

Practice Problems for Final Exam

- ① (a) Find a causal filter $\{a_0, a_1, \dots, a_6\}$ with $a_j \neq 0$ for $j=0, \dots, 6$ (and $a_j = 0$ for $j \notin \{0, 1, \dots, 6\}$) that passes arbitrary quadratic polynomials and eliminates seasonal components with period 5.

Sol. First, apply the filter $1 + B + B^2 + B^3 + B^4$, which will eliminate the seasonal component with period 5. Then apply a length 3 filter $\{b_0, b_1, b_2\}$ to get the composite filter

$$(b_0 + b_1 B + b_2 B^2)(1 + B + B^2 + B^3 + B^4) = \sum_{j=0}^6 a_j B^j$$

where $a_0 = b_0$

$$a_1 = b_0 + b_1$$

$$a_2 = b_0 + b_1 + b_2$$

$$a_3 = b_0 + b_1 + b_2$$

$$a_4 = b_0 + b_1 + b_2$$

$$a_5 = b_1 + b_2$$

$$a_6 = b_2$$

By part (i), the filter $\{a_0, a_1, \dots, a_6\}$ will pass arbitrary quadratic polynomials if

$$5(b_0 + b_1 + b_2) = 1$$

$$10b_0 + 15b_1 + 20b_2 = 0$$

$$30b_0 + 55b_1 + 90b_2 = 0$$

These equations have solution $(b_0, b_1, b_2)^T = (1, -1.2, .4)^T$. Then the filter $\{a_0, a_1, \dots, a_6\}$ is given by

$$\{a_0, a_1, \dots, a_6\} = \{1, -.2, .2, .2, .2, -.8, .4\}$$

(Remark: One might try to eliminate the seasonal component first using the lag 5 difference operator $\nabla_5 = 1 - B^5$. However, any causal filter we then apply to the output can only have 2 coefficients b_0 and b_1 (otherwise the filter would have powers of B greater than 6). You will find that with only b_0 and b_1 , you will not be able to come up with an overall filter $\{a_0, a_1, \dots, a_6\}$ that satisfy the requirements.)

(b) Find a symmetric filter $\{a_{-3}, a_{-2}, a_{-1}, a_0, a_1, a_2, a_3\}$ where $a_j \neq 0$ for $j = -3, \dots, 3$ and $a_{-j} = a_j$ that passes arbitrary cubic polynomials and eliminates seasonal components with period either 2 or 3.

Sol. By Problem 1.12, the desired symmetric filter should have coefficients a_0, a_1, a_2, a_3 that satisfy

$$\textcircled{1} \quad a_0 + 2a_1 + 2a_2 + 2a_3 = 1$$

$$\textcircled{2} \quad a_1 + 4a_2 + 9a_3 = 0$$

When applied to a seasonal component $\{S_t\}$ the output will be

$$a_3 S_{t-3} + a_2 S_{t-2} + a_1 S_{t-1} + a_0 S_t + a_1 S_{t+1} + a_2 S_{t+2} + a_3 S_{t+3}$$

$$= \begin{cases} (a_0 + 2a_3)S_t + (a_1 + a_2)S_{t-1} + (a_1 + a_2)S_{t-2} & \text{if period is 3} \\ (a_0 + 2a_2)S_t + 2(a_1 + a_3)S_{t-1} & \text{if period is 2} \end{cases}$$

From the above, to eliminate a seasonal component with either period 2 or 3, it is sufficient to impose the further constraints

$$\textcircled{3} \quad a_0 + 2a_3 = a_1 + a_2$$

$$\textcircled{4} \quad a_0 + 2a_2 = 2(a_1 + a_3)$$

The solution to the system of 4 linear equations given by $\textcircled{1}-\textcircled{4}$ is

$$(.43055, .29861, .03472, -.04861)^T = (a_0, a_1, a_2, a_3)^T$$

Then, the desired symmetric filter is given by

$$\left\{ \begin{array}{ccccccc} -.04861, & .03472, & .29861, & .43055, & .29861, & .03472, & -.04861 \end{array} \right\}$$

$$\begin{array}{ccccccc} a_{-3} & a_{-2} & a_{-1} & a_0 & a_1 & a_2 & a_3 \end{array}$$

