

$$\textcircled{1} \text{ i) } E[\nabla Y_t] = E[Y_t - Y_{t-1}] = E(Y_t) - E(Y_{t-1}) =$$

Since  $\{Y_t\}$  is stationary,  $E(Y_t) = E(Y_{t-1}) = \mu \Rightarrow$

$$\textcircled{=} \mu - \mu = 0 \text{ (constant over time)}$$

$$\begin{aligned} \text{Cov}[\nabla Y_t, \nabla Y_{t-k}] &= \text{Cov}[Y_t - Y_{t-1}, Y_{t-k} - Y_{t-k-1}] = \\ &= \text{Cov}(Y_t, Y_{t-k}) - \text{Cov}(Y_{t-1}, Y_{t-k}) - \\ &\quad - \text{Cov}(Y_t, Y_{t-k-1}) + \text{Cov}(Y_{t-1}, Y_{t-k-1}) \textcircled{=} \end{aligned}$$

Here, we can make use of the covariance  $\gamma_k$  of our stochastic process  $\{Y_t\}$

$$\gamma_k = \text{Cov}(Y_t, Y_{t-k}), \quad \text{Cov}(Y_{t-1}, Y_{t-k}) =$$

$$= \text{Cov}(Y_{t-1}, Y_{t-1-(k-1)}) = \gamma_{k-1}$$

$$\text{Cov}(Y_{t-1}, Y_{t-k-1}) = \text{Cov}(Y_{t-1}, Y_{t-1-(k+1)}) = \gamma_{k+1}$$

$$\text{Cov}(Y_{t-1}, Y_{t-k-1}) = \text{Cov}(Y_{t-1}, Y_{t-1-k}) = \gamma_k$$

$$\textcircled{=} \gamma_k - \gamma_{k-1} - \gamma_{k+1} + \gamma_k = 2\gamma_k - \gamma_{k-1} - \gamma_{k+1}$$

We can say that the covariance function for  $\{\nabla Y_t\}$  does not depend on time since  $\gamma_k, \gamma_{k-1}, \gamma_{k+1}$  don't depend on time, which is the result of stationarity of  $\{Y_t\}$

b) In i), we showed that if a process  $\{Y_t\}$  is stationary, then its first difference  $\{\nabla Y_t\}$  is also stationary. Since we now know that  $\nabla Y_t = Y_t - Y_{t-1}$  is stationary, then its first difference  $\nabla[Y_t - Y_{t-1}]$  will also be stationary.

$$(2) Y_t = 3 + e_t - \frac{1}{3}e_{t-1} + \frac{1}{2}e_{t-2}$$

$$\text{Var}(Y_t) = \text{Var}(3 + e_t - \frac{1}{3}e_{t-1} + \frac{1}{2}e_{t-2}) = \sigma_e^2 + \frac{1}{9}\sigma_e^2 + \frac{1}{4}\sigma_e^2 = \frac{49}{36}\sigma_e^2 = \gamma_0$$

$$\begin{aligned} \gamma_1 &= \text{Cov}(Y_t, Y_{t-1}) = \text{Cov}(3 + e_t - \frac{1}{3}e_{t-1} + \frac{1}{2}e_{t-2}, \\ &\quad 3 + e_{t-1} - \frac{1}{3}e_{t-2} + \frac{1}{2}e_{t-3}) = \text{Cov}(e_t, e_{t-1}) - \\ &\quad - \frac{1}{3}\text{Cov}(e_{t-1}, e_{t-1}) + \frac{1}{2}\text{Cov}(e_{t-2}, e_{t-1}) - \\ &\quad - \frac{1}{3}\text{Cov}(e_t, e_{t-2}) + \frac{1}{9}\text{Cov}(e_{t-1}, e_{t-2}) - \frac{1}{6}\text{Cov}(e_{t-2}, e_{t-2}) \\ &\quad + \frac{1}{2}\text{Cov}(e_t, e_{t-3}) - \frac{1}{6}\text{Cov}(e_{t-1}, e_{t-3}) + \frac{1}{4}\text{Cov}(e_{t-2}, e_{t-3}) = \\ &= -\frac{1}{3}\text{Cov}(e_{t-1}, e_{t-1}) - \frac{1}{6}\text{Cov}(e_{t-2}, e_{t-2}) = \\ &= -\frac{1}{3}\sigma_e^2 - \frac{1}{6}\sigma_e^2 = -\frac{1}{2}\sigma_e^2 \end{aligned}$$

