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Homework 2

Problem 2.3

Consider the simple two-sided moving smoother of the form

$$V_t = \frac{1}{4} (w_{t-1} + 2w_t + w_{t+1}), \quad w_t \sim N(0, \sigma_w^2)$$

Determine the autocovariance and autocorrelation functions as a function of lag h .

Autocovariance function

$$\gamma_V(h) = \text{Cov}(V_{t+h}, V_t)$$

$$\begin{aligned} \Rightarrow \gamma_V(h) &= \text{Cov}(V_t, V_t) = \frac{1}{16} \text{Cov}[w_{t-1} + 2w_t + w_{t+1}, w_{t-1} + 2w_t + w_{t+1}] \\ &= \frac{1}{16} [\text{Cov}(w_{t-1}, w_{t-1}) + 4\text{Cov}(w_t, w_t) + \text{Cov}(w_{t+1}, w_{t+1})] \\ &= \frac{1}{16} (\sigma_w^2 + 4\sigma_w^2 + \sigma_w^2) \\ &= \frac{1}{16} \cdot 6\sigma_w^2 = \frac{3}{8}\sigma_w^2 \end{aligned}$$

$$\begin{aligned} \gamma_V(1) &= \text{Cov}(V_{t+1}, V_t) = \frac{1}{16} \text{Cov}[w_t + 2w_{t+1} + w_{t+2}, w_{t-1} + 2w_t + w_{t+1}] \\ &= \frac{1}{16} \{ 2\text{Cov}(w_t, w_t) + 2\text{Cov}(w_{t+1}, w_{t+1}) \} \\ &= \frac{4}{16} \sigma_w^2 = \frac{1}{4} \sigma_w^2 = \gamma_V(-1) \end{aligned}$$

$$\begin{aligned} \gamma_V(2) &= \text{Cov}(V_{t+2}, V_t) = \frac{1}{16} \text{Cov}[w_{t+1} + 2w_{t+2} + w_{t+3}, w_{t-1} + 2w_t + w_{t+1}] \\ &= \frac{1}{16} [\text{Cov}(w_{t+1}, w_{t+1})] = \frac{\sigma_w^2}{16} = \gamma_V(-2) \end{aligned}$$

$$\gamma_V(h) = 0, \text{ for } |h| > 2. \quad \text{Hence,}$$

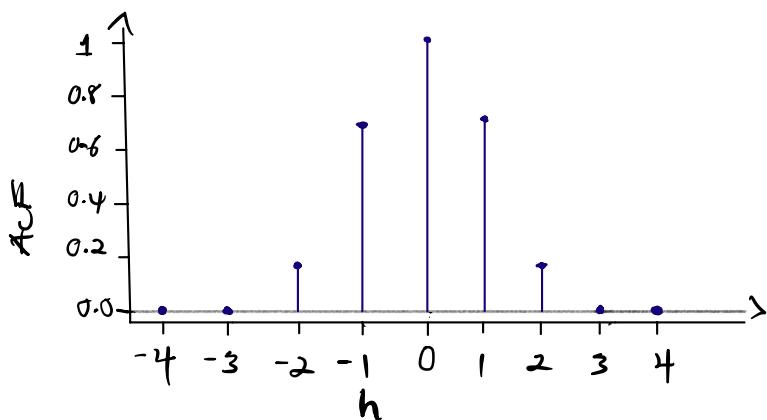
$$\gamma_V(h) = \begin{cases} \frac{3}{8}\sigma_w^2 & h=0 \\ \frac{1}{4}\sigma_w^2 & |h|=1 \\ \frac{1}{16}\sigma_w^2 & |h|=2 \\ 0 & |h| > 2 \end{cases}$$

Autocorrelation function

$$\rho_v(h) = \frac{\gamma(h)}{\gamma(0)}$$

$$\Rightarrow \rho_v(h) = \begin{cases} 1 & h=0 \\ \frac{2}{3} & h=\pm 1 \\ \frac{1}{6} & h=\pm 2 \\ 0 & |h| > 2 \end{cases}$$

A sketch of the ACF as a function of h



Problem 2.5

Consider the random walk with drift model

$$x_t = \delta + x_{t-1} + w_t$$

for $t = 1, 2, \dots$, with $x_0 = 0$, where w_t is white noise with variance σ_w^2