(2)

(a) Let $\{X_t\}$ be an MA(2) process with parameters θ_1, θ_2 and σ^2 ,

$$X_t = Z_t + \theta_1 Z_{t-1} + \theta_2 Z_{t-2}, \text{ where } \{Z_t\} \text{ is a zero-mean WN}(\sigma^2).$$

Find $\gamma_X(h)$ and $\rho_X(h)$, the ACVF and ACF, respectively, of $\{X_t\}$ for $h = 0, \pm 1, \pm 2, \dots$

Sol. We have

$$\text{Var}(X_t) = \sigma^2 + \theta_1^2 \sigma^2 + \theta_2^2 \sigma^2 = \sigma^2(1 + \theta_1^2 + \theta_2^2).$$

$$\text{Cov}(X_t, X_{t-1}) = \text{Cov}(Z_t + \theta_1 Z_{t-1} + \theta_2 Z_{t-2}, Z_{t-1} + \theta_1 Z_{t-2} + \theta_2 Z_{t-3})$$

$$= \text{Cov}(\theta_1 Z_{t-1}, Z_{t-1}) + \text{Cov}(\theta_2 Z_{t-2}, \theta_1 Z_{t-2})$$

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

$$\text{Cov}(X_t, X_{t-2}) = \text{Cov}(Z_t + \theta_1 Z_{t-1} + \theta_2 Z_{t-2}, Z_{t-2} + \theta_1 Z_{t-3} + \theta_2 Z_{t-4})$$

$$= \text{Cov}(\theta_2 Z_{t-2}, Z_{t-2})$$

$$= \theta_2 \sigma^2$$

$$\text{Then } \gamma_X(h) = \begin{cases} \sigma^2(1 + \theta_1^2 + \theta_2^2) & h = 0 \\ \sigma^2 \theta_1 (1 + \theta_2) & h = \pm 1 \\ \sigma^2 \theta_2 & h = \pm 2 \\ 0 & \text{otherwise} \end{cases}$$

$$\text{and } \rho_X(h) = \begin{cases} 1 & h = 0 \\ \frac{\theta_1 (1 + \theta_2)}{1 + \theta_1^2 + \theta_2^2} & h = \pm 1 \\ \frac{\theta_2}{1 + \theta_1^2 + \theta_2^2} & h = \pm 2 \\ 0 & \text{otherwise} \end{cases}$$

(b) Let $\{Z_t\}$ be a zero mean $WN(\sigma^2)$ process, and let $\{Y_t\}$

be the MA(1) process $Y_t = Z_t + \frac{1}{2}Z_{t-1}$. Let $X_t = Y_t + aY_{t-1}$, where a is a constant. Show that $\{X_t\}$ is an MA(2) process and find the parameters θ_1 and θ_2 of this process in terms of a . Find a so that $\{X_t\}$ has ACF with $\rho_X(0) = 1$, $\rho_X(1) = -\frac{1}{6}$ and $\rho_X(2) = -\frac{1}{3}$.

Sol. We have

$$\begin{aligned} X_t &= Y_t + aY_{t-1} = Z_t + \frac{1}{2}Z_{t-1} + a(Z_{t-1} + \frac{1}{2}Z_{t-2}) \\ &= Z_t + (a + \frac{1}{2})Z_{t-1} + \frac{a}{2}Z_{t-2} \end{aligned}$$

Thus, $\{X_t\}$ is an MA(2) process with parameters $\theta_1 = a + \frac{1}{2}$ and $\theta_2 = \frac{a}{2}$. From part (a), if we want $\rho_X(1) = -\frac{1}{6}$ and $\rho_X(2) = -\frac{1}{3}$, then we need

$$(1) \frac{\theta_1(1+\theta_2)}{1+\theta_1^2+\theta_2^2} = -\frac{1}{6} \quad \text{and} \quad (2) \frac{\theta_2}{1+\theta_1^2+\theta_2^2} = -\frac{1}{3}$$

