

AR(1)

Eqⁿ: $x_t = \phi x_{t-1} + z_t$, $\{z_t\} \sim WN(0, \sigma^2)$, indep.

For $|\phi| < 1$, only stationary solⁿ is

$$x_t = \sum_{j=0}^{\infty} \phi^j z_{t-j}$$

For $|\phi| > 1$, only stationary solⁿ is

$$x_t = \sum_{j=1}^{\infty} \phi^{-j} z_{t+j}$$

For $|\phi| = 1$, ~~A~~ any stationary solⁿ

Defⁿ (Linear Process)

$$\{z_t\}_{-\infty}^{\infty} \sim WN(0, \sigma^2)$$

$x_t = \sum_{j=-\infty}^{\infty} a_j z_{t+j}$ is called a Linear Process if $\sum_{j=-\infty}^{\infty} |a_j| < \infty$

Defⁿ (Moving Average Process)

$$\{z_t\}_{-\infty}^{\infty} \sim WN(0, \sigma^2)$$

$x_t = \sum_{j=0}^{\infty} a_j z_{t-j}$ is called Moving Average Process if $\sum_{j=0}^{\infty} |a_j| < \infty$

$x_t \sim$ MA Process depends only on present and past values of z_s 's ($s \leq t$). It is Cause + Effect dependence.

That's why MA process is ~~not~~ also called Causal Process.

$\text{Cov}(x_t, z_s) = 0$ if $s > t$.

So it is also called Future Uncorrelated Process.

Defⁿ (Non-Causal Process) :

$$Z_t \sim WN(0, \sigma^2)$$

$X_t = \sum_{j=-\infty}^{\infty} a_j Z_{t-j}$ is called Non-Causal Process if

$$\sum_{j=-\infty}^{\infty} |a_j| < \infty \quad \text{and} \quad \text{cov}(X_t, Z_s) \neq 0 \text{ for some } s > t$$

It is also called Future Correlated.

Note: For AR(1) process eqⁿ

$$X_t = \phi X_{t-1} + Z_t$$

• $|\phi| > 1 \Rightarrow$ unique non-causal process

• $|\phi| < 1 \Rightarrow$ unique causal process

Defⁿ (Strict Stationarity)

If $\{X_t\}_{-\infty}^{\infty}$ is a time series with property

$$(X_t, X_{t-1}, \dots, X_{t-k}) \stackrel{d}{=} (X_s, X_{s-1}, \dots, X_{s-k}) \quad \forall t, s \in \mathbb{Z} \text{ and } k \geq 0$$

it is called strictly stationary time series.

• $\{X_t\}$ strictly stationary

$\Rightarrow X_0, X_1, \dots$ have same cdf.

Note: strictly ~~stationary~~ stationary ~~process~~ Process are also Weakly stationary given that Mean and Variance func exists.

Note: Weakly stationary process may not be strictly stationary.

Eg: $Z_t \sim WN(0, \sigma^2)$ indep. and $Z_t \sim F_t$.

Filter:

$\{X_t\}_{-\infty}^{\infty}$ is strictly stationary time series.

$$y_t = g(x_t, x_{t-1}, \dots, x_{t-k})$$

$$g: \mathbb{R}^{k+1} \rightarrow \mathbb{R}$$

Note that $\{y_t\}_{-\infty}^{\infty}$ is also a strictly stationary time series.

g is called the Filter.

① Similarly, we can ~~use~~ define for a Weakly Stationary Process.

② Let $\{X_t\}_{-\infty}^{\infty}$ be a weakly stationary time series.

We want to get other weakly stationary time series.

We should consider Linear Filter.

$\{X_t\}_{-\infty}^{\infty}$ weakly stationary

$\Rightarrow y_t = \sum_{j=0}^k a_j x_{t-j}$ is also weakly stationary.

MA(q)

$$Z_t \sim WN(0, \sigma^2)$$

$$X_t = \sum_{i=1}^q \theta_i Z_{t-i} + Z_t \quad \text{is MA}(q) \text{ Process } (q \geq 1)$$

It is obtained from ~~weakly~~ stationary Process using Linear Filter.

Defⁿ (q-correlated process)

A stationary process is called q-correlated if

$$\text{Cov}(X_t, X_{t-k}) = 0 \quad \forall k > q, \forall t$$

Note: MA(q) process is q-correlated.

Result: If a stationary process $\{X_t\}$ is q-correlated, then \exists a ~~white noise~~ white noise $Z_t \sim WN(0, \sigma^2)$ such that $\{X_t\}$ is MA(q) using $\{Z_t\}$

Defⁿ (q-dependent process)

A strictly stationary time series is called q-dependent, if X_t and X_s are independent $\forall |t-s| > q$.

