

$H(\omega)$ & Endic Mean

2.1/ a) $X_t = B_0 + B_1 t + Z_t, Z_t \sim \mathcal{N}(0,1)$

$$E[X_t] = B_0 + B_1 t + E[Z_t] \quad \text{depends on } t$$

weakly stationary: 1) $\mu_x(t)$ independent of t

2) $\gamma_x(t+h, t)$ independent of t

b) Prove $\nabla X_t = X_t - X_{t-1}, \nabla X_t = B_0 + B_1 t + Z_t - B_0 - B_1(t-1) - Z_{t-1}$

$$\nabla X_t = B_1(t-t+1) + Z_t - Z_{t-1} = B_1 + Z_t - Z_{t-1}, E[\nabla X_t] = B_1$$

2) $\gamma_{x'}(t+h, t) = E[(X'_{t+h} - E[X'_{t+h}])(X'_t - E[X'_t])]$

$$= \text{cov}(\nabla X_{t+h}, \nabla X_t) = \text{cov}(B_1 + Z_{t+h} - Z_{t-1+h}, B_1 + Z_t - Z_{t-1})$$

Rules

$$\text{cov}(x, a) = 0$$

$$\text{cov}(x, x) = \text{var}(x)$$

$$\text{cov}(ax, by) = ab \text{cov}(Y, X)$$

$$\text{cov}(x+a, y+b) = \text{cov}(x, y)$$

$$\begin{aligned} &= \text{cov}(Z_{t+h}, Z_t) - \text{cov}(Z_{t-1+h}, Z_t) - \text{cov}(Z_{t+h}, Z_{t-1}) \\ &\quad + \text{cov}(Z_{t-1+h}, Z_{t-1}) \end{aligned}$$

$$h=0 \Rightarrow 0^2 - 0 - 0 + 0^2 = 0$$

$$h=1 \Rightarrow 0 - 0^2 - 0 + 0 = -0^2$$

$$h=-1 \Rightarrow 0 - 0 - 0^2 + 0 = -0^2$$

$$|h| > 1 \Rightarrow 0$$

1) & 2) \Rightarrow stationary

$$2.1c) \quad Z_t = Y_t \sim N(\mu_Y, \sigma^2), \quad \delta_Y(h)$$

$$X_t = B_0 + B_1 t + Y_t$$

$$\nabla X_t = B_1 + Y_t - Y_{t-1}$$

$$\mathbb{E}[\nabla X_t] = B_1$$

$$\delta_{\nabla X}(t+h, t) = \text{cov}(Y_{t+h-1}, Y_{t-1})$$

$$= \text{cov}(B_1 + Y_{t+h} - Y_{t+h-1}, B_1 + Y_t - Y_{t-1})$$

$$= \text{cov}(Y_{t+h}, Y_t) - \text{cov}(Y_{t+h}, Y_{t-1}) - \text{cov}(Y_{t+h-1}, Y_t) + \text{cov}(Y_{t+h-1}, Y_{t-1})$$

Def $\text{cov}(Y_{t+h}, Y_t) = \delta_Y(h)$

$$= \delta(h) - \text{cov}(Y_{t+h}, Y_{t-1}) - \text{cov}(Y_{t+h-1}, Y_t) + \text{cov}(Y_{t+h-1}, Y_{t-1})$$

$$\text{cov}(Y_{t+h-1}, Y_{t-1}) = \text{cov}(Y_{t+h}, Y_t) = \delta(h)$$

$t = t+1$

$\Rightarrow (t+h, t-1)$

$\textcircled{2} \quad t = t+1$

$$\Rightarrow (\underbrace{t+1+h}_{t+h}, t) = h+1$$

$\textcircled{3} \quad \underbrace{t+h-1}_{t+h-1}, t = h-1$

$\textcircled{4} \quad t+h-1, t-1 = c(Y_{t+h}, Y_t) = \delta(h)$

$t = t+1$

$$\Rightarrow \delta(h) - \delta(h+1) - \delta(h-1) + \delta(h)$$

$$= 2\delta(h) - \delta(h+1) - \delta(h-1)$$

$$\Rightarrow \delta(h) = \begin{cases} 2\sigma^2 & h=0 \\ \sigma^2 & h=\pm 1 \\ 0 & h>1 \end{cases}$$

