

# Time Series Analysis (STA 5015)

## Chapter 2 Solution

### 1. Problem 2.3

a. Note that

$$\begin{aligned}
 \text{Cov}(X_{t+h}, X_t) &= \text{Cov}(Z_{t+h} + .3Z_{t+h-1} - .4Z_{t+h-2}, Z_t + .3Z_{t-1} - .4Z_{t-2}) \\
 &= \gamma_Z(h) + .3\gamma_Z(h-1) - .4\gamma_Z(h-2) + .3\gamma_Z(h+1) + .09\gamma_Z(h) - .12\gamma_Z(h-1) \\
 &\quad - .4\gamma_Z(h+2) - .12\gamma_Z(h+1) + .16\gamma_Z(h) \\
 &= 1.25\gamma_Z(h) + .18\gamma_Z(h-1) - .4\gamma_Z(h-2) + .18\gamma_Z(h+1) - .4\gamma_Z(h+2),
 \end{aligned}$$

where  $\gamma_Z(h)$  is ACVF of  $\text{WN}(0,1)$ , that is  $\gamma_Z(h) = 1$  if  $h = 0$  and 0 otherwise. Therefore, ACVF of  $X$  is given by

$$\gamma_X(h) = \begin{cases} 1.25, & h = 0 \\ .18, & h = \pm 1 \\ -.4, & h = \pm 2 \\ 0 & \text{otherwise.} \end{cases}$$

Or, you can plug-in general formula introduced in Proposition 2.2.1.

b. Similar calculation with  $\gamma_{\tilde{Z}}(h) = .25$  if  $h = 1$  and 0 otherwise gives that

$$\gamma_Y(h) = \begin{cases} 1.25, & h = 0 \\ .18, & h = \pm 1 \\ -.4, & h = \pm 2 \\ 0 & \text{otherwise.} \end{cases}$$

Therefore, it has the **same** ACVF with that of part *a*. This shows that ACVF does not uniquely determine stationary process.

2. (a) Let  $\gamma_X(h)$  be the ACVF of  $\{X_t\}$  Then,

$$\begin{aligned}
 \text{Cov}(Y_{t+h}, Y_t) &= \begin{cases} \text{Cov}(X_{t+h}, X_t) & \text{if } t+h \text{ odd, } t \text{ odd,} \\ \text{Cov}(X_{t+h}, X_t + 3) & \text{if } t+h \text{ odd, } t \text{ even,} \\ \text{Cov}(X_{t+h} + 3, X_t) & \text{if } t+h \text{ even, } t \text{ odd,} \\ \text{Cov}(X_{t+h} + 3, X_t + 3) & \text{if } t+h \text{ even, } t \text{ even,} \end{cases} \\
 &= \begin{cases} \gamma_X(h) & \text{if } t+h \text{ odd, } t \text{ odd,} \\ \gamma_X(h) & \text{if } t+h \text{ odd, } t \text{ even,} \\ \gamma_X(h) & \text{if } t+h \text{ even, } t \text{ odd,} \\ \gamma_X(h) & \text{if } t+h \text{ even, } t \text{ even,} \end{cases}
 \end{aligned}$$

Therefore, ACVF of  $\{Y_t\}$  does not depends of  $t$ .

(b) However,  $\{Y_t\}$  is NOT a stationary process since

$$EY_t = \begin{cases} EX_t = 0 & \text{if } t \text{ is odd,} \\ EX_t + 3 = 3 & \text{if } t \text{ is even.} \end{cases}$$

implies that  $EY_t$  depends on  $t$ .

