

2.9.

$$\begin{aligned} a, E(Y_t) &= E(X_t + W_t) = E(X_t) \\ &= E(\phi X_{t-1} + Z_t) \\ &= E\left(\sum_{n=0}^t \phi^n Z_{t-n}\right) = 0 \end{aligned}$$

$$\begin{aligned} \text{Cov}(Y_t, Y_{t+h}) &= \text{Cov}(X_t + W_t, X_{t+h} + W_{t+h}) \\ &= \text{Cov}(X_t, X_{t+h}) = \gamma_X(h) = \frac{\sigma^2 \phi^h}{1 - \phi^2}, h \geq 0 \end{aligned}$$

b,

$$U_t = Y_t - \phi Y_{t-1} \quad U_t \text{ and } U_s \text{ are independent whenever } |s - t| > 1$$

$$\gamma_U(h) = 0, |h| > 1$$

$$E(U_t) = E(Y_t - \phi Y_{t-1}) = 0$$

$$\begin{aligned} \gamma_U(h) &= \text{Cov}(Y_t - \phi Y_{t-1}, Y_{t+h} - \phi Y_{t+h-1}) \\ &= \text{Cov}(Y_t, Y_{t+h}) - \phi \text{Cov}(Y_{t-1}, Y_{t+h}) - \phi \text{Cov}(Y_t, Y_{t+h-1}) \\ &\quad + \phi^2 \text{Cov}(Y_{t-1}, Y_{t+h-1}) \\ &= \gamma_Y(h) - \phi \gamma_Y(h+1) - \phi \gamma_Y(h-1) + \phi^2 \gamma_Y(h) \\ &= \frac{\sigma^2 \phi^h}{1 - \phi^2} - \phi \frac{\sigma^2 \phi^{h+1}}{1 - \phi^2} - \phi \frac{\sigma^2 \phi^{h-1}}{1 - \phi^2} + \phi^2 \frac{\sigma^2 \phi^h}{1 - \phi^2} \\ &= \sigma^2 \left[\frac{1}{1 - \phi^2} (\phi^h - \phi^{h+2} - \phi^{h-1} + \phi^{h+2}) \right] = 0 \quad \forall h \neq 0 \end{aligned}$$

$$\gamma_U(0) = E(Y_t^2) - \phi E(Y_{t-1} Y_t) - \phi$$

$\Rightarrow \{u_t\}$ is 1-correlated

c) ARMA(1,1)

$$Y_t - \phi Y_{t-1} = Z_t + \theta Z_{t-1}$$

$$= Z_t + \theta_1 Z_{t-1} + \cancel{\theta_2 Z_{t-2}}$$

It is to derive from that u_t is a MA(1) process

$$\Rightarrow Y_t - \phi Y_{t-1} = Z_t + \theta Z_{t-1}$$

Since $\{Y_t\}$ is stationary, it follows that $\{Y_t\}$ is ARMA(1,1)

2.10

$$X_t - 0.5 X_{t-1} = Z_t + 0.5 Z_{t-1}, \{Z_t\} \sim WN(0, \sigma^2)$$

$$\phi(z) = \cancel{1 - 0.5z} 1 - 0.5z$$

zeros of $\phi(z)$ have $|z| = 2$

\Rightarrow all zeros of $\phi(z)$ stay outside of the unit circle

$\Rightarrow \phi(z) \neq 0 \quad \forall |z| < 1$ which means $\{X_t\}$ is causal

$$\Rightarrow X_t = \sum_{j=0}^{\infty} \psi_j Z_{t-j}$$

$$\psi_0 = 1, \quad \psi_1 = \theta_1 + \psi_0 \phi_1 = 0.5 - 1.0.5 = 0$$

$$\psi_2 = \theta_2 + \psi_1 \phi_1 + \psi_0 \phi_2 = 0 + 0 + 0 = 0$$

$$\psi_j = 0 \quad \forall j \geq 1$$

$$\Rightarrow X_t = Z_t$$

The MA polynomial $\theta(z) = 1 + 0.5z$ which also has a zero at $z = -2$ which is outside of unit circle. \Rightarrow invertible

$$\pi_0 = 1, \quad \pi_1 = -\phi_1 - \theta_1 \pi_0 = -0.5 - 0.5 = -1, \quad \pi_k = 0 \quad \forall k \geq 2$$

2.11.