$$2.2 \text{ f) } \delta_u \quad u_t = \mu + z_t + \theta z_{t-1} \quad z \sim N(0, \sigma_z^2)$$

$$E[u_t] = \mu$$

$$\begin{aligned} \text{cov}(u_{t+h}, u_t) &= \text{cov}(z_{t+h}, z_t) + \text{cov}(z_{t+h}, \theta z_{t-1}) \\ &\quad + \text{cov}(\theta z_{t-1+h}, z_t) + \text{cov}(\theta z_{t-1+h}, \theta z_{t-1}) \\ &= \text{cov}(\quad) + \theta \text{cov}(\quad) \\ &\quad + \theta \text{cov}(\quad) + \theta^2 \text{cov}(\quad) \end{aligned}$$

$$h=0 \Rightarrow \sigma^2 + \sigma^2 \theta^2 = \sigma^2(1 + \theta^2)$$

$$h=1 \Rightarrow \theta \cdot \sigma^2$$

$$h \geq 2 \Rightarrow 0$$

δ_u - is defined for $h \in \{-1, 1\}$

$M_q(q)$ is a moving average process of order q

$$x_t = z_t + \theta_1 z_{t-1} + \dots + \theta_q z_{t-q}$$

$M_q(1)$ has memory of $t, t-1$

which fits with $\delta_u - u_t$ is therefore a $M_q(1)$ process

$$2.8) \cdot g) \quad \rho(h) = \frac{\gamma(h)}{\gamma(0)}$$

$$\rho(1) = \frac{\gamma(1)}{\gamma(0)} = \frac{\theta \sigma^2}{\sigma^2(1+\theta^2)} = \frac{\theta}{1+\theta^2}$$

$$\gamma(0) = \sigma^2(1+\theta^2)$$

$$I \quad \sigma^2 = \frac{\gamma(0)}{1+\theta^2}$$

$$II \quad \rho(1) \cdot (1+\theta^2) = \theta$$

$$III \quad \rho(1) + \rho(1)\theta^2 - \theta = 0$$

$$\frac{-b \pm \sqrt{b^2 - 4ac}}{2a}$$

$$\theta^2 \rho - \theta + \rho = 0$$

$$\theta = \frac{1 \pm \sqrt{1^2 - 4\rho}}{2\rho}$$

$$\hat{\theta} = \frac{1 \pm \sqrt{1 - 4\rho(1)^2}}{2\rho(1)}$$

$$\hat{\sigma}^2 = \frac{\gamma(0)}{1 + \hat{\theta}^2}$$

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MA(1) - 84

2.3 / 1) $\text{cov}(x_1, x_3 | x_2)$

$$x_t = z_t + \Theta z_{t-1} \quad -\text{MA}(1)$$

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$\Rightarrow p(h) = 0 \quad h \geq 2$

2) partial correlation for MA(1) process

1) $P_{x_1 x_3 x_2} = \frac{\sigma_{x_1 x_3 \cdot x_2}}{\sqrt{\sigma_{x_1 x_1 \cdot x_2}} \cdot \sqrt{\sigma_{x_3 x_3 \cdot x_2}}}$

2) PACF - Partial Correlation Function - MA(1),

$$\rho(h) = \phi_{hh} = \frac{-(-\Theta)^h}{(1 + \Theta^2 + \dots + \Theta^{2h})}$$

$$\text{cov}(x_1, x_3) = \begin{bmatrix} \Sigma_{11} & \Sigma_{13} \\ \Sigma_{31} & \Sigma_{33} \end{bmatrix}$$

$$\rho_{13 \cdot 2} = \frac{\rho_{13} - \rho_{21} \rho_{23}}{(1 - \rho_{21}^2)^{1/2} (1 - \rho_{23}^2)^{1/2}} \quad (t+1, t-1)$$

$$\text{cov}(x_{t+h}, x_t) = \text{cov}(z_{t+h} \cdot z_t) + \Theta \text{cov}(z_{t+h-1}, z_t) + \Theta (z_{t+h}, z_{t-1}) \text{cov}(z_{t-1}, z_t)$$

$$(z_{t+h} + \Theta z_{t+h-1}) \Rightarrow h=0 \Rightarrow \sigma^2 + \Theta^2 \sigma^2 = \sigma^2 (1 + \Theta^2)$$