$$\begin{aligned} \gamma_2 &= \text{Cov}(Y_t, Y_{t-2}) = \text{Cov}(3 + e_t - \frac{1}{3}e_{t-1} + \frac{1}{2}e_{t-2}, \\ &\quad 3 + e_{t-2} - \frac{1}{3}e_{t-3} + \frac{1}{2}e_{t-4}) \quad \text{we can see that} \\ &\quad \text{only one term } (e_{t-2}) \text{ exists in both } Y_t \text{ and } Y_{t-2}, \text{ so} \end{aligned}$$

$$\Rightarrow \frac{1}{2}\text{Cov}(e_{t-2}, e_{t-2}) = \frac{1}{2}\sigma_e^2$$

For time lag  $s \geq 3$ ,  $\gamma_s = 0$  since there will be no overlap  
Now, we can find ACF:

$$\rho_0 = 1$$

$$\rho_1 = \frac{\text{Cov}(Y_t, Y_{t-1})}{\sqrt{\text{Var}(Y_t)} \sqrt{\text{Var}(Y_{t-1})}} = \frac{-\frac{1}{2}\sigma_e^2}{\gamma_0} = \frac{-\frac{1}{2}\sigma_e^2}{\frac{49}{36}\sigma_e^2} = -\frac{18}{49}$$

$$\rho_2 = \frac{\text{Cov}(Y_t, Y_{t-2})}{\sqrt{\text{Var}(Y_t)} \sqrt{\text{Var}(Y_{t-2})}} = \frac{\frac{1}{2}\sigma_e^2}{\gamma_0} = \frac{\frac{1}{2}\sigma_e^2}{\frac{49}{36}\sigma_e^2} = \frac{18}{49}$$

$$\rho_s = 0, \text{ when } s \geq 3$$



③ We know that for MA(1) process  $y_t = e_t - \theta e_{t-1}$ ,

$$\rho_k = \begin{cases} 1 & \text{if } k=0 \\ -\theta/(1+\theta^2) & \text{if } k=1 \\ 0 & \text{if } k \geq 2 \end{cases}$$

If  $\theta$  is changed to  $1/\theta$ , then  $y_t = e_t - \frac{1}{\theta} e_{t-1}$ , and

$$\gamma_0 = \text{Var}(y_t) = \text{Var}(e_t - \frac{1}{\theta} e_{t-1}) = \sigma_e^2 + \frac{1}{\theta^2} \sigma_e^2 = \sigma_e^2 \left( \frac{1+\theta^2}{\theta^2} \right)$$

$$\gamma_1 = \text{Cov}(y_t, y_{t-1}) = \text{Cov}(e_t - \frac{1}{\theta} e_{t-1}, e_{t-1} - \frac{1}{\theta} e_{t-2}) = \text{Cov}(-\frac{1}{\theta} e_{t-1}, e_{t-1}) = -\frac{1}{\theta} \sigma_e^2$$

$$\gamma_2 = \text{Cov}(y_t, y_{t-2}) = \text{Cov}(e_t - \frac{1}{\theta} e_{t-1}, e_{t-2} - \frac{1}{\theta} e_{t-3}) = 0 \text{ (since there is no overlap)}$$

Similarly,  $\text{Cov}(y_t, y_{t-k}) = 0$  for  $k \geq 2$

So,  $\rho_1 = \text{Cov}(y_t, y_{t-1}) / \text{Var}(y_t) = \frac{-\frac{1}{\theta} \sigma_e^2}{\sigma_e^2 \left( \frac{1+\theta^2}{\theta^2} \right)} =$

$$= -\frac{1}{\theta} \times \frac{\theta^2}{1+\theta^2} = -\frac{\theta}{1+\theta^2}, \quad \rho_0 = 1 \text{ and } \rho_k = 0 \text{ for } k \geq 2$$

We can see that the autocorrelation function for an MA(1) does not change.

