

$x_t = z_t + \theta_1 z_{t-1} + \dots + \theta_q z_{t-q}$  : فراسن میانگین سرکش  
MA(1) میانگین سرکش ناپسندیده است و صورت میانگین سرکش (MA) گویند.

$$MA(1) \Rightarrow x_t = z_t + \theta_1 z_{t-1}$$

$$\begin{aligned} \text{cov}(x_t, x_{t-1}) &= E[(x_t - \mu)(x_{t-1} - \mu)] = E[x_t x_{t-1}] \\ &= E[(z_t + \theta_1 z_{t-1})(z_{t-1} + \theta_1 z_{t-2})] \\ &= E[z_t z_{t-1} + \theta_1 z_t z_{t-2} + \theta_1 z_{t-1}^2 + \theta_1^2 z_{t-1} z_{t-2}] \\ &= E[z_t z_{t-1}] + \theta_1 E[z_t z_{t-2}] + \theta_1 E[z_{t-1}^2] + \theta_1^2 E[z_{t-1} z_{t-2}] \\ z_i &\stackrel{iid}{\sim} N(0, \sigma^2) \quad \theta_1 E[z_{t-1}^2] = [\theta_1 \sigma^2 = \text{cov}(x_t, x_{t-1}) = \gamma_1] \end{aligned}$$

بنابراین طور خلاصه بررسی MA(1) خواهد شد:

$$E[x_t] = 0$$

$$\begin{aligned} \text{var}(x_t) &= E[x_t^2] - E^2[x_t] = E[x_t^2] = E[(z_t + \theta_1 z_{t-1})^2] \\ &= E[z_t^2 + \theta_1^2 z_{t-1}^2 + 2 z_t \theta_1 z_{t-1}] \\ &= E[z_t^2] + \theta_1^2 E[z_{t-1}^2] + 2 \theta_1 E[z_t z_{t-1}] \\ &= \sigma^2 + \theta_1^2 \sigma^2 = \boxed{\sigma^2(1 + \theta_1^2)} = \text{var}(x_t) \end{aligned}$$

$$\gamma_1 = +\theta_1 \sigma^2$$

$$\rho_1 = \frac{\theta_1 \sigma^2}{\sigma^2(1 + \theta_1^2)} = \frac{\theta_1}{1 + \theta_1^2}$$

$$\boxed{\rho_1 = \frac{\theta_1}{1 + \theta_1^2}}$$

$\theta_1 z_{t-1} + \theta_2 z_{t-2}$

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$x_t = z_t + \theta_1 z_{t-1} + \theta_2 z_{t-2}$  : مدل ساده رتیبل (دوم)

$$\gamma_0 = \text{Var}(x_t) = E[x_t^2] - 0 = E[x_t^2] =$$

$$E[z_t^2] + \theta_1 E[z_t z_{t-1}] + \theta_2 E[z_t z_{t-2}] +$$

$$\theta_1 E[z_t z_{t-1}] + \theta_1^2 E[z_{t-1}^2] + \theta_1 \theta_2 E[z_{t-1} z_{t-2}] +$$

$$\theta_2 E[z_t z_{t-2}] + \theta_2 \theta_1 E[z_{t-1} z_{t-2}] + \theta_2^2 E[z_{t-2}^2]$$

$$= \sigma^2 + \theta_1^2 \sigma^2 + \theta_2^2 \sigma^2 = \boxed{\sigma^2(1 + \theta_1^2 + \theta_2^2)} = \gamma_0$$

$$\gamma_1 = \text{Cov}(x_t, x_{t-1}) = E[x_t x_{t-1}] =$$

$$E[z_t z_{t-1} + \theta_1 z_{t-1}^2 + \theta_2 z_{t-2} z_{t-1}] +$$

$$\theta_1 z_{t-1} z_{t-2} + \theta_1^2 z_{t-1}^2 + \theta_1 \theta_2 z_{t-2} +$$

$$\theta_2 z_t z_{t-3} + \theta_2 \theta_1 z_{t-1} z_{t-3} + \theta_2^2 z_{t-2} z_{t-3}]$$

$$= E[\theta_1 z_{t-1}^2 + \theta_1 \theta_2 z_{t-2}^2] = \theta_1 E[z_{t-1}^2] + \theta_1 \theta_2 E[z_{t-2}^2]$$

$$= \theta_1 \sigma^2 + \theta_1 \theta_2 \sigma^2 = \boxed{\theta_1(1 + \theta_2) \sigma^2 = \gamma_1}$$