Note: Let $\{Z_t\}_{t=-\infty}^{\infty}$ iid $(0, \sigma^2)$

$Y_t = g(Z_t, Z_{t-1}, \dots, Z_{t-q})$ is also strictly stationary as g is filter.

Y_t is q-dependent.

• $\{Z_t\}_{t=-\infty}^{\infty} \stackrel{iid}{\sim} N(0, \sigma^2)$

a, b, c are constants.

Which of the following are stationary?

If yes, find ACVF

Is it strictly stationary?

(a) $X_t = a + bZ_{t-1} + cZ_{t-2}$

(b) $X_t = Z_1 \cos(ct) + Z_2 \sin(ct)$

(c) $X_t = Z_t \cos(ct) + Z_{t-1} \sin(ct)$

→

(a) $E(X_t) = a$

$\text{Var}(X_t) = \sigma^2(b^2 + c^2)$

$\text{Cov}(X_t, X_s) = \text{Cov}(a + bZ_{t-1} + cZ_{t-2}, a + bZ_{s-1} + cZ_{s-2})$

$= b^2 \text{Var}(Z_{t-1}) + c^2 \text{Var}(Z_{t-2})$
 $= (b^2 + c^2) \sigma^2$

$$= \begin{cases} 0 & \text{if } |t-s| \geq 2 \\ bc\sigma^2 & \text{if } |t-s| = 1 \\ (b^2 + c^2)\sigma^2 & \text{if } |t-s| = 0 \end{cases}$$

strongly stationary since linear filter.

(b) $E(X_t) = 0$

$\text{Var}(X_t) = \sigma^2$

$\text{Cov}(X_t, X_{t+h}) = \text{Cov}(Z_1 \cos(t+h) + Z_2 \sin(t+h), Z_1 \cos t + Z_2 \sin t)$

$= \sigma^2 \cos h$

$X_t \sim N(0, \sigma^2)$

strongly stationary

$$c) E(X_t) = 0$$

$$\text{Var}(X_t) = \sigma^2$$

$$\text{Cov}(X_t, X_{t+h}) = \text{Cov}(Z_t \cos(ct) + Z_{t-1} \sin(ct), Z_{t+h} \cos(c(t+h)) + Z_{t+h-1} \sin(c(t+h)))$$

$$= \begin{cases} \sigma^2, & h=0 \\ \sigma^2 (\sin(c(t+h)) \cos(ct)), & h=1 \\ \sigma^2 (\sin(ct) \cos(c(t+h))), & h=-1 \\ 0, & \text{otherwise} \end{cases}$$

not stationary.

$$d) X_t = a + bZ_t$$

$$e) X_t = Z_0 \cos(ct)$$

$$f) X_t = Z_t Z_{t-1}$$

$$E(Z_t Z_{t-1}^2 Z_{t-2})$$

$$\rightarrow (f) E(X_t) = 0$$

$$\begin{aligned} \text{Var}(X_t) &= E(Z_t^2) E(Z_{t-1}^2) - E(Z_t)^2 E(Z_{t-1})^2 \\ &= \sigma^4 \end{aligned}$$

$$\text{Cov}(X_t, X_{t+h}) = \begin{cases} \sigma^4 & \text{if } h=0 \\ 0 & \text{if } h \neq 0 \end{cases}$$

~~filter~~ \therefore stationary

Since ~~a~~ filter, it is strongly stationary.

● $X_t \sim \text{MA}(2)$

$X_t = Z_t + \theta Z_{t-2}$, where $Z_t \sim \text{WN}(0,1)$, uncorrelated

(a) Find ACVF and ACF when $\theta = 0.8$

(b) Compute $\text{Var}\left(\frac{X_1 + \dots + X_4}{4}\right)$ when $\theta = 0.8$

(c) Repeat (b) for $\theta = -0.8$

$\rightarrow \gamma(h) = \text{Cov}(X_t, X_{t+h}) = \begin{cases} (1+\theta^2)\sigma^2 & \text{if } h=0 \\ \pm\theta & \text{if } |h|=2 \\ 0 & \text{otherwise} \end{cases}$

$\rho(h) = \begin{cases} 1 & \text{if } h=0 \\ \frac{\theta}{1+\theta^2} & \text{if } |h|=2 \\ 0 & \text{otherwise} \end{cases}$

$\text{Var}\left(\frac{X_1 + \dots + X_4}{4}\right)$

$= \frac{1}{16} [\text{Var}(X_1) 4 + 4 \text{Cov}(X_1, X_3)]$

$= \frac{1}{4} [\text{Var}(X_1) + \text{Cov}(X_1, X_3)]$

$= \frac{1}{4} [1 + \theta^2 + \theta]$

● X_1, \dots, X_n, X_{n+1} time series

We want to predict X_{n+1} by a func of X_1, \dots, X_n

i.e. $f(X_1, \dots, X_n)$ s.t. expected square error is minimised.