(4)  $y_t = 3y_{t-1} + e_t$  (nonstationary AR(1) model)

i) We will show that  $y_t = -\sum_{j=1}^{\infty} \left(\frac{1}{3}\right)^j e_{t+j}$

satisfies the above AR(1) equation (or its equivalent  $y_t - 3y_{t-1} = e_t$ )

$$\begin{aligned} & -\sum_{j=1}^{\infty} \left(\frac{1}{3}\right)^j e_{t+j} - 3\left(-\sum_{j=1}^{\infty} \left(\frac{1}{3}\right)^j e_{t-1+j}\right) = -\sum_{j=1}^{\infty} \left(\frac{1}{3}\right)^j e_{t+j} + \\ & + 3\left(\frac{1}{3}e_t + \sum_{j=2}^{\infty} \left(\frac{1}{3}\right)^j e_{t-1+j}\right) = -\sum_{j=1}^{\infty} \left(\frac{1}{3}\right)^j e_{t+j} + e_t + \\ & + 3\left(\sum_{j=1}^{\infty} \left(\frac{1}{3}\right)^{j+1} e_{t+j}\right) = -\sum_{j=1}^{\infty} \left(\frac{1}{3}\right)^j e_{t+j} + e_t + 3\left(\frac{1}{3} \sum_{j=1}^{\infty} \left(\frac{1}{3}\right)^j e_{t+j}\right) = \\ & = -\sum_{j=1}^{\infty} \left(\frac{1}{3}\right)^j e_{t+j} + \sum_{j=1}^{\infty} \left(\frac{1}{3}\right)^j e_{t+j} + e_t = e_t \end{aligned}$$

ii)  $y_t = -\sum_{j=1}^{\infty} \left(\frac{1}{3}\right)^j e_{t+j}$

$E(y_t) = E\left(-\sum_{j=1}^{\infty} \left(\frac{1}{3}\right)^j e_{t+j}\right) = -\sum_{j=1}^{\infty} \left(\frac{1}{3}\right)^j E(e_{t+j}) = 0$  (constant over time)

$$\begin{aligned} \gamma_0 = \text{Var}(y_t) &= \text{Var}\left(-\sum_{j=1}^{\infty} \left(\frac{1}{3}\right)^j e_{t+j}\right) = \sum_{j=1}^{\infty} \left(\frac{1}{3}\right)^{2j} \text{Var}(e_{t+j}) = \\ &= \sigma_e^2 \sum_{j=1}^{\infty} \left(\frac{1}{3}\right)^{2j} = \sigma_e^2 \left(\frac{1}{9} + \frac{1}{81} + \dots\right) = \frac{1}{9} \sigma_e^2 \left(1 + \frac{1}{9} + \dots\right) = \\ &= \frac{1}{9} \sigma_e^2 \left(1 + \left(\frac{1}{3}\right)^2 + \left(\frac{1}{3}\right)^4 + \dots\right) = \frac{1}{9} \sigma_e^2 / \left(1 - \frac{1}{9}\right) = \frac{1}{9} \sigma_e^2 \times \frac{9}{8} = \frac{1}{8} \sigma_e^2 \end{aligned}$$

