

HW 25 10/16

1. 給定 AR(p) 序列, 求 (a) 以 lag operators 表示 (令 L 為 lag operator, 滿足 $Ly_t = y_{t-1}$)

Lag operator 定義: $Ly_t = y_{t-1}$, $L^2 y_t = y_{t-2}$, $L^k y_t = y_{t-k}$

⇒ 把模型改寫成含 L 的形式, 原式

$$(I) \quad y_t = 1.3y_{t-1} - 0.5y_{t-2} + \varepsilon_t$$

$$\Rightarrow y_t = 1.3Ly_t - 0.5L^2 y_t + \varepsilon_t$$

$$\Rightarrow y_t - 1.3Ly_t + 0.5L^2 y_t = \varepsilon_t, (1 - 1.3L + 0.5L^2)y_t = \varepsilon_t$$

$$\Rightarrow \Phi(L) = 1 - 1.3L + 0.5L^2, \text{ 因此 AR(2) 模型可寫成 } \Phi(L)y_t = \varepsilon_t$$

$$(II) \quad y_t = 1.2y_{t-1} - 0.4y_{t-2} + \varepsilon_t$$

$$y_t = 1.2Ly_t - 0.4L^2 y_t + \varepsilon_t$$

$$\Rightarrow y_t - 1.2Ly_t + 0.4L^2 y_t = \varepsilon_t$$

$$\Rightarrow (1 - 1.2L + 0.4L^2)y_t = \varepsilon_t$$

$$\Rightarrow \Phi(L) = 1 - 1.2L + 0.4L^2, \text{ 因此 AR(2) 模型可寫成 } \Phi(L)y_t = \varepsilon_t$$

$$(III) \quad y_t = 1.2y_{t-1} + 1.2y_{t-2} + \varepsilon_t$$

$$y_t(1 - 1.2L - 1.2L^2) = \varepsilon_t$$

$$(VI) \quad y_t = 0.7y_{t-1} + 0.25y_{t-2} - 0.175y_{t-3} + \varepsilon_t$$

$$y_t(1 - 0.7L - 0.25L^2 + 0.175L^3) = \varepsilon_t$$

$$(IV) \quad y_t = -1.2y_{t-1} + \varepsilon_t$$

$$y_t(1 + 1.2L) = \varepsilon_t$$

(b) 判斷是否為平穩序列 Stationary

↳ AR(p) 過程平穩 \Leftrightarrow 其特徵方程的根 (in terms of L) 皆滿足 $|z| > 1$.

$$(I) \quad 1 - 1.2L + 0.2L^2 = 0, \quad 1 - 1.2z + 0.2z^2 = 0, \quad z = 1, 0.2 < 1, \Rightarrow \text{不平穩}$$

$$(II) \quad 1 - 1.2L + 0.4L^2 = 0, \quad z = 0.6 \pm 0.2i, \quad |z| = 0.63 < 1 \rightarrow \text{不平穩}$$

$$(III) \quad | -1.2L - 1.2L^2 | > 1, z = 1.8, -0.6 \rightarrow \text{不穩定}$$

$$(IV) \quad | +1.2L | > 1, L = -\frac{1}{1.2} = -0.833, |L| < 1 \rightarrow \text{不穩定}$$

$$(VI) \quad | -0.7L - 0.15L^2 + 0.175L^3 | > 1, z = 1.15, 1.2, -2, \text{全部 } |z| > 1 \rightarrow \text{穩定}$$

$$4. \quad y_t = y_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim (0, \sigma^2) \quad \text{pf } y_t \text{ 為非定態}$$

平穩序列 (弱定態) 條件:

1. $E(y_t)$ 為常數

2. $\text{Var}(y_t)$ 為常數

3. $\text{Cov}(y_t, y_{t-k})$ 只與 k 有關

$$y_t = y_{t-1} + \varepsilon_t, \quad \text{代入 } y_{t-1} = y_{t-2} + \varepsilon_{t-1} \text{ 得 } y_t = y_{t-2} + \varepsilon_{t-1} + \varepsilon_t$$

$$\text{繼續展開, } y_t = y_0 + \sum_{i=1}^t \varepsilon_i$$

$$E(y_t) = E(y_0) + \sum_{i=1}^t E(\varepsilon_i) = E(y_0) \rightarrow \text{期望值為常數}$$

$$\text{Var}(y_t) = \text{Var}\left(\sum_{i=1}^t \varepsilon_i\right) = \sum_{i=1}^t \text{Var}(\varepsilon_i) = t\sigma^2 \rightarrow \text{隨 } t \uparrow, \text{Var} \uparrow \text{ (線性)}$$

$$\text{Cov}(y_t, y_s) = E[(y_t - E(y_t))(y_s - E(y_s))]$$

$$\because E(y_t) = E(y_s) = E(y_0) \Rightarrow \text{Cov}(y_t, y_s) = E[(y_t - y_0)(y_s - y_0)]$$

$$\text{代入展開式 } y_t - y_0 = \sum_{i=1}^t \varepsilon_i, \quad y_s - y_0 = \sum_{j=1}^s \varepsilon_j$$

$$\therefore \text{Cov}(y_t, y_s) = E\left[\left(\sum_{i=1}^t \varepsilon_i\right)\left(\sum_{j=1}^s \varepsilon_j\right)\right] \quad \because \varepsilon_i \text{ 之間 iid, } E(\varepsilon_i \varepsilon_j) = \begin{cases} \sigma^2, & i=j \\ 0, & i \neq j \end{cases}$$

$$\therefore \text{Cov}(y_t, y_s) = \sum_{i=1}^t \sum_{j=1}^s E(\varepsilon_i \varepsilon_j) = \sum_{i=1}^{\min(t,s)} \sigma^2$$

$$\text{若 } t > s, \quad \text{Cov}(y_t, y_s) = s\sigma^2 = \text{Var}(y_s)$$

平穩序列應滿足 $\text{Cov}(y_t, y_s) = \gamma(t-s)$, 即只和時間差 $t-s$ 有關
but 這裡卻是和 s 有關, 這代表 往後 observe 更久 (s 更大), Cov 中,
data 波動幅度 \uparrow , \therefore 此過程為 Non-stationary