An approximate 98% confidence interval for μ is:

$$\left(\bar{X}_n - 1,96 \frac{\sigma}{\sqrt{n}}, \bar{X}_n + 1,96 \frac{\sigma}{\sqrt{n}} \right), \quad \sigma^2 = \sum_{|h| < \infty} \gamma(h)$$

~~σ^2~~

$$\sigma^2 = \sum_{|h| < \infty} \left(1 - \frac{|h|}{n}\right) \gamma(h)$$

$$\Rightarrow \sigma^2 = (1 + 2 \sum_{h=1}^{\infty} \gamma(h))$$

for AR(1): $\gamma(h) = \frac{\sigma^2 \phi^{|h|}}{1 - \phi^2}$

$$\Rightarrow \sigma^2 = (1 + 2 \sum_{h=1}^{\infty} \phi^h) \frac{\sigma^2}{(1 - \phi^2)} = \frac{\sigma^2}{(1 - \phi)^2} = \frac{2}{(1 - 0,6)^2} = 12,5$$

$$\Rightarrow \bar{X}_n \pm 1,96 \frac{\sigma}{\sqrt{n}} = 0,271 \pm \frac{1,96}{10(1 - 0,6)} = 0,271 \pm 0,49 = (-0,219, 0,716)$$

Since $0 \in (-0,219, 0,716)$ ~~is~~, the data are compatible with the hypothesis that $\mu = 0$

2.12. For MA(1) process, $\gamma(h) = \text{Cov}(X_t, X_{t+h})$

$$= \text{Cov}(Z_t + \theta Z_{t-1}, Z_{t+h} + \theta Z_{t+h-1})$$

$$= \begin{cases} \sigma^2(1 + \theta^2), & h=0 \\ \sigma^2 \theta, & h=\pm 1 \\ 0, & |h| > 1 \end{cases}$$

$$\Rightarrow \sigma^2 = \sigma^2(1 + \theta^2) = (1 - 0,6)^2 = 0,16$$

An approximate 95% confidence interval for μ therefore is

$$\left(0,157 - 1,96 \cdot \frac{\sqrt{0,16}}{\sqrt{100}}, 0,157 + 1,96 \cdot \frac{\sqrt{0,16}}{\sqrt{100}} \right)$$

$$= (0,0786, 0,2354)$$

\Rightarrow The data are not compatible with the hypothesis $\mu=0$

2.13

$$w_{ij} = \sum_{k=1}^{\infty} \{ p(k+i) + p(k-i) - 2p(i)p(k) \}$$

$$\times \{ p(k+j) + p(k-j) - 2p(j)p(k) \}$$

q, For AR(1) process,

$$w_{ii} = (1 - \phi^{2i})(1 + \phi^2)(1 - \phi^2)^{-1} - 2i\phi^{2i}$$

The 95% confidence bounds for $\hat{p}(i)$ are: $\hat{p}(i) \pm 1,96 n^{-1/2} w_{ii}^{1/2}$

$$\Rightarrow 95\% \text{ cb for } p(1): \hat{p}(1) \pm 1,96 \cdot 10^{-1} \cdot \left(\frac{0,47}{25} \right)$$

$$= 0,438 \pm 1,96 \cdot \frac{9}{10} \cdot \frac{1}{25} = (0,3674, 0,5086)$$

$$95\% \text{ cb for } p(2): \hat{p}(2) \pm 1,96 n^{-1/2} w_{22}^{1/2}$$

$$= 0,145 \pm 1,96 \left(\frac{0,657}{25} \right) = (-0,0610352, 0,351035)$$

We also have that $p(1) = \frac{\phi}{1 - \phi^2} = \phi^1 = 0,8$

$$p(2) = 0,8^2 = 0,64$$

\Rightarrow The data are not compatible

b) For MA(1) process with $\theta = 0.6$

$$w_{ii} = \begin{cases} 1 - 3\rho^2(1) + 4\rho^4(1) & , i=1 \\ 1 + 2\rho^2(1) & , i>1 \end{cases}$$