نیازی نداشته باشد که ماتریس های خارجی میانگین مترک درجه دوم داشته باشد:

$$\gamma_0 = (1 + \theta_1^2 + \theta_2^2) \sigma^2$$

$$P_0 = \frac{1}{1 + \theta_1^2 + \theta_2^2}$$

$$\gamma_1 = \theta_1(\theta_2 + 1) \sigma^2$$

$$P_1 = \frac{\theta_1(\theta_2 + 1)}{1 + \theta_1^2 + \theta_2^2}$$

$$\gamma_2 = \theta_2 \sigma^2$$

$$P_2 = \frac{\theta_2}{1 + \theta_1^2 + \theta_2^2}$$

$$\gamma_2 = \text{cov}(x_t, x_{t-2}) = E[(z_t + \theta_1 z_{t-1} + \theta_2 z_{t-2})(z_{t-2} + \theta_1 z_{t-3} + \theta_2 z_{t-4})]$$

$$= E[z_t z_{t-2} + \theta_1 z_t z_{t-3} + \theta_2 z_t z_{t-4} + \theta_1 z_{t-1} z_{t-2} + \\ \theta_1^2 z_{t-1} z_{t-3} + \theta_1 z_{t-1} z_{t-4} + \theta_2 z_{t-2}^2] \quad \cancel{\theta_1 \theta_2 z_{t-2}^2} + \\ \theta_2 \theta_1 z_{t-2} z_{t-3} + \theta_2^2 z_{t-2} z_{t-4}]$$

$$= E[\theta_2 z_{t-2}^2] = \theta_2 E[z_{t-1}^2] = \boxed{\theta_2 \sigma^2 = \gamma_2}$$

$$S_k = \begin{cases} \frac{+\theta_k + \theta_1 \theta_{k+1} + \dots + \theta_{q-1} \theta_q}{1 + \theta_1^2 + \dots + \theta_q^2} & \text{if } 1 \leq k \leq q \\ 0 & \text{if } k > q \end{cases}$$

• فراسنیهان التقریرسیو:  $x_t = \phi_1 x_{t-1} + \dots + \phi_p x_{t-p} + z_t$

• فراسنیهان التقریرسیو مرتبہ اول:  $x_t = \phi_1 x_{t-1} + z_t$

$$\bullet \gamma_0 = \text{var}(x_t) = \text{var}(\phi_1 x_{t-1} + z_t) = \phi_1^2 \gamma_0 + \sigma^2$$

$$\Rightarrow \gamma_0 - \phi_1^2 = \sigma^2 \Rightarrow \gamma_0 = \frac{\sigma^2}{1 - \phi_1^2}$$

$$\gamma_1 = \text{cov}(x_t, x_{t-1}) = E[(x_t - M)(x_{t-1} - M)]$$

• important: if we assume stationary process; this means

$$E[x_t] = \mu, E[x_{t-1}] + E[z_t] = \mu = \phi_1 \mu + 0 \Rightarrow$$

$$\text{since } |\phi_1| < 1 (\text{because of stationary}) \Rightarrow \mu = E[x_t] = 0$$

• important: why is  $|\phi_1| < 1$ :

$$x_t = \phi_1 x_{t-1} + z_t = \phi_1 (\phi_1 x_{t-2} + z_{t-1}) + z_t$$

$$= \phi_1^2 x_{t-2} + \phi_1 z_{t-1} +$$

$$= \phi_1^3 x_{t-3} + \phi_1^2 z_{t-2} + \phi_1 z_{t-1} + z_t$$

$$= \phi_1^k x_{t-k} + \sum_{j=0}^{k-1} \phi_1^j z_{t-j} \stackrel{k \rightarrow \infty}{\approx} \phi_1^k x_{t-k}$$

$$\text{for being stationary } \lim_{k \rightarrow \infty} \phi_1^k x_{t-k} = 0 \Rightarrow \begin{cases} |\phi_1| < 1 \\ |\phi_1| = 1 \\ |\phi_1| > 1 \end{cases}$$