Part (a)

W.T.S: The above model can be written as

$$x_t = \delta t + \sum_{k=1}^t w_k.$$

Proof

We have

$$x_t = \delta + x_{t-1} + w_t \quad \text{--- } ①, \text{ and let}$$

$$x_t = \delta t + \sum_{k=1}^t w_k. \quad \text{--- } ②$$

Using eqn ③, x_{t-1} can be expressed as

$$x_{t-1} = \delta(t-1) + \sum_{k=1}^{t-1} w_k \quad \text{--- } ③$$

Now, put ③ into ①

$$\Rightarrow x_t = \delta + \left[\delta(t-1) + \sum_{k=1}^{t-1} w_k \right] + w_t$$

$$= \delta + \delta t - \delta + \sum_{k=1}^{t-1} w_k + w_t$$

$$= \delta t + \sum_{k=1}^t w_k$$

Thus,

$$x_t = \delta t + \sum_{k=1}^t w_k$$

is indeed an alternative way to write the random walk with drift model under consideration.



Part (b): Mean and autocovariance functions of σ_t .

$$x_t = \delta_t + \sum_{k=1}^t w_k, \quad t = 1, 2, 3, \dots$$

For the mean function, we have

$$\begin{aligned} M_{x_t} &= E(x_t) = E\left[\delta_t + \sum_{k=1}^t w_k\right] \\ &= \delta_t + \sum_{k=1}^t E(w_k) \quad \text{by the linearity property of } E(\cdot) \\ &\quad \text{since } w_k \text{ are independent.} \\ &= \delta_t \quad (\text{since } E(w_k) = 0 \forall k) \end{aligned}$$

Therefore $M_{x_t} = \delta_t$, which depends on the time, t .

■

The autocovariance function of σ_t is given by

$$\begin{aligned} \gamma_{\sigma_t}(s, t) &= \text{Cov}\left(\delta_s + \sum_{k=1}^s w_k, \delta_t + \sum_{j=1}^t w_j\right) \\ &= \text{Cov}\left(\sum_{k=1}^s w_k, \sum_{j=1}^t w_j\right) \\ &= \min\{s, t\} \sigma_w^2 \end{aligned}$$

which also depends on the times, s and t .

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Part (c)

By definition, a time series x_t is stationary if the following two conditions hold:

- (i) The mean function, M_{xt} , is constant and does not depend on t .
- (ii) The autocorrelation function, $\gamma_x(s, t)$, depends on times s and t only through their lag or time difference.

It is therefore clear from the results we obtained in part (b) that x_t is not stationary, because the value of M_{xt} depends on t and moreover $\gamma_x(s, t)$ depends on the times s and t , which violate the two conditions stated above.



Part (d)

$$\text{W.T.S: } f_{x(t-1, t)} = \sqrt{\frac{t-1}{t}} \rightarrow 1 \text{ as } t \rightarrow \infty.$$

Proof

First, we show that $f_{x(t-1, t)} = \sqrt{\frac{t-1}{t}}$.

By definition,

$$f_{x(s, t)} = \frac{\gamma_x(s, t)}{\sqrt{\gamma_x(s) \cdot \gamma_x(t)}} ,$$

and we found in part (b) that $\gamma_x(s, t) = \min\{s, t\} \bar{\sigma}_w^2$.

$$\Rightarrow f_{x(t-1, t)} = \frac{(t-1) \bar{\sigma}_w^2}{\sqrt{(t-1) \bar{\sigma}_w^2 \cdot t \bar{\sigma}_w^2}}$$

$$= \frac{(t-1) \bar{\sigma}_w^2}{\sqrt{t(t-1) (\bar{\sigma}_w^2)^2}} = \sqrt{\frac{(t-1)^2}{t(t-1)}} = \sqrt{\frac{t-1}{t}}$$

For the remaining part, we have to take the limit of $f(x_t)$ as $t \rightarrow \infty$.

$$\Rightarrow \lim_{t \rightarrow \infty} f(x_{t-1}, t) = \lim_{t \rightarrow \infty} \left(\sqrt{\frac{t-1}{t}} \right)$$

$$\leq \sqrt{1} \\ = 1$$

Hence,

$$f(x_{t-1}, t) = \sqrt{\frac{t-1}{t}} \rightarrow 1 \text{ as } t \rightarrow \infty,$$

as required. \blacksquare

This implies that for large t the series at t x_t can be (linearly) predicted perfectly using only the value at $t-1$ (x_{t-1}).