$$(z_t + \Theta z_{t-1}) \quad h=\pm 1 \Rightarrow \sigma^2 \Theta$$

$$\gamma(0) = \sigma^2 (1 + \Theta^2) \quad \gamma(\pm 1) = \sigma^2 \Theta$$

$$\rho(h) = \frac{\gamma(h)}{\gamma(0)} = \frac{\gamma(h)}{\sigma^2 (1 + \Theta^2)} \Rightarrow \rho(1) = \frac{\Theta^2 \Theta}{\sigma^2 (1 + \Theta^2)} = \frac{\Theta}{(1 + \Theta^2)}$$

$$\rho_{11} = \rho_1, \quad \rho_{22} = \frac{\left| \begin{array}{cc} 1 & \rho(1) \\ \rho(1) & \rho(2) \end{array} \right|}{\left| \begin{array}{cc} 1 & \rho(1) \\ \rho(1) & 1 \end{array} \right|} = \frac{\left(\frac{\Theta}{1 + \Theta^2} \right)^2 \frac{(1 + \Theta^2)^2}{(1 - \frac{\Theta^2}{1 + \Theta^2})^2}}{1 - \frac{\Theta^2}{1 + \Theta^2}} = \frac{\Theta^2}{(1 + \Theta^2)^2 - \Theta^2}$$

$$= \frac{\Theta^2}{1 + 2\Theta^2 + \Theta^4 - \Theta^2} = \frac{\Theta^2}{1 + \Theta^2 + \Theta^4}$$

$$(1 + \Theta^2)(1 + \Theta^2) \\ = 1 + 2\Theta^2 + \Theta^4$$

2.9 a) Explain $\hat{\gamma} = \frac{1}{n} \sum_{t=-\infty}^{\infty} Y_{t+h} Y_t$ $h \in \mathbb{Z}$

$$\text{Symmetric } \hat{\gamma}(h) = \begin{cases} \frac{1}{n} \sum_{t=1}^{n-h} (x_{t+h} - \bar{x}_n)(x_t - \bar{x}_n), & h \in [0, n-1] \\ \hat{\gamma}(-h) & h \in [-n+1, 0] \\ 0 & \text{else} \end{cases}$$

where $Y_t = \begin{cases} x_t - \bar{x}_n, & t \in [1, n] \\ 0 & t \notin [1, n] \end{cases}$

1) let $n \rightarrow \infty \Rightarrow \hat{\gamma} = \frac{1}{n} \sum_{t=1}^{\infty} Y_{t+h} Y_t$

2) $t=0 \Rightarrow \hat{\gamma}(0) = 0$ by def

3) Symmetric: when $n \rightarrow \infty, t \in [-1, -n] \Rightarrow \hat{\gamma} = \hat{\gamma}(-h)$

$t \in [-1, -n]$ and $s \in [1, n] \Rightarrow \hat{\gamma}(-(-t)) = \hat{\gamma}(s)$

$$\Rightarrow \hat{\gamma} = \sum_{t=-1}^{-\infty} \hat{\gamma}(-h) + 0 + \sum_{t=0}^{\infty} \hat{\gamma}(h) = \sum_{t=-\infty}^{\infty} \hat{\gamma}(h) = \frac{1}{n} \sum_{t=-\infty}^{\infty} Y_{t+h} Y_t$$

b) $a \in \mathbb{R}^m$ show

$$\sum_{i=1}^m \sum_{j=1}^m a_i \hat{\gamma}(i-j) a_j = n^{-1} \sum_{i=1}^m \sum_{j=1}^m \sum_t a_i Y_{t+i-j} Y_t a_j$$

let $s = t - j$ $= n^{-1} \sum \sum \sum a_i Y_{s+i} Y_{s+j} a_j$

RHS of eq $\left\{ \begin{array}{ll} t > 0 & \text{cov}(Y_{s+i}, Y_{s+j}) = \begin{cases} (\hat{\gamma}_{s+i})^2 & i=j \\ 0 & i \neq j \end{cases} \\ t=0 & \hat{\gamma}(0) = 0 \\ t < 0 & \text{cov}(Y_{-(s+i)}, Y_{-(s+j)}) = \begin{cases} (\hat{\gamma}_{-(s+i)})^2 & i=j \\ 0 & i \neq j \end{cases} \end{array} \right.$