- if  $\phi_1 = 1$ :  $x_t = \phi_1 x_{t-1} + z_t = x_{t-1} + z_t$   
This is a random walk, variance increases forever  
Therefore, it is not stationary
- if  $\phi_1 = -1$ :  $x_t = -x_{t-1} + z_t$   
This means the process oscillates forever, mean exists  
but variance does not converge  $\Rightarrow$  not stationary
- if  $|\phi_1| > 1$ : Then  $\phi_1^k x_{t-k}$  explodes
- if  $|\phi_1| < 1$ : Then the process is stationary  $\Rightarrow E[x_t] = 0$

$$\gamma_1 = E[x_t x_{t-1}] = x_{t-1}^2 + z_t x_{t-1}] =$$

$$\phi_1 E[x_{t-1}^2] + E[x_{t-1} z_t] = \phi_1 \frac{\sigma^2}{1-\phi_1^2} = \boxed{\gamma_1 = \frac{\phi_1}{1-\phi_1^2} \sigma^2}$$

$$E[x_t z_t]$$

$\varepsilon_t$  is independent from past values

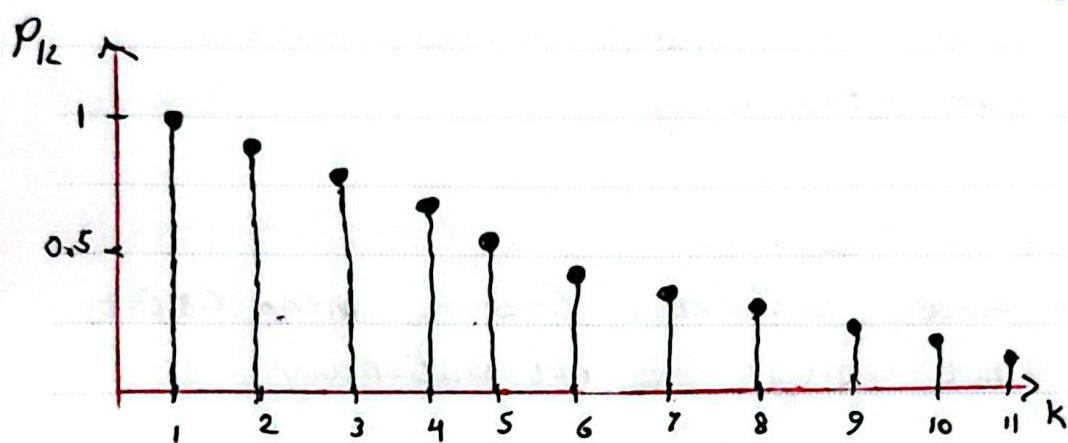
$x_{t-1}$  depends only on  $\varepsilon_{t-k}$

$\varepsilon_t$  is independent from  $\varepsilon_{t-k}$

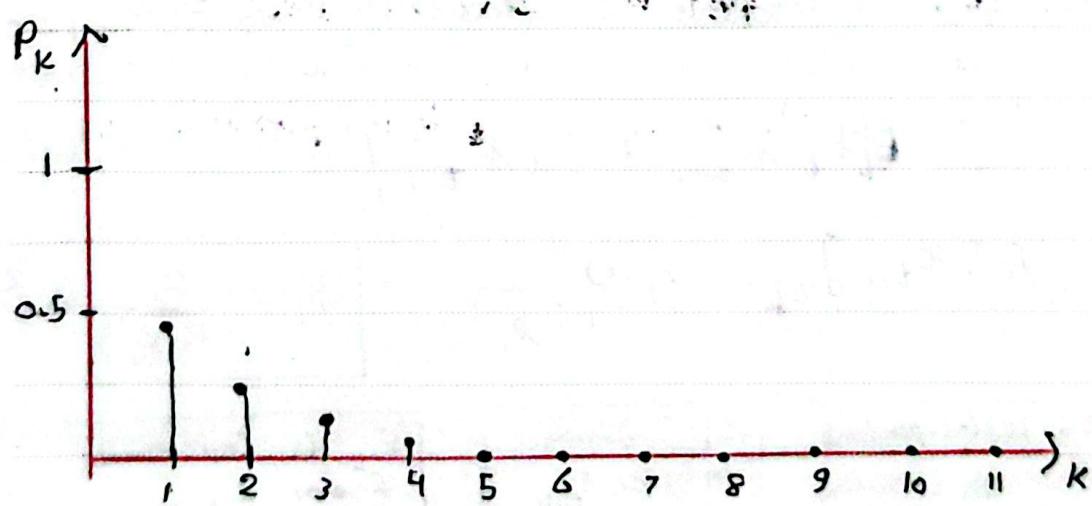
$$\Rightarrow E[x_{t-1} z_t] = 0$$

AR(1)