Part (e)

I suggest using a transformation based on differencing as follows.

$$x_t = \delta + x_{t-1} + w_t \\ \Rightarrow x_t - x_{t-1} = \delta + w_t \quad \text{--- } \textcircled{*}$$

We now prove that the transformed series in $\textcircled{*}$ is stationary.

$$\text{Let } z_t = x_t - x_{t-1}$$

$$\Rightarrow E(z_t) = E(\delta + w_t) = \delta + E(w_t) = \delta$$

Moreover,

$$\begin{aligned} \gamma_z(h) &= \text{Cov}(z_{t+h}, z_t) = \text{Cov}(w_{t+h}, w_t) \\ \Rightarrow \gamma_z(0) &= \text{Cov}(w_t, w_t) \leq \sigma_w^2 \\ \Rightarrow \gamma_z(1) &= \text{Cov}(w_{t+1}, w_t) = 0 \quad (\text{since } w_t \text{ are uncorrelated}) \\ &= \gamma_z(-1) \end{aligned}$$

$$\gamma_z(h) = \begin{cases} \sigma_w^2 & h=0 \\ 0 & h \neq 0 \end{cases}$$

Hence, we have proved that the transformed series is stationary because the mean function does not depend on t and the autocovariance function only depends on h .

Problem 2.7

Given

$$x_t = U_1 \sin(2\pi \omega_0 t) + U_2 \cos(2\pi \omega_0 t),$$

where U_1 and U_2 are independent random variables with zero means and $E(U_1^2) = E(U_2^2) = \sigma^2$.

The constant ω_0 determines the period or time it takes the process to make one complete cycle.

W.T.S: The above series is weakly stationary with autocovariance function

$$\gamma(h) = \sigma^2 \cos(2\pi \omega_0 h).$$

Proof:

It suffices to find the mean function and the autocovariance of the series.

The mean function is given by

$$\mu_{x_t} = E(x_t) = E(U_1 \sin(2\pi \omega_0 t) + U_2 \cos(2\pi \omega_0 t))$$

$$= E(U_1) \sin(2\pi \omega_0 t) + E(U_2) \cos(2\pi \omega_0 t)$$

$$= 0, \quad \text{since } E(U_1) = E(U_2) = 0$$

_____ ①

The autocovariance function is also given by

$$\gamma_{x(h)} = \text{Cov}(x_{t+h}, x_t)$$

$$= \text{Cov} \left[U_1 \sin(2\pi \omega_0 (t+h)) + U_2 \cos(2\pi \omega_0 (t+h)), U_1 \sin(2\pi \omega_0 t) + U_2 \cos(2\pi \omega_0 t) \right]$$

For simplicity;

Let $A = 2\pi \omega_0 t$ and $B = 2\pi \omega_0 h$. Then

$$\gamma_{x(h)} = \sin A \sin(A+B) \text{Cov}(U_1, U_1) + \cos A \cos(A+B) \text{Cov}(U_2, U_2)$$

Note that $E(U_1^2) = \text{Var}(U_1) = \sigma^2$ and $E(U_2^2) = \text{Var}(U_2) = \sigma^2$.

$$\begin{aligned}
 \Rightarrow \gamma_h &= \sigma^2 [\sin A \sin(A+B) + \cos A \cos(A+B)] \\
 &= \sigma^2 [\sin A (\sin A \cos B + \cos A \sin B) + \cos A (\cos A \cos B - \sin A \sin B)] \\
 &= \sigma^2 [\sin^2 A \cos B + \sin A \cancel{\sin B} \cos A + \cos^2 A \cos B - \sin A \cancel{\sin B} \cos A] \\
 &= \sigma^2 [\sin^2 A \cos B + \cos^2 A \cos B] \\
 &= \sigma^2 [\cos B (\sin^2 A + \cos^2 A)], \quad \text{but } \sin^2 A + \cos^2 A = 1 \text{ by the Pythagorean identity} \\
 &= \sigma^2 \cos B \\
 &= \sigma^2 \cos(2\pi\omega_0 h) \quad \text{_____} \quad \textcircled{2}
 \end{aligned}$$

From ① and ②, it can be seen that the mean and autocovariance functions are independent of time, which shows that the series, α_t , is weakly stationary with autocovariance function given by ② as required.



