad k=1, 2, \dots$$

— (5)

The equation (5) are  $p^{\text{th}}$  order

linear difference equations, implying that the ACF for an AR(p) model can be found through the  $p$  roots of the associated polynomial in eqn (10)

$$\checkmark \text{ie. } m^p - \phi_1 m^{p-1} - \phi_2 m^{p-2} - \dots - \phi_p = 0.$$

For ex. if roots are real and distinct we have

$$\checkmark P(k) = c_1 m_1^k + c_2 m_2^k + \dots + c_p m_p^k, \quad k=1, 2, \dots$$

— (6)

where  $C_1, C_2, \dots, C_p$  are particular constants. However, the roots may not all be distinct or real.

Thus the ACF of an  $AR(p)$  process can be a mixture of exponential decay and damped sinusoid expressions depending on the roots of eqn (10)