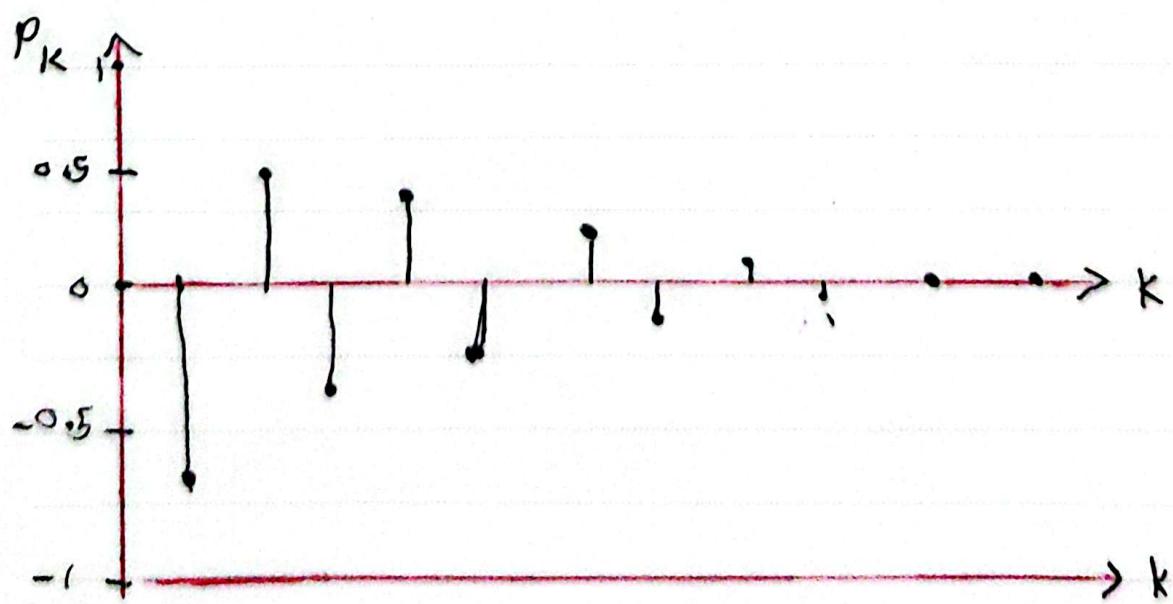
• توابع خود معمولی



$$\phi_1 = 0.9$$



$$\phi_1 = 0.4$$



$$\phi_1 = -0.7$$

$$x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + z_t \quad ; \text{process error.}$$

$$\gamma_0 = \text{var}(x_t) = E[x_t^2] =$$

$$E[\phi_1 x_t x_{t-1} + \phi_2 x_t x_{t-2} + x_t z_t] =$$

$$\gamma_0 = \phi_1 E[x_t x_{t-1}] + \phi_2 E[x_t x_{t-2}] + E[x_t z_t]$$

$$\gamma_0 = \phi_1 \gamma_1 + \phi_2 \gamma_2 + E[\phi_1 x_{t-1} z_t + \phi_2 x_{t-2} z_t + z_t^2]$$

= note that  $z_t$  is independent from all past values  $x_{t-k}$  - because  $x_{t-k}$  is only dependent on  $z_{t-k}$   
 = and  $z_t$  iid  $WN(0, \sigma^2)$  - hence  $z_t$  is independent of  $x_{t-k}$

$$\gamma_0 = \phi_1 \gamma_1 + \phi_2 \gamma_2 + E[z_t^2] = \boxed{\phi_1 \gamma_1 + \phi_2 \gamma_2 + \sigma^2 = \gamma_0}$$

$$\gamma_1 = E[x_t x_{t-1}] = \phi_1 E[x_{t-1}^2] + \phi_2 E[x_{t-2} x_{t-1}] + E[z_t x_{t-1}]$$

$$\Rightarrow \boxed{\gamma_1 = \phi_1 \gamma_0 + \phi_2 \gamma_1 + \phi_1 \gamma_0}$$

$$\Rightarrow \boxed{\gamma_1 = \frac{\phi_1}{1-\phi_2} \gamma_0}$$

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$$\gamma_2 = E[(\phi_1 x_{t-1} + \phi_2 x_{t-2} + z_t)(x_{t-2})]$$