Problem 2-8

Given the two series

$$x_t = w_t$$

$$y_t = w_t - \theta w_{t-1} + u_t,$$

where w_t and u_t are independent white noise series with variances σ_w^2 and σ_u^2 , respectively, and θ is an unspecified constant.

Part (a) :

We wish to express the ACF, $\gamma_y(h)$, for $h=0, \pm 1, \pm 2, \dots$ of the series y_t as a function of σ_w^2 , σ_u^2 , and θ .

To this end, we need to first find the autocovariance function of y_t .

$$\begin{aligned}\gamma_y(0) &= \text{Cov}(y_{t+h}, y_t) = \text{Cov}(w_{t+h} - \theta w_{t+h-1} + u_{t+h}, w_t - \theta w_{t-1} + u_t) \\ &\Rightarrow \gamma_y(0) = \text{Cov}(w_t - \theta w_{t-1} + u_t, w_t - \theta w_{t-1} + u_t) \\ &= \text{Cov}(w_t, w_t) + \theta^2 \text{Cov}(w_{t-1}, w_{t-1}) + \text{Cov}(u_t, u_t) \\ &= \sigma_w^2 + \theta^2 \sigma_w^2 + \sigma_u^2 \\ &= \sigma_w^2(1 + \theta^2) + \sigma_u^2 \\ \\ \Rightarrow \gamma_y(1) &= \text{Cov}(w_{t+1} - \theta w_t + u_{t+1}, w_t - \theta w_{t-1} + u_t) \\ &= -\theta \text{Cov}(w_t, w_t) \\ &= -\theta \sigma_w^2 = \gamma_y(-1)\end{aligned}$$

when $|h| > 1$, $\gamma_y(h) = 0$.

Thus,

$$\gamma_y(h) = \begin{cases} \sigma_w^2(1 + \theta^2) + \sigma_u^2 & h = 0 \\ -\theta \sigma_w^2 & h = \pm 1 \\ 0 & |h| > 1 \end{cases}$$

which implies that the ACF, $\rho_y(h)$ is given by

$$\rho_y(h) = \begin{cases} 1 & h = 0 \\ \frac{-\theta \sigma_w^2}{(1+\theta)\sigma_w^2 + \sigma_u^2} & h = \pm 1 \\ 0 & |h| > 1 \end{cases},$$

for the fact that $\rho_y(h) = \frac{\gamma_{y(h)}}{\gamma_{y(0)}}$. ■

Part (b) :

We want to determine CCF, $\rho_{xy}(h)$ relating x_t and y_t .

The cross-covariance function, $\gamma_{xy}(h)$ can be computed as

$$\gamma_{xy}(h) = \text{cov}(x_{t+h}, y_t) = \text{cov}(w_{t+h}, w_t - \theta w_{t-1} + u_t)$$

$$\begin{aligned} \Rightarrow \gamma_{xy}(0) &= \text{cov}(w_t, w_t - \theta w_{t-1} + u_t) \\ &= \text{cov}(w_t, w_t) \quad \text{since } w_{t-1} \text{ and } u_t \text{ are uncorrelated.} \\ &= \sigma_w^2 \end{aligned}$$

$$\begin{aligned} \gamma_{xy}(1) &= \text{cov}(w_{t+1}, w_t - \theta w_{t-1} + u_t) \\ &= 0 \quad \text{and} \end{aligned}$$

$$\begin{aligned} \gamma_{xy}(-1) &= \text{cov}(w_{t-1}, w_t - \theta w_{t-1} + u_t) \\ &= -\theta \text{cov}(w_{t-1}, w_{t-1}) = -\theta \sigma_w^2 \end{aligned}$$

We notice that $\gamma_{xy}(h) = 0$ for $|h| \geq 2$. So, generally, we have

$$\gamma_{xy}(h) = \begin{cases} \sigma_w^2 & h = 0 \\ -\theta \sigma_w^2 & h = -1 \\ 0 & h = 1, |h| \geq 2 \end{cases}.$$