The 95% confidence interval for $\rho(1)$ ($\rho(1) = \frac{\theta}{1+\theta} = \frac{15}{34}$)

$$\hat{\rho}(1) \pm \frac{1.96}{\sqrt{n}} w_{11} = 0.438 \pm \frac{1.96}{10} \cdot 0.45397$$

$$= (0.39902; 0.526979) \ni \frac{15}{34}$$

The 95% confidence interval for $\rho(2)$: ($\rho(2) = 0$)

$$\hat{\rho}(2) \pm \frac{1.96}{\sqrt{n}} = 0.145 \pm \frac{1.96}{10} = (-0.051; 0.341) \ni 0$$

\Rightarrow The data are compatible

2.14 $X_t = A \cos(\omega t) + B \sin(\omega t)$, $t = 0, \pm 1, \dots$
 $\gamma(h) = \cos(\omega h)$

a) Find $P_1 X_2$

The best linear predictor of X_{n+1} in terms of $\{1, X_0, \dots, X_n\}$

$$\text{is } P_n X_{n+1} = a_n' X_n$$

where $X_n = (X_n, \dots, X_1)$ and:

$$\begin{bmatrix} \gamma(0) & \gamma(1) & \dots & \gamma(n-1) \\ \gamma(1) & \gamma(0) & \dots & \gamma(n-2) \\ \vdots & \vdots & \ddots & \vdots \\ \gamma(n-1) & \gamma(n-2) & \dots & \gamma(0) \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{bmatrix} = \begin{bmatrix} \gamma(1) \\ \gamma(2) \\ \vdots \\ \gamma(n) \end{bmatrix}$$

$$\begin{pmatrix} 1 & \cos(\omega) & \cos((n-1)\omega) \\ \cos(\omega) & 1 & \cos(n\omega) \\ \cos((n-1)\omega) & \cos(n\omega) & 1 \end{pmatrix} \begin{pmatrix} a_1 \\ a_2 \\ a_3 \end{pmatrix} = \begin{pmatrix} \cos(\omega) \\ \cos(2\omega) \\ \vdots \\ \cos(n\omega) \end{pmatrix}$$

$$\Rightarrow a = [\cos(\omega) \quad 0 \quad 0 \quad \dots]'$$

and hence the best linear prediction of Y_{n+1} in terms of Y_1, \dots, Y_n is

$$P_n Y_{n+1} = a_n' Y_n = \cos(\omega) Y_n$$

with mean square error

$$\begin{aligned} E(Y_{n+1} - P_n Y_{n+1})^2 &= E(Y_{n+1}^2) - \\ &= \sigma^2(0) - a_n' \sigma_n(1) = 1 - \cos^2(\omega) = \sin^2(\omega) \end{aligned}$$

$$\Rightarrow \begin{cases} P_1 Y_2 = \cos(\omega) Y_1 \\ P_2 Y_3 = \cos(\omega) Y_2 \end{cases}$$

Ex 9

$$\sum_{j=1}^{\infty} \cos((1-j)\omega) \phi_j = \underline{\cos(\omega_i)} \quad , i=1, \dots$$

$$\underline{\cos(\omega_i) (\phi_j - 1) = \cos(\omega_i) \phi_j}$$

$$a_1 \rightarrow 1 - (\frac{1}{2}b - 1) \cos(\omega) \quad X_3 = a_2 X_1 + a_1 X_2$$

2.14.