3. First note that

$$EX_t = E \sin(2\pi Ut) = \int_0^1 \sin(2\pi ut) du = \left. \frac{-\cos(2\pi ut)}{2\pi t} \right|_0^1 = \frac{-\cos(2\pi t) + \cos 0}{2\pi t} = 0,$$

since  $t$  is an integer value. For the covariance calculation, observe that

$$\text{Cov}(X_{t+h}, X_t) = E(X_{t+h}X_t) = E(\sin(2\pi U(t+h)) \sin(2\pi Ut)).$$

Therefore, if  $h = 0$ , then

$$\begin{aligned} \text{Var}(X_t) &= E(\sin^2(2\pi Ut)) = \int_0^1 \sin^2(2\pi ut) du = \int_0^1 \frac{1 - \cos(4\pi ut)}{2} du \\ &= \frac{1}{2} \left( u - \frac{1}{4\pi t} \sin(4\pi ut) \right) \Big|_0^1 = \frac{1}{2} \end{aligned}$$

If  $h \neq 0$ , then

$$\begin{aligned} \text{Cov}(X_{t+h}, X_t) &= \int_0^1 \sin(2\pi u(t+h)) \sin(2\pi ut) du = \int_0^1 \frac{1}{2} \{ \cos(2\pi uh) - \cos(2\pi u(2t+h)) \} du \\ &= \frac{1}{2} \left( \frac{1}{2\pi h} \sin(2\pi uh) - \frac{1}{2\pi(2t+h)} \sin(2\pi u(2t+h)) \right) \Big|_0^1 \\ &= \frac{1}{2} \left( \frac{\sin(2\pi h) - \sin 0}{2\pi h} - \frac{\sin(2\pi(2t+h)) - \sin 0}{2\pi(2t+h)} \right) = 0. \end{aligned}$$

Hence,  $\{X_t\}$  is a weakly stationary time series.

4. (a) Since  $X_2 - \rho(\sigma_2/\sigma_1)X_1$  is the linear combination of  $X_1$  and  $X_2$ , it follows normal distribution (recall HW#1) with mean

$$E(X_2 - \rho(\sigma_2/\sigma_1)X_1) = E(X_2) - \rho(\sigma_2/\sigma_1)E(X_1) = \mu_2 - \rho(\sigma_2/\sigma_1)\mu_1.$$

$$\begin{aligned} \text{Var}(X_2 - \rho(\sigma_2/\sigma_1)X_1) &= \text{Cov}(X_2 - \rho(\sigma_2/\sigma_1)X_1, X_2 - \rho(\sigma_2/\sigma_1)X_1) \\ &= \text{Var}(X_2) - 2\rho(\sigma_2/\sigma_1)\text{Cov}(X_1, X_2) + (\rho(\sigma_2/\sigma_1))^2\text{Var}(X_1) \\ &= \sigma_2^2 - 2\rho^2\sigma_2^2 + \rho^2\sigma_2^2 = (1 - \rho^2)\sigma_2^2. \end{aligned}$$

All in all,

$$X_2 - \rho \frac{\sigma_2}{\sigma_1} X_1 \sim \mathcal{N}(\mu_2 - \rho(\sigma_2/\sigma_1)\mu_1, (1 - \rho^2)\sigma_2^2).$$

- (b) For multivariate normal distribution, zero correlation implies independence. Note that

$$\begin{aligned}\text{Cov}(X_2 - \rho\sigma_2/\sigma_1 X_1, X_1) &= \text{Cov}(X_2, X_1) - \rho(\sigma_2/\sigma_1)\text{Cov}(X_1, X_1) \\ &= \rho\sigma_1\sigma_2 - \rho(\sigma_2/\sigma_1)\sigma_1^2 = 0,\end{aligned}$$

in turn  $X_2 - \rho\sigma_2/\sigma_1 X_1$  and  $X_1$  are independent.