Find best such predictor.

$$E[(x_{n+1} - f(x_1, \dots, x_n))^2]$$

$$= E[(x_{n+1} - E(x_{n+1} | x_1, \dots, x_n))^2]$$

$$= E[E[(x_{n+1} - f(x_1, \dots, x_n))^2 | x_1, \dots, x_n]]$$

$$= E[\text{Var}(x_{n+1} | x_1, \dots, x_n) + (E[x_{n+1} | x_1, \dots, x_n] - f(x_1, \dots, x_n))^2]$$

minimized iff

$$E[x_{n+1} | x_1, \dots, x_n] = f(x_1, \dots, x_n)$$

Note: It is difficult to get conditional expectation even in computer. So we use BLUE, which depends only on mean and var-covariance ~~fun~~ func.

We can estimate mean and var-covariance func.

Q Find the set of values of ρ for which $P(h)$ is ACF for some stationary time series.

$$P(h) = \begin{cases} 1 & \text{if } h=0 \\ \rho & \text{if } |h|=1 \\ 0 & \text{otherwise} \end{cases}$$

$$\rightarrow \Sigma_n = \begin{bmatrix} 1 & \rho & 0 & 0 & \dots & 0 \\ \rho & 1 & \rho & 0 & \dots & 0 \\ 0 & \rho & 1 & \rho & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & \dots & 1 \end{bmatrix}$$

$$a_n \sum_n a_n' \geq 0$$

$$b_n \sum_n b_n' \geq 0$$

$$a_n = 1$$

$$b_n = (1, -1, 1, -1, \dots)$$

$$\Rightarrow \begin{cases} n + 2(n-1)\rho \geq 0 \\ \Rightarrow \rho \geq -\frac{n}{2(n-1)} \end{cases} \quad \left| \begin{cases} n - 2(n-1)\rho \geq 0 \\ \Rightarrow \rho \leq \frac{n}{2(n-1)} \end{cases} \right.$$

$$\therefore |\rho| \leq \frac{n}{2(n-1)} \quad \forall n \Rightarrow |\rho| \leq \frac{1}{2}$$

If $|p| \leq \frac{1}{2}$ to show $\exists x_t$ s.t. $p(h)$ is ACF of x_t .

$\rightarrow x_t$ has to be MA(1) (if it exists)

$$x_t = \theta z_{t-1} + z_t$$

$$\rho(1) = \frac{\theta}{1+\theta^2} = p \Rightarrow \frac{1}{p} = \theta + \frac{1}{\theta} \Rightarrow \frac{1}{p} \geq 2$$

$$\Rightarrow p + p\theta^2 - \theta = 0$$

Solⁿ for θ in \mathbb{R} exists iff

$$1 - 4p^2 \geq 0 \Rightarrow |p| \leq \frac{1}{2}$$

$\therefore \exists$ a time series with $p(h)$ as ACF.

① $\gamma: \mathbb{Z} \rightarrow \mathbb{R}$ is given s.t.

(i) $\gamma(0) > 0$

Δi) $g(h) = g(-h)$

(iii) $\delta(h) \leq \delta(0) \quad \forall h$

(iii) $\gamma(h) \leq \gamma(0) \quad \forall h$
 (iv) $\forall a_1, \dots, a_n \in \mathbb{R}, \sum_{i,j=1}^n a_i a_j \gamma(i-j) \geq 0$

Then \exists a ~~st~~ stationary time series x_t with ACVF, $\rho(\cdot)$.

→ Define $D_n = \left((8(i-j)) \right)_{i,j=1}^n$

$$X_n \sim N_n(0, D_n)$$

$$D_{n+1} = \left((\delta(i-j)) \right)_{i,j=1}^{n+1}$$

$$E \quad y_{n+1} \sim N_{n+1}(Q, D_{n+1}) \text{ s.t.}$$

$$\gamma_{n+1} = \begin{pmatrix} \gamma_n \\ \gamma_n \end{pmatrix} \quad \text{and} \quad \gamma_n \equiv \chi_n$$

Q. 1. 2. 3. 4. 5. 6. 7. 8. 9. 10.

$$\therefore \exists U \stackrel{d}{=} V \text{ s.t. } \begin{pmatrix} \tilde{x}_n \\ U \end{pmatrix} \sim N_{n+1}(\tilde{0}, D_{n+1})$$

$$\begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix} = \begin{pmatrix} z_1 \\ z_2 \\ \vdots \\ z_{n+1} \end{pmatrix}$$

$\therefore Z_1, Z_2, \dots, Z_n, Z_{n+1}, \dots$ time series obtained inductively.