$$\gamma_2 = \phi_1 E[x_{t-1} x_{t-2}] + \phi_2 E[x_{t-2}^2] + E[z_t x_{t-2}]$$

$$\boxed{\gamma_2 = \phi_1 \gamma_1 + \phi_2 \gamma_0}$$

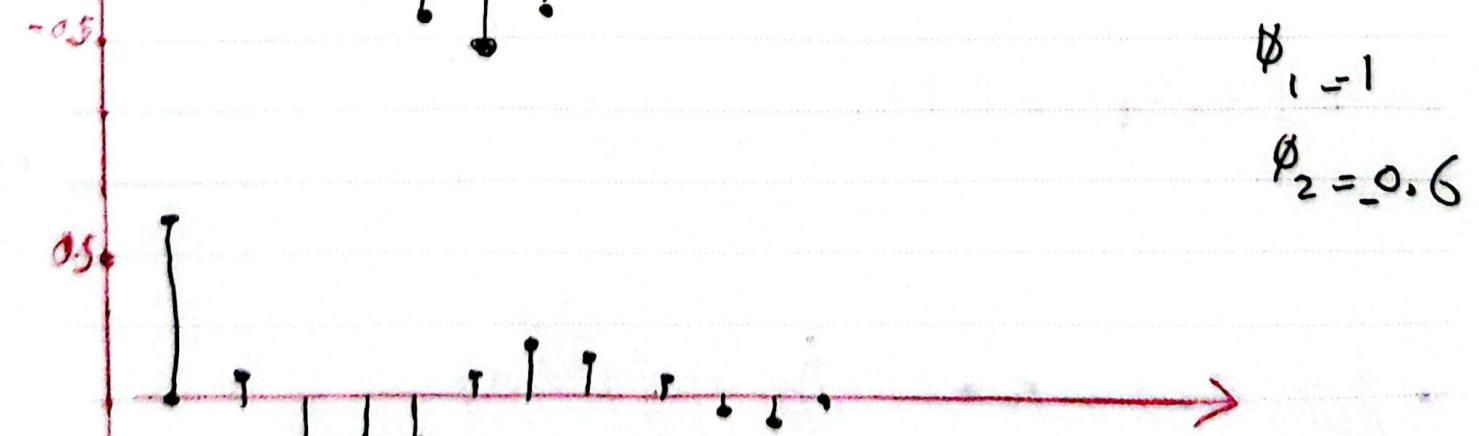
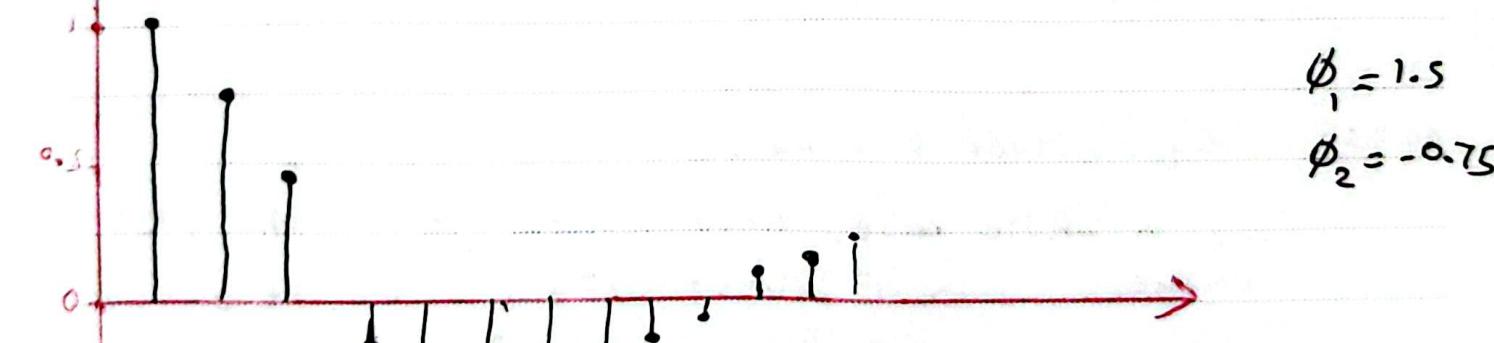