In terms of a , (1) is $\frac{(a+\frac{1}{2})(1+\frac{a}{2})}{1+(a+\frac{1}{2})^2+\frac{a^2}{4}} = -\frac{1}{6}$

$$\text{or } \frac{a + \frac{a^2}{2} + \frac{1}{2} + \frac{a}{4}}{1 + a^2 + a + \frac{1}{4} + \frac{a^2}{4}} = -\frac{1}{6}$$

$$\text{or } \frac{5a + 2a^2 + 2}{5 + 5a^2 + 4a} = -\frac{1}{6} \quad (3)$$

$$\text{and (2) is } \frac{\frac{a}{2}}{1 + a^2 + a + \frac{1}{4} + \frac{a^2}{4}} = -\frac{1}{3}$$

$$\text{or } \frac{2a}{5 + 5a^2 + 4a} = -\frac{1}{3} \quad (4)$$

Using Eq. (4), we have $-6a = 5 + 5a^2 + 4a$ or $5a^2 + 10a + 5 = 0$

$$\text{or } a^2 + 2a + 1 = 0$$

$$\text{or } (a+1)^2 = 0$$

$$\Rightarrow a = -1$$

Check that $a = -1$ satisfies (3):

$$\frac{-5 + 2 + 2}{5 + 5 - 4} = -\frac{1}{6} \quad \text{or} \quad \frac{-1}{6} = -\frac{1}{6}$$

So $a = -1$ satisfies both (3) and (4). So we can conclude that $\{X_t\}$ with $a = -1$ has the given ACF.

③ Suppose $\{X_t\}$ is an MA(2) process with parameters θ_1, θ_2 and σ^2 , i.e., $X_t = Z_t + \theta_1 Z_{t-1} + \theta_2 Z_{t-2}$, where $\{Z_t\}$ is a zero-mean WN(σ^2).

(a) Let $\rho_x(h)$ be the ACF of $\{X_t\}$, show that $|\rho_x(1)| \leq \frac{1}{\sqrt{2}}$ and $|\rho_x(2)| \leq \frac{1}{2}$ for any θ_1, θ_2 , and σ^2 .

Sol. First, we have that $\rho_x(1) = \frac{\theta_1(1+\theta_2)}{1+\theta_1^2+\theta_2^2}$ and $\rho_x(2) = \frac{\theta_2}{1+\theta_1^2+\theta_2^2}$.

First, consider $\rho_x(2)$. We first note that we should have $\theta_2 > 0$ to maximize $\rho_x(2)$. Further, for any $\theta_2 > 0$, $\rho_x(2)$ will be maximized over θ_1 by taking $\theta_1 = 0$. Therefore, the maximum of $\rho_x(2)$ is

$\max_{\theta_2 > 0} \frac{\theta_2}{1+\theta_2^2}$. Taking the derivative w.r.t. θ_2 and setting this to 0

$$\text{gives } \frac{(1+\theta_2^2) - \theta_2 \cdot 2\theta_2}{(1+\theta_2^2)^2} = 0 \Leftrightarrow 1+\theta_2^2 - 2\theta_2^2 = 0 \Leftrightarrow 1 = \theta_2^2$$

So $\theta_2 = +1$ (and $\theta_1 = 0$) maximizes $\rho_x(2)$. The maximum value is $\frac{1}{1+0^2+1^2} = \frac{1}{2}$. Therefore $|\rho_x(2)| \leq \frac{1}{2}$.

Now, consider $\rho_x(1)$. First, let us note that to maximize $\rho_x(1)$ over θ_1 and θ_2 we can assume that $\theta_2 \neq -1$ because when $\theta_2 = -1$, $\rho_x(1) = 0$ (which is clearly not the maximum).

For a fixed $\theta_2 \neq -1$, differentiating $\rho_x(1)$ w.r.t. θ_1 and setting to 0 gives $\frac{(1+\theta_1^2+\theta_2^2)(1+\theta_2) - \theta_1(1+\theta_2)2\theta_1}{(1+\theta_1^2+\theta_2^2)^2} = 0$

$$\Leftrightarrow 1+\theta_1^2+\theta_2^2 = 2\theta_1^2 \quad \text{since } 1+\theta_2 \neq 0$$

$$\Leftrightarrow 1+\theta_2^2 = \theta_1^2 \quad \downarrow$$

Thus, we get that $\theta_1 = \pm \sqrt{1+\theta_2^2}$ will potentially maximize $\rho_x(1)$ for a given value of θ_2 . Let $\rho_x(1|\theta_2)$ be the maximum value of $\rho_x(1)$ for the given θ_2 . Thus, we wish to maximize $\rho_x(1|\theta_2)$ over θ_2 .