From part (a), $\gamma_y(0) = (1+\theta)\bar{\sigma}_w^2 + \bar{\sigma}_y^2$ and for π_t we know that

$$\gamma_{\pi}(0) = \bar{\sigma}_w^2.$$

Thus,

$$P_{xy}(h) = \frac{\gamma_{xy}(h)}{\sqrt{\gamma_{\pi}(0) \gamma_y(0)}}, h = 0, \pm 1, \pm 2, \dots$$

$$= \begin{cases} \frac{\bar{\sigma}_w^2}{\sqrt{\bar{\sigma}_w^2((1+\theta)\bar{\sigma}_w^2 + \bar{\sigma}_y^2)}} & h = 0 \\ 0 & h = 1 \\ \frac{-\theta\bar{\sigma}_w^2}{\sqrt{\bar{\sigma}_w^2((1+\theta)\bar{\sigma}_w^2 + \bar{\sigma}_y^2)}} & h = -1 \\ 0 & |h| \geq 2 \end{cases}$$

■

Part (c)

W.T.S: π_t and y_t are jointly stationary.

First, we notice that π_t is stationary because

$$E(\pi_t) = 0 \text{ and } \gamma_{\pi}(h) = \begin{cases} \bar{\sigma}_w^2 & h = 0 \\ 0 & h \neq 0 \end{cases},$$

which are independent of time t .

Moreover, from part (a), $\gamma_{y(h)}$ only depends on the lag h and $E(y_t) = E(u_t) - \theta E(u_{t-1}) + E(u_t)$
 $= 0$, showing that y_t is also stationary.

Finally, the cross-covariance function, $\gamma_{xy}(h)$, in part (b) only depends on the lag h .

Therefore,

we conclude that x_t and y_t are jointly stationary since they are each stationary and their cross-covariance function $\gamma_{xy}(h)$ is a function only of lag h . ■

Problem 2.9

Let w_t , for $t = 0, \pm 1, \pm 2, \dots$ be a normal white noise process, and consider the series

$$x_t = w_t w_{t-1}.$$

We wish to determine the mean and autocovariance functions of x_t , and state whether it is stationary.

$$w_t \sim N(0, \sigma_w^2), t = 0, \pm 1, \pm 2, \dots$$

The mean function of x_t is computed as

$$\begin{aligned} M_{x_t} &= E(x_t) = E(w_t w_{t-1}) \\ &= E(w_t) \cdot E(w_{t-1}) \quad (\text{by the independence of } w_t \text{ and } w_{t-1}) \\ &= 0. \end{aligned}$$

In addition, the autocovariance function is

$$\begin{aligned} \gamma_x(h) &= \text{Cov}(x_{t+h}, x_t) \\ &= E[(x_{t+h} - M_{x_{t+h}})(x_t - M_{x_t})] \\ &= E[x_{t+h} x_t] \quad (\text{because } M_{x_{t+h}} = M_{x_t} = 0) \\ &= E[(w_{t+h} w_{t+h-1})(w_t w_{t-1})] \end{aligned}$$

when $h = 0$

$$\begin{aligned} \gamma_x(0) &= E[w_t w_{t-1} w_t w_{t-1}] \\ &= E[w_t^2 w_{t-1}^2] = E(w_t^2) \cdot E(w_{t-1}^2) \\ &= \text{Var}(w_t) \cdot \text{Var}(w_{t-1}) \\ &= (\sigma_w^2)^2 \quad \text{W}_{t+1} \text{ and } w_{t-1} \text{ are uncorrelated} \end{aligned}$$

$$\gamma_x(1) = E[w_{t+1} w_t w_t w_{t-1}] = E(w_t^2) \cdot E(w_{t+1} w_{t-1}) = 0 = \gamma_x(-1)$$

Now, since w_t is a white noise process $\gamma_{\alpha}(h) = 0$ for $h \neq 0$.

Hence, the covariance function of α_t is

$$\gamma_{\alpha}(h) = \begin{cases} (\sigma_w^2)^2 & h = 0 \\ 0 & h \neq 0 \end{cases}$$

From the results we have so far, we can state with certainty that α_t is stationary since the mean function is independent of time t and the autocovariance function depends only on the lag h .

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