$$X_{n+1} = a_1 X_{n-1} + a_2 X_{n-2} + \dots + a_n X_1$$

$$0, \gamma(\omega)^{-1} \gamma(1) = \cos(\omega)$$

$$\Rightarrow \begin{cases} p_1 X_2 = a_1 X_1 = \cos(\omega) X_1 \\ E(X_2 - p_1 X_2)^2 = \gamma(0) - a_1 \gamma(1) = 1 - \cos^2(\omega) = \sin^2(\omega) \end{cases}$$

$$\begin{aligned} b) \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} &= P^{-1} \begin{bmatrix} \gamma(1) \\ \gamma(2) \end{bmatrix} = \begin{bmatrix} \gamma(0) & \gamma(1) \\ \gamma(1) & \gamma(0) \end{bmatrix}^{-1} \begin{bmatrix} \gamma(1) \\ \gamma(2) \end{bmatrix} \\ &= \begin{bmatrix} 1 & \cos(\omega) \\ \cos(\omega) & 1 \end{bmatrix}^{-1} \begin{bmatrix} \cos(\omega) \\ \cos(2\omega) \end{bmatrix} = \begin{bmatrix} 2\cos(\omega) \\ -1 \end{bmatrix} \end{aligned}$$

$$\Rightarrow \begin{cases} p_2 X_3 = -X_1 + 2\cos(\omega) X_2 \\ E(X_3 - p_2 X_3)^2 = \gamma(0) - (a_1^2 + a_2^2) \begin{bmatrix} \gamma(1) \\ \gamma(2) \end{bmatrix}^T \end{cases}$$

$$= 1 - [2\cos(\omega) \quad -1] \begin{bmatrix} \cos(\omega) \\ \cos(2\omega) \end{bmatrix} = 0$$

$$c) \tilde{P}_n \tilde{P}_{n+1} = \sum_{j=1}^{\infty} a_j X_{n+1-j}$$

trong đó $a = [a_1, a_2, \dots]^T$ là v.v. của hệ phương trình

$$\sum_{j=1}^{+\infty} a_j \delta(i-j) = \gamma(h+i-1), \quad \forall i=1,2$$

$$\Rightarrow \Gamma_{\infty} a_{\infty} = \gamma_{\infty}(h)$$

$$h=1 \rightarrow \Gamma_{\infty} a_{\infty} = \gamma_{\infty}(1) \Rightarrow \begin{cases} \gamma(0)a_1 + \gamma(1)a_2 + \gamma(2)a_3 + \dots = \gamma(1) \\ \gamma(1)a_1 + \gamma(0)a_2 + \dots = \gamma(2) \\ \vdots \end{cases}$$

2.15.

$$(\Rightarrow) \begin{cases} a_1 + \cos(\omega)a_2 + \cos(2\omega)a_3 + \dots = \cos(\omega) \\ \cos(\omega)a_1 + a_2 + \cos(2\omega)a_3 + \dots = \cos(2\omega) \\ \vdots \end{cases}$$

2.15

$$X_{n+1} = Z_{n+1} + \sum_{j=1}^p \phi_j X_{n+1-j}$$

$$\Rightarrow P_n X_{n+1} = \frac{P_n Z_{n+1}}{0} + \sum_{j=1}^p \phi_j P_n X_{n+1-j} = \sum_{j=1}^p \phi_j X_{n+1-j}$$

2.18.

$$MA(1): X_t = Z_t - \theta Z_{t-1}, \quad Z_t \sim WN(0, \sigma^2)$$

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

$$= \sum_{j=0}^{\infty} (\theta B)^j X_t = \sum_{j=0}^{\infty} \theta^j X_{t-j}, \quad Z_t \sim WN(0, \sigma^2)$$

Tại đây ta có thể \tilde{P}_n vào hai vế, ta có:

$$\tilde{P}_n z_{n+1} = \sum_{j=0}^{\infty} \theta^j \tilde{P}_n x_{n+1-j}$$

$$\Leftrightarrow 0 = \tilde{P}_n x_{n+1} + \sum_{j=1}^{\infty} \theta^j x_{n+1-j}$$

$$\Leftrightarrow \tilde{P}_n x_{n+1} = - \sum_{j=1}^{\infty} \theta^j x_{n+1-j}$$