5. In a compact form, we have

$$(1-.5B)X_t = (1+.5B)Z_t \Rightarrow \psi(B) = (1+.5B)(1-.5B)^{-1}, \quad \pi(B) = (1-.5B)(1+.5B)^{-1}.$$

Using geometric sum, we have

$$\psi(B) = (1+.5B)(1+.5B+.5^2B^2+\dots),$$

thus

$$\psi_1 = 1, \psi_2 = 2(.5)^2, \psi_3 = 2(.5)^3, \psi_4 = 2(.5)^4, \psi_5 = 2(.5)^5.$$

Alternatively (which I prefer) is to use identity

$$(1 + \psi_1 B + \psi_2 B^2 + \psi_3 B^3 + \dots)(1 - .5B) = 1 + .5B$$

Similar calculation for  $\pi(B)$  gives that

$$\pi_1 = -1, \pi_2 = 2(-.5)^2, \pi_3 = 2(-.5)^3, \pi_4 = 2(-.5)^4, \pi_5 = 2(-.5)^5.$$

6. DIY

7. Problem 2.12

For MA(1) process  $X_t = Z_t - .6Z_{t-1}$ , note that

$$\gamma_X(h) = \begin{cases} (1 + \theta^2)\sigma^2 & , h = 0 \\ \theta\sigma^2 & , h = \pm 1 \\ 0 & , \text{o.w} \end{cases} = \begin{cases} 1.36 & , h = 0 \\ -.6 & , h = \pm 1 \\ 0 & , \text{o.w} \end{cases}$$

Thus, long-run variance is given by

$$\nu = \sum_{h=-\infty}^{\infty} \gamma_X(h) = 1.36 + 2(-.6) = .16.$$

The 95% confidence interval is therefore given by

$$\bar{X} \pm 1.96\sqrt{\frac{\nu}{n}} = (.0786, .2354).$$

Since 0 is not include in the confidence interval we reject the null hypotheses of  $H_0 : \mu = 0$  under 5% significance level.

8. Problem 2.13

(a) Recall that AR(1) model  $X_t = \rho X_{t-1} + Z_t$  has ACVF and ACF by

$$\gamma_X(h) = \frac{\phi^{|h|}}{1 - \phi^2} \sigma^2, \quad \rho_X(h) = \phi^{|h|}.$$

Thus, plug-into Bartlett's formula gives

$$\begin{aligned} w_{ii} &= \sum_{k=1}^i \phi^{2i} (\phi^k - \phi^{-k})^2 + \sum_{k=i+1}^{\infty} \phi^{2k} (\phi^i + \phi^{-i})^2 \\ &= (1 - \phi^{2i})(1 + \phi^2)(1 - \phi^2)^{-1} - 2i\phi^{2i}. \end{aligned}$$

For example,

$$w_{11} = (1 - \phi^2)(1 + \phi^2)(1 - \phi^2)^{-1} - 2\phi^2 = 1 - \phi^2 = .36$$

$$w_{22} = (1 - \phi^4)(1 + \phi^2)(1 - \phi^2)^{-1} - 4\phi^4 = (1 + \phi^2)^2 - 4\phi^4 = 1.0512$$

Therefore, 95% confidence interval for  $\rho(i)$  is calculated as

$$\hat{\rho}(1) \pm \frac{1.96}{\sqrt{n}} \sqrt{w_{11}} = (.3204, .5556)$$

$$\hat{\rho}(2) \pm \frac{1.96}{\sqrt{n}} \sqrt{w_{22}} = (-.056, .346)$$

Since CI do not include the true values of  $\rho(1) = .8$  and  $\rho(2) = .64$ , the data are not consistent with an AR(1) model with  $\phi = .8$ .

(b) For MA(1) model  $X_t = Z_t + \theta Z_{t-1}$ ,

$$\rho_X(h) = \begin{cases} 1 & , h = 0 \\ \frac{\theta}{1+\theta^2} & , h = \pm 1 \\ 0 & , \text{o.w} \end{cases}$$

Thus,

$$w_{11} = 1 - 3\rho(1)^2 + 4\rho(1)^4 = .5676, \quad w_{22} = 1 + 2\rho(1)^2 = 1.3893.$$

95% confidence interval is

$$\hat{\rho}(1) \pm 1.96 \frac{1.96}{\sqrt{n}} \sqrt{w_{11}} = (.290, .585)$$

$$\hat{\rho}(2) \pm \frac{1.96}{\sqrt{n}} \sqrt{w_{22}} = (-.086, .376)$$

Now, confidence intervals contain true values of  $\rho(1) = .441$  and  $\rho(2) = 0$ , thus data is consistent with an MA(1) model with  $\theta = .6$ .