LHS: Use $s = t - j$

$$\Rightarrow \text{cov}(Y_{s+i}, Y_{s+j}) = \text{cov}(Y_{t+i-j}, Y_t) \Rightarrow h = i-j$$

$$\Rightarrow Y_{t-j+i}, Y_{t-j+j} \Rightarrow Y_{t+i-j}, Y_t \quad \hat{\gamma}(i-j) = \text{LHS}$$

2.5 a)

Show

$$\bar{X}_n - \mu = \left(\sum_{j=0}^q \theta_j \right) \bar{Z}_n + \sum_{j=0}^q \theta_j \left(\frac{1}{n} U_j - \frac{1}{n} V_n(j) \right),$$

$$X_t = u + \sum_{j=0}^q \theta_j Z_{t-1}$$

$$\bar{X}_t = \frac{1}{n} \sum_{t=0}^n \left(u + \sum_{j=0}^q \theta_j Z_{t-1} \right)$$

$$= \frac{n\mu}{\mu} + \frac{1}{n} \sum_{t=0}^n \sum_{j=0}^q \theta_j Z_{t-1}$$

$$\bar{X}_t - \mu = \frac{1}{n} \sum_{j=0}^q \theta_j \sum_{t=0}^n Z_{t-1}$$

$$\boxed{\sum_{t=0}^n Z_{t-1} = \sum_{t=0}^n Z_t + \sum_{k=1-j}^0 Z_{1-k} - \sum_{k=n-j+1}^n Z_{n-k}}$$

$$\sum_{k=1-j}^0 Z_{1-k} - \sum_{k=n-j+1}^n Z_{n-k}$$

$$U(j) \quad j=5 \Rightarrow \sum_{k=-4}^0 Z_{1-k} \Rightarrow Z_5 + Z_4 + \dots + Z_1$$

$$V(i) \quad j=5 \Rightarrow \sum_{k=n-5+1}^n Z_{n-k} = Z_{n-(n-4)} + Z_{n-(n-3)} + \dots + Z_4 + Z_5$$

$$\rightarrow \bar{X}_t - u = \sum_{j=0}^q \theta_j \bar{Z}_t + \frac{1}{n} \left(\sum_{k=1-j}^0 Z_{1-k} - \sum_{k=n-j+1}^n Z_{n-k} \right)$$

|| n
U_j V_j(n)

2.5 b) Prove

$$P\left(\frac{1}{n}|V_j(n)| > \varepsilon\right) \leq \frac{q}{\varepsilon^2 n^2}$$

Chesbyshew ineq

$$\begin{aligned} P(|X - \mu| \leq k\sigma) &\geq 1 - \frac{1}{k^2} \\ = P(|X - \mu| > k\sigma) &\leq \frac{1}{k^2} \\ = P(|X - \mu| \geq k) &\leq \frac{\sigma^2}{k^2} \\ \Rightarrow P(|V_j(n)| > \varepsilon \cdot n) &\leq \frac{\sigma^2}{\varepsilon^2 n^2} \end{aligned}$$

$\sum_{j=1}^q Z_n \sim N(0, q)$ since $\{Z_1, \dots, Z_q\}$ iid

$$\Rightarrow P\left(\frac{1}{n}|V_j(n)| > \varepsilon\right) \leq \frac{\sigma^2}{\varepsilon^2 n^2} = \frac{j \cdot \sigma^2}{\varepsilon^2 n^2} \leq \frac{q \cdot 1}{\varepsilon^2 n^2}$$

Prove $\sum_{j=1}^n P\left(\frac{1}{n}|V_j(n)| > \varepsilon\right) < \infty$, $M_n = P\left(\frac{1}{n}|V_j(n)| > \varepsilon\right)$

$$\Rightarrow \sum_{j=1}^n M_n < \sum_{j=1}^n \frac{q}{\varepsilon^2 n^2} = n \cdot \frac{q}{\varepsilon^2 n^2} < \infty$$

Borel-Cantelli $\{A_n, n \geq 1\}$ seq of events

$$\text{If } \sum_{n=1}^{\infty} P(A_n) < \infty \Rightarrow \lim_{n \rightarrow \infty} A_n \xrightarrow{\text{a.s.}} \emptyset$$

$$\lim_{n \rightarrow \infty} \frac{q}{\varepsilon^2 n} = 0 \stackrel{\text{borel}}{\Rightarrow} \sum_{j=1}^{\infty} I_{M_n} \stackrel{\text{a.s.}}{\xrightarrow{n \rightarrow \infty}} 0$$