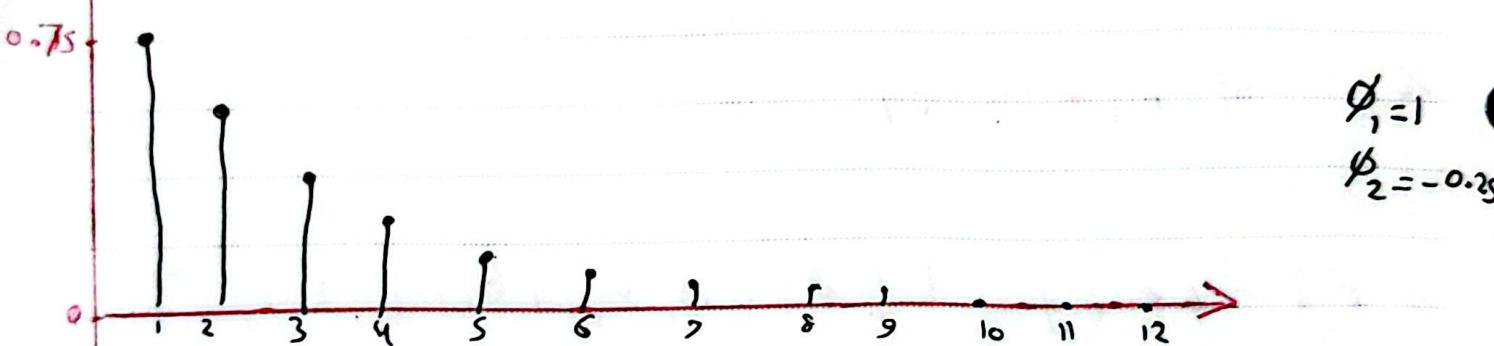
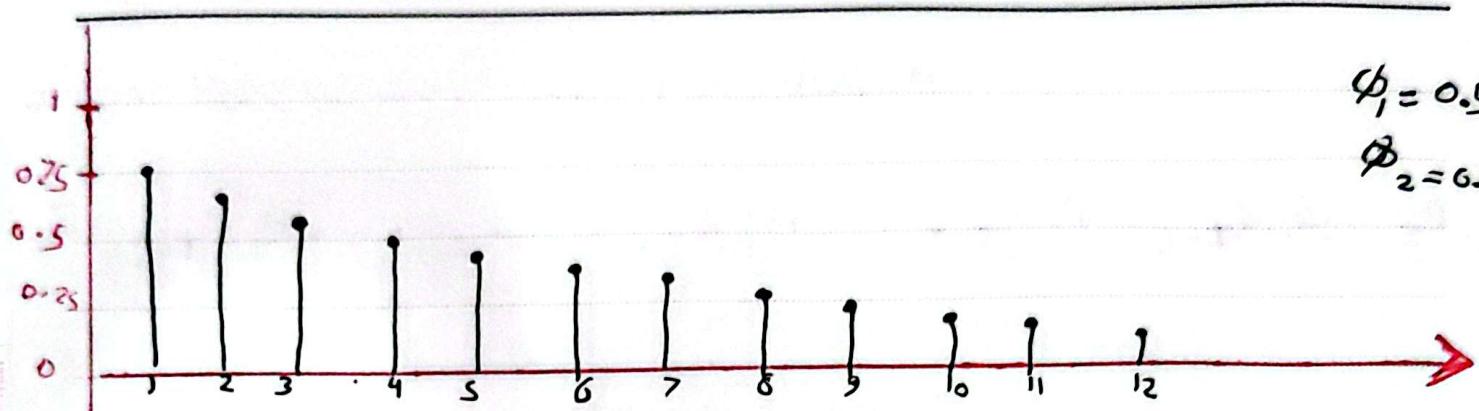
$$\Rightarrow \gamma_0 = \gamma_0 \left( \frac{\phi_1^2}{1-\phi_2} + \frac{\phi_2 \phi_1^2}{1-\phi_2} + \phi_2^2 \right) + \sigma^2$$