9. (a) We will use trigonometric identity

$$\cos \alpha \cos \beta = \frac{1}{2} (\cos(\alpha + \beta) + \cos(\alpha - \beta))$$

$$\sin \alpha \sin \beta = \frac{1}{2} (\sin(\alpha + \beta) + \sin(\alpha - \beta))$$

Note that

$$\begin{aligned} & (2 \cos \omega) X_{n-1} - X_{n-2} \\ &= (2 \cos \omega) (A \cos(\omega(n-1)) + B \sin(\omega(n-1))) - A \cos(\omega(n-2)) - B \sin(\omega(n-2)) \\ &= 2A \cos \omega \cos(\omega(n-1)) + 2B \cos \omega \sin(\omega(n-1)) - A \cos(\omega(n-2)) - B \sin(\omega(n-2)) \\ &= A (\cos(\omega n) + \cos(\omega(n-2))) + B (\sin(\omega n) + \sin(\omega(n-2))) - A \cos(\omega(n-2)) - B \sin(\omega(n-2)) \\ &= A \cos(\omega n) + A \cos(\omega(n-2)) + B \sin(\omega n) + B \sin(\omega(n-2)) - A \cos(\omega(n-2)) - B \sin(\omega(n-2)) \\ &= A \cos(\omega n) + B \sin(\omega n) = X_n. \end{aligned}$$

Thus,

$$X_n = (2 \cos \omega) X_{n-1} - X_{n-2}.$$

- (b) We can understand this model as AR(2) with zero error, so

$$\tilde{P}_n X_{n+1} = (2 \cos \omega) X_n - X_{n-1}.$$

10. For MA(2)  $X_t = Z_t + 2Z_{t-1} - 2Z_{t-2}$ , observe that  $P_1 X_2 = a_0 + a_1 X_1$ . Thus, we want to find  $a_0$  and  $a_1$  minimizing  $\text{MSPE} = E(X_2 - P_1 X_2)^2 = E(X_2 - a_0 - a_1 X_1)^2$ . Solving “derivative = 0” gives

$$\frac{\partial \text{MSPE}}{\partial a_0} = E(X_2 - a_0 - a_1 X_1)(-2) = 0$$

$$\frac{\partial \text{MSPE}}{\partial a_1} = E(X_2 - a_0 - a_1 X_1)(-X_1) = 0$$

Therefore, we have

$$a_0 = 0, \quad a_1 = \frac{E X_1 X_2}{E X_1^2} = \frac{\gamma(1)}{\gamma(0)} = -\frac{2}{9}.$$

since

$$\gamma(0) = E(Z_t + 2Z_{t-1} - 2Z_{t-2}, Z_t + 2Z_{t-1} - 2Z_{t-2}) = 1 + 4 + 4 = 9$$

$$\gamma(1) = E(Z_{t+1} + 2Z_t - 2Z_{t-1}, Z_t + 2Z_{t-1} - 2Z_{t-2}) = 2 - 4 = -2.$$

Also, MSPE is calculated as

$$\begin{aligned} \text{MSPE} &= E \left( X_2 + \frac{2}{9} X_1 \right)^2 = E(X_2^2) + \frac{4}{9} E(X_1 X_2) + \frac{4}{81} E X_1^2 \\ &= \frac{85}{81} \gamma(0) + \frac{4}{9} \gamma(1) = \frac{85}{81} 9 + \frac{4}{9} (-2) = \frac{77}{9} \end{aligned}$$