2.5g) CLT: $Y_n \equiv \sqrt{n}(\bar{X}_n - \mu)$

Show $Y_n = (\sum_{j=0}^q \theta_j)(\sqrt{n}(\bar{Z}_n + W_n))$

$$W_n = \sum_{j=0}^q \theta_j(n^{-1/2} U_j - n^{-1/2} V_n(j))$$

prove $n^{-1/2} U_j \xrightarrow{P} 0 \quad n^{-1/2} V_n(j) \xrightarrow{P} 0$

s.t. $\sqrt{n}(\bar{X}_n - \mu) = Y_n + W_n$

$$W_n = o_p(1)$$

Cramer-Slutsky: if $Y_n \xrightarrow{P} X$

i) $X_n = Y_n + Z_n$ and $Z_n \xrightarrow{P} 0 \Rightarrow X_n \xrightarrow{d} 0$

ii) $X_n = Y_n Z_n$ and $Z_n \xrightarrow{P} 1 \Rightarrow X_n \xrightarrow{d} Y$

Proof

$$E(V_j^2) = E[\dots] = j \leq q \quad j = 1, \dots, q$$

From b) we know: $P(\frac{1}{n}|V_n(j)| > \varepsilon) \leq \frac{q}{\varepsilon^2 n^2}$ and $\sum_{j=0}^q M_n = \frac{q}{\varepsilon^2 \cdot n} \xrightarrow{n \rightarrow \infty} 0$

$$\Rightarrow \frac{1}{\sqrt{n}} |V_n(j)| \leq \frac{q}{n^2 \varepsilon^2} \Leftrightarrow |V_n(j)| = \frac{\sqrt{n} q}{n^2 \varepsilon^2} = \frac{q}{n \cdot \varepsilon^2} \xrightarrow{n \rightarrow \infty} 0$$

$$\Rightarrow \sum_{j=0}^q \frac{1}{\sqrt{n}} P(|V_n(j)| > \varepsilon) \leq \frac{q}{\varepsilon^2 n^2} \Leftrightarrow P(|V_n(j)| > \varepsilon) \leq \frac{n \cdot \sqrt{n} q}{n^2 \varepsilon^2} \xrightarrow{n \rightarrow \infty} 0$$

$$P(|U_j| > \varepsilon) = P(|U_0| > \varepsilon n) \leq \frac{q}{\varepsilon^2 n^2} \xrightarrow{n \rightarrow \infty} 0$$

$$\Rightarrow \sum_{j=0}^q \frac{1}{\sqrt{n}} P(|U_j| > \varepsilon) \leq \frac{q}{\varepsilon^2 n^2} \Leftrightarrow \sum_{j=0}^q P(|U_j| > \varepsilon n) \leq \frac{n \cdot \sqrt{n} \cdot q}{\varepsilon^2 n^2} \xrightarrow{n \rightarrow \infty} 0$$

$$\Rightarrow W_n = \sum_{j=0}^q \theta_j (\frac{1}{\sqrt{n}} U_j - \frac{1}{\sqrt{n}} V_j) \xrightarrow{n \rightarrow \infty} \sum_{j=0}^q \theta_j \cdot (0 - 0) = 0$$

$$\Rightarrow W_n \xrightarrow{n \rightarrow \infty} 0$$

$$\Rightarrow \sqrt{n}(\bar{x}_n - u) = Y_n + o \text{ nur } n \rightarrow \infty$$
$$= \left(\sum_{j=0}^q \theta_j \right) (\sqrt{n} \bar{\varepsilon}_n)$$

$$\sqrt{n} \bar{\varepsilon}_n \sim N(0, \sigma^2)$$

$$E(cx) = c E(x) = u$$

$$\text{Var}(cx) = c^2 \text{Var}(x) = c^2 \sigma^2$$

$$\Rightarrow Y_n \sim N\left(0, \left(\sum_{j=0}^q \theta_j\right)^2 \cdot \sigma^2\right)$$

$$\bar{\varepsilon}_n \sim N(0, 1) \Rightarrow \sigma^2 = 1 = N\left(0, \sum_{j=0}^q \theta_j\right)$$