5. 给定 y_t 为定态 AR(2) 序列 $y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \varepsilon_t$,

其中 $\varepsilon_t \stackrel{iid}{\sim} (0, \sigma^2)$, 求 (a) $E(y_t)$ (b) $\text{Var}(y_t)$ (c) $\gamma(j)$ (d) $\rho(j)$

(a) $E(y_t)$ 令 $E(y_t) = \mu$, $\mu = c + \phi_1 \mu + \phi_2 \mu \Rightarrow \mu(1 - \phi_1 - \phi_2) = c$

$$\Rightarrow E(y_t) = \mu = \frac{c}{1 - \phi_1 - \phi_2}$$

(b) $\text{Var}(y_t)$ 令 $y_t - \mu = x_t$, 则 $x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + \varepsilon_t$

利用 Yule-Walker 方程 $\gamma(0) = \phi_1 \gamma(1) + \phi_2 \gamma(2) + \sigma^2$ — ①

$$\gamma(1) = \phi_1 \gamma(0) + \phi_2 \gamma(1) \text{ — ②}$$

② $\gamma(1)(1 - \phi_2) = \phi_1 \gamma(0) \Rightarrow \gamma(1) = \frac{\phi_1}{1 - \phi_2} \gamma(0)$ 代入 ①, $\gamma(0) = \phi_1 \frac{\phi_1}{1 - \phi_2} \gamma(0) + \phi_2 \gamma(2) + \sigma^2$

$$\gamma(2) = \phi_1 \gamma(1) + \phi_2 \gamma(0) \Rightarrow \gamma(0) \left[1 - \frac{\phi_1^2 (1 + \phi_2)}{1 - \phi_2} - \phi_2 \right] = \sigma^2$$

$$\text{Var}(y_t) = \gamma(0) = \frac{(1 - \phi_2) \sigma^2}{(1 + \phi_2)(1 - \phi_2^2 - \phi_1^2)}$$

(c) $\gamma(j)$ $\gamma(j) = \phi_1 \gamma(j-1) + \phi_2 \gamma(j-2)$, $j \geq 2$

$$\gamma(0), \gamma(1) = \frac{\phi_1}{1 - \phi_2} \gamma(0)$$

(d) $\rho(j)$ $\rho(j) = \frac{\gamma(j)}{\gamma(0)}$, $\rho(j) = \phi_1 \rho(j-1) + \phi_2 \rho(j-2)$, $\rho(0) = 1$

6. $y_t = 1.3 y_{t-1} - 0.5 y_{t-2} + \varepsilon_t$, $\varepsilon_t \stackrel{iid}{\sim} (0, \sigma^2)$

(a) 以 lag operator 表示式

$$y_t = 1.3 L y_t - 0.5 L^2 y_t + \varepsilon_t \Rightarrow (1 - 1.3L + 0.5L^2) y_t = \varepsilon_t$$

$$\Phi(L) y_t = \varepsilon_t, \Phi(L) = 1 - 1.3L + 0.5L^2$$

(b) 判断是否为平稳过程

$$1 - 1.3z + 0.5z^2 = 0, \quad z = 0.65 \pm 0.278i; \quad |z| = \sqrt{0.65^2 + 0.278^2} = 0.709 < 1$$

\Rightarrow AR(2) model 不平稳

(c) $E(y_t)$

$$\because \text{没有常数项}, \therefore E(y_t) = 1.3E(y_{t-1}) - 0.5E(y_{t-2})$$

$$\text{令 } E(y_t) = \mu, \quad \mu = 1.3\mu - 0.5\mu, \quad (1 - 1.3 + 0.5)\mu = 0, \quad \mu = 0, \quad E(y_t) = 0$$

(d) $r(j)$

$$\begin{cases} r(0) = 1.3r(1) - 0.5r(2) + \sigma^2 \end{cases}$$

$$\begin{cases} r(1) = 1.3r(0) - 0.5r(1) \end{cases}$$

$$\rightarrow r(1)(1 + 0.5) = 1.3r(0) \rightarrow r(1) = 0.867r(0)$$

$$\Rightarrow r(j) = 1.3r(j-1) - 0.5r(j-2), \quad j \geq 2$$

(e) Yule - Walker

$$\begin{cases} r(0) = 1.3r(1) - 0.5r(2) + \sigma^2 \end{cases}$$

$$\begin{cases} r(1) = 1.3r(0) - 0.5r(1) \end{cases}$$

$$\begin{cases} r(2) = 1.3r(1) - 0.5r(0) \end{cases}$$

(f) $\text{Var}(y_t) = r(0)$

$$r(1) = \frac{13}{15} r(0)$$

$$r(2) = 1.3r(1) - 0.5r(0) = 1.3(0.867r(0)) - 0.5r(0) = 0.6267r(0)$$

$$r(0) = 1.3(0.867r(0)) - 0.5(0.6267r(0)) + \sigma^2$$

$$r(0) [1 - (1.271 - 0.31335)] = \sigma^2$$

$$r(0) = \frac{\sigma^2}{0.1825} = 5.37\sigma^2, \quad \text{Var}(y_0) = 5.37\sigma^2$$