For a fixed θ_2 , when we plug in the values $\theta_1 = \pm \sqrt{1+\theta_2^2}$ we

get $\frac{\pm \sqrt{1+\theta_2^2} (1+\theta_2)}{1+(1+\theta_2^2)+\theta_2^2}$. We wish to maximize this

over $\theta_2 \neq -1$. Rather than maximizing the above over θ_2 , we will maximize the square of the above over θ_2 , since the square is a monotone function so the value of θ_2 that maximizes the square also maximizes the above. Thus, we wish to maximize

$$(*) \frac{(1+\theta_2^2)(1+\theta_2)^2}{(2(1+\theta_2^2))^2} = \frac{(1+\theta_2)^2}{4(1+\theta_2^2)} = \frac{(1+\theta_2^2)+2\theta_2}{4(1+\theta_2^2)} = \frac{1}{4} + \frac{\theta_2}{2(1+\theta_2^2)}$$

We have already computed that $\frac{\theta_2}{1+\theta_2^2}$ is maximized at $\theta_2 = 1$, and the maximum value of $\frac{\theta_2}{1+\theta_2^2}$ is $\frac{1}{2}$. Therefore, (*) is maximized at $\theta_2 = 1$, and its maximum value is $\frac{1}{4} + \frac{1}{2} \cdot \frac{1}{2} = \frac{1}{2}$.

Since (*) is the square of $p_x(i)$ at a given θ_2 . Therefore, the maximum value of $p_x(i)^2$ is $\frac{1}{2}$, which gives that the maximum value of $|p_x(i)|$ is $\frac{1}{\sqrt{2}}$. Therefore, $|p_x(i)| \leq \frac{1}{\sqrt{2}}$.

④ Let $\{X_t\}$ be an ARMA(1,1) process with parameters $\phi = \frac{1}{2}$ and $\theta = \frac{1}{2}$, and $\sigma^2 = 1$, i.e., $X_t - \frac{1}{2}X_{t-1} = Z_t + \frac{1}{2}Z_{t-1}$, where $\{Z_t\}$ is a zero-mean WN(1). The ACVF of the ARMA(1,1) process is $\gamma_X(0) = \sigma^2 \left(1 + \frac{(\theta + \phi)^2}{1 - \phi^2}\right)$ with $\phi = \frac{1}{2}, \theta = \frac{1}{2}, \sigma^2 = 1$
 $\gamma_X(1) = \sigma^2 \left(\theta + \phi + \frac{(\theta + \phi)\phi}{1 - \phi^2}\right)$
 $\gamma_X(h) = \phi^{h-1} \gamma_X(1) \quad h \geq 2$

$$\begin{aligned} \gamma_X(0) &= \frac{7}{3} \\ \gamma_X(1) &= \frac{5}{3} \\ \gamma_X(h) &= \left(\frac{1}{2}\right)^{h-1} \left(\frac{5}{3}\right) \end{aligned}$$

(a) Give $P(X_2 | X_1)$, the best linear predictor of X_2 in terms of X_1 (this is also denoted by $P_1 X_2$), Compute the mean squared error of $P(X_2 | X_1)$.

Sol, Recall, $P(X_2 | X_1) = a X_1$, where a satisfies

$$\gamma_X(0)a = \gamma_X(1), \text{ or } a = \frac{\gamma_X(1)}{\gamma_X(0)} = \frac{5/3}{7/3} = \frac{5}{7}$$

So $P(X_2 | X_1) = \frac{5}{7} X_1$. The minimum mean squared error is

$$E[(X_2 - P(X_2 | X_1))^2] = \gamma_X(0) - \frac{5}{7} \gamma_X(1) = \frac{7}{3} - \left(\frac{5}{7}\right)\left(\frac{5}{3}\right) = \frac{24}{21} = \frac{8}{7}$$

(b) Find $P(X_3 | X_2, X_1)$. Compute the MSE of $P(X_3 | X_2, X_1)$.