$$\Rightarrow \boxed{\gamma_0 = \frac{\sigma^2 (1-\phi_2)}{(1+\phi_2)((1-\phi_2^2)-\phi_1^2)}}$$

$$\boxed{\gamma_1 = \frac{\phi_1}{1-\phi_2} \gamma_0}$$

$$\quad \quad \quad \boxed{\gamma_2 = \left( \frac{\phi_1^2}{1-\phi_2} + \phi_2 \right) \gamma_0}$$

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*Dose*

• خاصية الترسيخ متأخر (lagged)

$$x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + \dots + \phi_p x_{t-p} + \theta_1 z_{t-1} + \dots + \theta_q z_{t-q} + z_t$$

• الترسيخ متأخر متعدد (multiple): ARMA(1,1)

$$x_t = \phi_1 x_{t-1} + \theta_1 z_{t-1} + z_t$$

$$\Rightarrow E[x_t z_t] = E[z_t (\phi_1 x_{t-1} + \theta_1 z_{t-1} + z_t)] \\ E[\phi_1 x_{t-1} z_t + \theta_1 x_{t-1} z_{t-1} + z_t^2]$$

note:  $x_t = (\text{stuff from past}) + z_t = A_t + z_t$

$z_t$  is white noise, uncorrelated to all the past values,  $\Rightarrow E[(A_t + z_t) z_t] = E[A_t z_t + z_t^2]$   
 $= E[A_t z_t] + E[z_t^2] = E[z_t^2]$

$$\Rightarrow E[x_t z_t] = E[z_t^2] = \text{var}(z_t) = \boxed{\sigma^2 = E[x_t z_t]}$$

- $E[x_t z_{t-1}] = E[(A_t + \theta_1 z_{t-1})(z_{t-1})] = E[A_t z_{t-1} + \theta_1 z_{t-1}^2] =$   
 $E[A_t z_{t-1}] + E[z_{t-1}^2] =$   
 $E[\phi_1 x_{t-1} + \theta_1 z_{t-1}] + 0 = E[\phi_1 x_{t-1} + \theta_1 z_{t-1}^2] + 0$   
 $= E[\phi_1 x_{t-1}, z_{t-1}] + \theta_1 E[z_{t-1}^2] = \phi_1 \sigma^2 + \theta_1 \sigma^2$   
 $E[x_t z_{t-1}] = \sigma^2(\phi_1 + \theta_1)$

note:  $\text{var}(A+B+C) = \text{var}(A) + \text{var}(B) + \text{var}(C) + 2\text{cov}(A,B) + 2\text{cov}(B,C) + 2\text{cov}(A,C)$

- $\gamma_0 = \text{var}(x_t) = \text{var}(\phi_1 x_{t-1} + \theta_1 z_{t-1} + z_t) =$   
 $\phi_1^2 \text{var}(x_{t-1}) + \theta_1^2 \text{var}(z_{t-1}) + \text{var}(z_t) + \underbrace{2\text{cov}(\phi_1 x_{t-1}, z_t)}_{+ 2\text{cov}(\theta_1 z_{t-1}, z_t) + 2\text{cov}(\phi_1 x_{t-1}, \theta_1 z_{t-1})}$   
 $\phi_1^2 \sigma^2 + \theta_1^2 \sigma^2 + \sigma^2 + 2 \times 0 + 2 \times 0 + 2\phi_1 \theta_1 \sigma^2$   
 $\Rightarrow \gamma_0 = \phi_1^2 \gamma_0 + (\theta_1^2 + 1 + 2\phi_1 \theta_1) \sigma^2$   
 $\Rightarrow \boxed{\gamma_0 = \frac{\theta_1^2 + 2\phi_1 \theta_1 + 1}{1 - \phi_1^2} \sigma^2}$

note:  $\text{cov}(x_{t-1}, z_t) = E[x_{t-1} z_t] - E[x_{t-1}] E[z_t] = E[x_{t-1} z_t]$   
 $E[x_{t-1} z_t] = \frac{\phi_1}{\sigma} E[x_{t-2} z_t] + E[\frac{\theta_1}{\sigma} z_{t-1} z_t] + \theta_1 E[z_{t-2} z_t]$   
PAPCO  
 $\boxed{E[x_{t-1} z_t] = 0}$

: داریم

بنابراین بُری (۱,۱)

$$\gamma_0 = \frac{1 + 2\theta_1\phi_1 + \theta_1^2}{1 - \phi_1^2} \sigma^2$$

$\gamma_{1,1}$

$$\gamma_1 = \text{cov}(x_t, x_{t-1}) = E[x_t x_{t-1}] =$$

$$E[(\phi_1 x_{t-1} + z_t + \theta_1 z_{t-1})(x_{t-1})] =$$

$$E[\phi_1 x_{t-1}^2] + \theta_1 E[x_{t-1} z_{t-1}] + E[x_{t-1} z_t] =$$

$$= \phi_1 \text{var}(x_{t-1}) + \theta_1 \sigma^2 + 0 = \phi_1 \gamma_0 + \theta_1 \sigma^2$$