$$\begin{aligned} \gamma_1 = \text{Cov}(y_t, y_{t-1}) &= \text{Cov}\left(-\sum_{j=1}^{\infty} \left(\frac{1}{3}\right)^j e_{t+j}, -\sum_{j=1}^{\infty} \left(\frac{1}{3}\right)^j e_{t-1+j}\right) = \\ &= \text{Cov}\left(-\frac{1}{3} e_{t+1}, -\left(\frac{1}{3}\right)^2 e_{t+1}\right) + \text{Cov}\left(-\left(\frac{1}{3}\right)^2 e_{t+2}, -\left(\frac{1}{3}\right)^3 e_{t+2}\right) + \dots = \\ &= \sigma_e^2 \left(\left(\frac{1}{3}\right)^3 + \left(\frac{1}{3}\right)^5 + \dots\right) = \frac{1}{27} \sigma_e^2 \left(1 + \left(\frac{1}{3}\right)^2 + \dots\right) = \frac{1}{27} \sigma_e^2 / \left(1 - \frac{1}{9}\right) = \\ &= \frac{1}{27} \sigma_e^2 \times \frac{9}{8} = \frac{\sigma_e^2}{24} = \frac{1}{8} \sigma_e^2 \times \left(\frac{1}{3}\right)^1 \end{aligned}$$

So,  $\gamma_k = \text{Cov}(y_t, y_{t-k}) = \frac{1}{8} \sigma_e^2 \times \left(\frac{1}{3}\right)^k$ , which only on time lag  
Since mean and covariance conditions are satisfied,  $\{y_t\}$  is stationary.



iii) If we look at <sup>2</sup> the original representation  $(Y_t = 3Y_{t-1} + e_t)$ , we can see that past values in the stochastic process determine future values. However, in the new formulation,  $Y_t = -\sum_{j=1}^{\infty} (\frac{1}{3})^j e_{t+j}$ , current values are calculated using future values, which is not actually possible in reality and thus we can consider that new representation as unsatisfactory.

⑤  $Y_t = A + Bt + X_t$ , where  $\{X_t\}$  is a random walk

i)  $E(Y_t) = E(A + Bt + X_t) = A + Bt + E(X_t) = A + Bt$

For the process to be stationary, its mean function should be constant over time. Since in our case this is not true,  $\{Y_t\}$  is non-stationary.

Now we will check  $\{\nabla Y_t\}$  for stationarity.

$$\begin{aligned}\nabla Y_t &= Y_t - Y_{t-1} = A + Bt + X_t - A - B(t-1) - X_{t-1} = \\ &= B + X_t - X_{t-1} = B + e_1 + e_2 + \dots + e_t - e_1 - e_2 - \dots - e_{t-1} = \\ &= B + e_t, \text{ which is just white noise with mean equal to } B, \text{ and thus } \{\nabla Y_t\} \text{ is stationary.}\end{aligned}$$

(the white noise process was proved to be stationary in the lecture)

ii) If  $A$  and  $B$  are random variables, then  $E(Y_t) = E(A) + E(B)t + E(X_t) = E(A) + E(B)t$ , which still depends on time and thus  $\{Y_t\}$  is non-stationary.

Now, let's check  $\{\nabla Y_t\}$  for stationarity

$$\nabla Y_t = Y_t - Y_{t-1} = B + e_t$$

$$E(\nabla Y_t) = E(B) + E(e_t) = E(B) \text{ (constant over time)}$$

$$\begin{aligned}Y_k &= \text{Cov}(\nabla Y_t, \nabla Y_{t-k}) = \text{Cov}(B + e_t, B + e_{t-k}) = \\ &= \text{Cov}(B, B) + \text{Cov}(e_t, B) + \text{Cov}(B, e_{t-k}) + \text{Cov}(e_t, e_{t-k})\end{aligned}$$

⑥ Since  $e_t$  and  $e_{t-k}$  are i.i.d r.v,  $\text{Cov}(e_t, e_{t-k}) = 0$  and

$$\text{Cov}(e_t, B) = \text{Cov}(e_{t-k}, B) = \text{Cov}(B, e_{t-k}) \Rightarrow \sigma_B^2 + 2\text{Cov}(e, B),$$

which does not depend on time. Thus  $\{\nabla Y_t\}$  is stationary

we can remove the subscript  $t$ .