Sol, $P(X_3 | X_2, X_1) = a_1 X_2 + a_2 X_1$, where $a = (a_1, a_2)^T$ satisfies

$$\begin{bmatrix} \gamma_X(0) & \gamma_X(1) \\ \gamma_X(1) & \gamma_X(0) \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} = \begin{bmatrix} \gamma_X(1) \\ \gamma_X(2) \end{bmatrix} \Leftrightarrow \begin{bmatrix} 7/3 & 5/3 \\ 5/3 & 7/3 \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} = \begin{bmatrix} 5/3 \\ 5/6 \end{bmatrix}$$

$$\Leftrightarrow \begin{bmatrix} 14 & 10 \\ 10 & 14 \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} = \begin{bmatrix} 10 \\ 5 \end{bmatrix}$$

The solution is

$$\begin{bmatrix} a_1 \\ a_2 \end{bmatrix} = \begin{bmatrix} 14 & 10 \\ 10 & 14 \end{bmatrix}^{-1} \begin{bmatrix} 10 \\ 5 \end{bmatrix} = \frac{1}{96} \begin{bmatrix} 14 & -10 \\ -10 & 14 \end{bmatrix} \begin{bmatrix} 10 \\ 5 \end{bmatrix} = \frac{1}{96} \begin{bmatrix} 90 \\ -30 \end{bmatrix} = \begin{bmatrix} \frac{15}{16} \\ -\frac{5}{16} \end{bmatrix}$$

Then $P(X_3 | X_2, X_1) = \frac{15}{16} X_2 - \frac{5}{16} X_1$. The minimum MSE is

$$\begin{aligned} E[(X_3 - P(X_3 | X_2, X_1))^2] &= \frac{7}{3} - \left(\frac{15}{16}\right)\left(\frac{5}{3}\right) - \left(\frac{5}{16}\right)\left(\frac{5}{6}\right) \\ &= \frac{224 - 150 + 25}{96} = \frac{99}{96} = \frac{33}{32} \approx 1.03125. \end{aligned}$$

(c) Compute $P(X_n | X_2, X_1)$ and give the minimum MSE.

Compute the limit of this MSE as $n \rightarrow \infty$.

Sol, $P(X_n | X_2, X_1) = a_1 X_2 + a_2 X_1$, where $a = (a_1, a_2)^T$ satisfies

$$\begin{bmatrix} 7/3 & 5/3 \\ 5/3 & 7/3 \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} = \begin{bmatrix} \delta_X(n-2) \\ \delta_X(n-1) \end{bmatrix} = \begin{bmatrix} (\frac{1}{2})^{n-3} (\frac{5}{3}) \\ (\frac{1}{2})^{n-2} (\frac{5}{3}) \end{bmatrix}$$

$$\text{or } \begin{bmatrix} 14 & 10 \\ 10 & 14 \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} = (\frac{1}{2})^{n-3} \begin{bmatrix} 10 \\ 5 \end{bmatrix}$$

$$\text{Then } \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} = (\frac{1}{2})^{n-3} \underbrace{\begin{bmatrix} 14 & 10 \\ 10 & 14 \end{bmatrix}^{-1} \begin{bmatrix} 10 \\ 5 \end{bmatrix}}_{\text{done in part (b)}} = (\frac{1}{2})^{n-3} \begin{bmatrix} \frac{15}{16} \\ -\frac{5}{16} \end{bmatrix}$$

$$\text{Then } P(X_n | X_2, X_1) = (\frac{1}{2})^{n-3} \left(\frac{15}{16} X_2 - \frac{5}{16} X_1 \right)$$

The minimum MSE is

$$\begin{aligned} E[(X_n - P(X_n | X_2, X_1))^2] &= \delta_X(0) - (\frac{1}{2})^{2n-6} \left((\frac{15}{16})(\frac{5}{3}) - (\frac{5}{16})(\frac{5}{3}) \right) \\ &= \frac{7}{3} - (\frac{1}{2})^{2n-6} \frac{150-25}{96} \\ &= \frac{7}{3} - (\frac{1}{2})^{2n-6} \frac{125}{96} \end{aligned}$$

$$\text{As } n \rightarrow \infty, E[(X_n - P(X_n | X_2, X_1))^2] \rightarrow \frac{7}{3}.$$