$$\gamma_1 = \frac{\phi_1 + 2\theta_1\phi_1^2 + \theta_1^2\phi_1}{1 - \phi_1^2} \sigma^2 + \theta_1 \sigma^2$$

$$\gamma_1 = \left( \frac{\phi_1 + 2\theta_1\phi_1^2 + \theta_1^2\phi_1 + \theta_1 - \theta_1\phi_1^2}{1 - \phi_1^2} \right) \sigma^2$$

$$\gamma_1 = \frac{\phi_1 + \theta_1\phi_1^2 + \theta_1^2\phi_1 + \theta_1}{1 - \phi_1^2} \sigma^2$$

$$\begin{aligned}\gamma_2 &= \text{cov}(x_t, x_{t-2}) = E[x_t x_{t-2}] = \\ E[\phi_1 x_{t-1} + \theta_1 z_{t-1} + z_t x_{t-2}] &= \\ \phi_1 E[x_{t-1} x_{t-2}] + \theta_1 E[z_{t-1} x_{t-2}] + E[z_t x_{t-2}] &= \\ = \phi_1 \gamma_1 + 0 + 0 &= \phi_1 \gamma_1\end{aligned}$$

$\Rightarrow$

:  $\rightarrow$  ARMA(1,1) ok.

$$\boxed{\gamma_0 = \frac{1 + 2\theta_1 \phi_1 + \theta_1^2}{1 - \phi_1^2} \sigma^2} \Rightarrow$$

$$\boxed{\gamma_1 = \frac{\phi_1 + \theta_1 \phi_1^2 + \theta_1^2 \phi_1 + \theta_1}{1 - \phi_1^2} \sigma^2}$$

$$\boxed{\gamma_2 = \phi_1 \gamma_1}$$

$$\gamma_k = \phi_1 \gamma_{k-1} \quad \forall k \geq 2 - k \in \mathbb{N}$$

$$\Rightarrow \rho_0 = 1, \quad \rho_1 = \frac{\gamma_1}{\gamma_0} = \frac{(\phi_1 + \theta_1)(1 + \phi_1 \theta_1)}{1 + 2\theta_1 \phi_1 + \theta_1^2},$$

$$\rho_2 = \frac{\gamma_2}{\gamma_0} = \frac{\phi_1 (\phi_1 + \theta_1) (1 + \phi_1 \theta_1)}{1 + 2\theta_1 \phi_1 + \theta_1^2}$$

$$z_t \stackrel{iid}{\sim} WN(0, \sigma^2) \quad E[z_t] = 0, \quad \text{cov}(z_i, z_j) \neq 0$$

## • MA(q) behaviour in ACF:

$$x_t = z_t + \theta_1 z_{t-1} + \dots + \theta_q z_{t-q}$$

- each  $x_t$  is a finite linear combination of white-noise terms  $z_t, z_{t-1}, \dots, z_{t-q}$ . When you compute  $\text{cov}(x_t, x_{t+k})$ , for  $k > q$ , there is no common  $\theta$ -index in the sums. So, every expectation vanishes.  $E[z_i z_j] = 0, \forall i \neq j$   
hence:

$$\gamma_k = \text{cov}(x_t, x_{t+k}) = 0, \quad k > q$$

## • AR(p) general behaviour in ACF:

$$x_t = \phi_1 x_{t-1} + \dots + \phi_p x_{t-p} + z_t$$

- The ACF of a non-trivial AR(p) does not become exactly zero at a finite lag. it decays, typically exponentially, or as damped sinusoid

• for AR(1):  $\rho(k) = \phi^k$ 

- if  $\phi > 0$ : ACF is always positive monotone decrease

- if  $\phi < 0$ : ACF alternates sign and ~~damping~~ damped sinusoid

- AR(2): ACF obeys Yule-Walker relation.

$$\rho_1 = \frac{\phi_1}{1 - \phi_2} \quad -\rho_2 = \phi_1 \rho_1 + \phi_2$$

solve for  $\phi_1, \phi_2$ :  $\phi_1 = \rho_1(-1 - \phi_2)$      $\phi_2 = \frac{\rho_2 - \rho_1^2}{1 - \rho_1^2}$

- AR(p,q):

- short-run lag structure: controlled by MA(q). The MA part fixes exact values of  $y_k$  for  $k \leq q$ .
- long-run tail structure: controlled by AR(p).
- . It determines whether the tail decays exponentially-oscillates, and how slowly/fast it decays.