Trung bình bình phương sai số :

$$\begin{aligned} E(x_{n+1} - \tilde{P}_n x_{n+1})^2 &= E\left(x_{n+1} + \sum_{j=1}^{\infty} \theta^j x_{n+1-j}\right)^2 \\ &= E(z_{n+1})^2 = \sigma^2 \end{aligned}$$

2.21:

$$X_t = z_t + \theta z_{t-1}, \quad (z_t) \sim WN(0, \sigma^2)$$

$$a, \quad a_n = (a_1, a_2) \quad W = (x_1, x_2), \quad \Sigma = [\gamma(1), \gamma(2)]$$

$$\Gamma_n a_n = \gamma$$

$$\begin{bmatrix} \gamma(1) & \gamma(1) \\ \gamma(1) & \gamma(1) \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} = \begin{bmatrix} \gamma(1) \\ \gamma(1) \end{bmatrix}$$

$$\begin{bmatrix} 1+\theta^2 & \theta \\ \theta & 1+\theta^2 \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} = \begin{bmatrix} \theta \\ 0 \end{bmatrix} \Rightarrow \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} = \frac{1}{(1+\theta^2)^2 - \theta^2} \begin{bmatrix} 1+\theta^2 & -\theta \\ -\theta & 1+\theta^2 \end{bmatrix} \begin{bmatrix} \theta \\ 0 \end{bmatrix}$$

$$\Leftrightarrow \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} = \frac{1}{1+\theta^2+\theta^4} \begin{bmatrix} \theta+\theta^3 \\ -\theta^2 \end{bmatrix}$$

$$b, Y = X_3, W = (X_4, X_5) \quad \gamma = [\gamma(1), \gamma(2)] \begin{pmatrix} a & b \\ c & d \end{pmatrix}$$

$$\begin{bmatrix} \gamma(1) & \gamma(2) \\ \gamma(2) & \gamma(1) \end{bmatrix}$$

$$\frac{1}{(ad-bc)} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix}$$

$$\begin{bmatrix} \gamma(1) & \gamma(2) \\ \gamma(2) & \gamma(1) \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} = \begin{bmatrix} \gamma(1) \\ \gamma(2) \end{bmatrix}$$

$$\Rightarrow \begin{bmatrix} 1+\theta^2 & \theta \\ \theta & 1+\theta^2 \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} = \begin{bmatrix} \theta \\ \theta \end{bmatrix} \Rightarrow \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} = \frac{1}{1+\theta^2+\theta^4} \begin{bmatrix} \theta - \theta^2 + \theta^3 \\ \theta - \theta^2 + \theta^3 \end{bmatrix}$$

$$c, \begin{bmatrix} \gamma(0) & \gamma(1) & \gamma(2) \\ \gamma(1) & \gamma(0) & \gamma(1) \\ \gamma(2) & \gamma(1) & \gamma(0) \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ a_3 \end{bmatrix} = \begin{bmatrix} \gamma(2) \\ \gamma(1) \\ \gamma(1) \end{bmatrix}$$

$$Y = X_2$$

$$W(X_1, X_3)$$

$$\gamma_2 = \begin{bmatrix} \gamma(1) \\ \gamma(1) \end{bmatrix}$$

$$\begin{bmatrix} 1+\theta^2 & \theta & 0 \\ \theta & 1+\theta^2 & \theta \\ 0 & \theta & 1+\theta^2 \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ a_3 \end{bmatrix} = \begin{bmatrix} 0 \\ \theta \\ \theta \end{bmatrix}$$

$$\begin{bmatrix} a_1 \\ a_2 \\ a_3 \end{bmatrix} = \begin{bmatrix} \frac{-\theta^4 + \theta^3 - \theta^2}{1 + \theta^2 + \theta^4 + \theta^6} \\ \frac{\theta^3 - \theta^2 + \theta}{\theta^4 + 1} \\ \frac{\theta^5 - \theta^4 + \theta^3 - \theta^2 + \theta}{1 + \theta^2 + \theta^4 + \theta^6} \end{bmatrix}$$

$$\text{Error} = \text{Var } E(X_3 - P(X_3 | W))^2 = \frac{a^2(1+\theta^2)}{n}$$