

Exercise 6.1

CONSIDER AR(1) MODEL

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

where $\varepsilon_t \sim WN(0, \sigma_\varepsilon^2)$

1) FIND THE 1-STEP AHEAD FORECAST OF X_{t+1} .

FIND THE VARIANCE OF THE 1-STEP AHEAD FORECAST.

WE KNOW $X_t = \phi X_{t-1} + \varepsilon_t$

SO, BY APPEALING TO THE ASSUMPTION OF PARAMETER STABILITY, THIS EQUATION WILL HOLD FOR TIMES $t+1, t+2, \text{ AND } \text{SO ON}$.

$$X_{t+1} = \phi X_t + \varepsilon_{t+1}$$

$$X_{t+2} = \phi X_{t+1} + \varepsilon_{t+2}$$

$$X_{t+3} = \phi X_{t+2} + \varepsilon_{t+3}$$

⋮

$$X_{t+k} = \phi X_{t+k-1} + \varepsilon_{t+k}$$

THE 1-STEP AHEAD FORECAST IS DEFINED BY THE FORMULA

$$\hat{X}_t(1) = E[X_{t+1} | F_t] = [X_{t+1}]$$

WE COMPUTE $\hat{X}_t(1)$

$$\hat{X}_t(1) = E[X_{t+1} | F_t] = [X_{t+1}]$$

$$= [\phi X_t + \hat{\epsilon}_{t+1}]$$

$$= [\phi X_t] + [\epsilon_{t+1}]$$

$$= \phi [X_t] + [\epsilon_{t+1}]$$



$$[\epsilon_{t+1}] = E[\epsilon_{t+1} | F_t] = 0$$

$$[X_t] = E[X_t | F_t] = X_t$$

GIVEN THAT ALL INFORMATION IS KNOWN UP TO AND INCLUDING THAT AT TIME t IS AVAILABLE, THE VALUE OF X AT TIME t IS KNOWN.

ϵ_{t+1} IS A WHITE NOISE PROCESS AND IT IS INDEPENDENT OF THE PAST (HISTORY) F_t

THEREFORE:

$$\hat{X}_t(1) = \phi X_t + 0$$

$$\hat{X}_t(1) = \phi X_t$$

THE ERROR OF 1-STEP AHEAD FORECAST IS:

$$\begin{aligned} e_t(1) &= \underbrace{X_{t+1}} - \underbrace{\hat{X}_t(1)} \\ &= \underbrace{\phi X_t + \epsilon_{t+1}} - \underbrace{\phi X_t} \\ &= \epsilon_{t+1} \end{aligned}$$

THE VARIANCE OF THE ERROR IS:

$$\text{Var}(e_t(1)) = \text{Var}(\varepsilon_{t+1}) = \sigma_\varepsilon^2$$

2) FIND THE 2-STEP AHEAD FORECAST OF X_{t+2} .

FIND THE VARIANCE OF THE 2-STEP AHEAD FORECAST.

WE CAN WRITE $X_{t+2} = \phi X_{t+1} + \varepsilon_{t+2}$

THEN:

$$\hat{X}_t(2) = E[X_{t+2} | F_t] = [X_{t+2}]$$

$$= [\phi X_{t+1} + \varepsilon_{t+2}]$$

$$= \underbrace{\phi [X_{t+1}]}_{\downarrow} + \underbrace{[\varepsilon_{t+2}]}_{=0} =$$

THIS IS 1-STEP
AHEAD FORECAST

$$= \hat{X}_t(1) = \phi X_t$$

BECAUSE ε_{t+2} IS INDEPENDENT
OF HISTORY F_t

$$= \phi \hat{X}_t(1) =$$

$$= \phi (\phi X_t) = \phi^2 X_t$$

SO $\hat{X}_t(2) = \phi \hat{X}_t(1) = \phi^2 X_t$

THE ERROR OF 2-STEP AHEAD FORECAST IS

$$\begin{aligned}e_t(2) &= \underbrace{X_{t+2}} - \underbrace{\hat{X}_t(2)} \\&= \underbrace{\phi X_{t+1} + \varepsilon_{t+2}} - \underbrace{\phi \hat{X}_t(1)} \\&= \underbrace{\phi (X_{t+1} - \hat{X}_t(1))} + \varepsilon_{t+2} \\&\quad = e_t(1) = \varepsilon_{t+1} \\&= \phi \varepsilon_{t+1} + \varepsilon_{t+2}\end{aligned}$$

THE VARIANCE OF THE ERROR IS:

$$\begin{aligned}\text{Var}(e_t(2)) &= \text{Var}(\phi \varepsilon_{t+1} + \varepsilon_{t+2}) \\&= \text{Var}(\phi \varepsilon_{t+1}) + \text{Var}(\varepsilon_{t+2}) \\&= \phi^2 \underbrace{\text{Var}(\varepsilon_{t+1})}_{=\sigma_\varepsilon^2} + \underbrace{\text{Var}(\varepsilon_{t+2})}_{=\sigma_\varepsilon^2} \\&= \phi^2 \sigma_\varepsilon^2 + \sigma_\varepsilon^2 \\&= (\phi^2 + 1) \sigma_\varepsilon^2\end{aligned}$$

3) FIND THE K-STEP AHEAD FORECAST OF X_{t+k} .

FIND THE VARIANCE OF THE K-STEP AHEAD FORECAST.

COMMENT ON PROPERTIES OF THIS FORECAST WHEN K INCREASES.

$$\hat{X}_t(k) = E[X_{t+k} | F_t] = [X_{t+k}]$$

$$= [\phi X_{t+k-1} + \varepsilon_{t+k}]$$

$$= \underbrace{\phi [X_{t+k-1}]}_{\downarrow} + \underbrace{[\varepsilon_{t+k}]}_{=0}$$

THIS IS THE K-1-STEP
AHEAD FORECAST

$$= \phi \underbrace{\hat{X}_t(k-1)}_{\downarrow}$$

$$= \phi \left(\phi \hat{X}_t(k-2) \right)$$

$$= \phi^2 \hat{X}_t(k-2)$$

$$= \phi^2 \left(\phi \hat{X}_t(k-3) \right)$$

$$= \phi^3 \hat{X}_t(k-3)$$

⋮

$$= \phi^k \hat{X}_t(0)$$

$$= \phi^k \hat{X}_t$$

WE SEE THAT

$$\hat{X}_t(k) = \phi^k X_t \rightarrow 0$$

AS k INCREASES.

THIS IS THE MEAN REVERSION PROPERTY SINCE

$$E(X_t) = 0$$

$$\rightarrow E(X_t) = E(\phi X_{t-1}) + E(\varepsilon_t)$$

$$\underbrace{E(X_t)}_{\mu} = \phi \underbrace{E(X_{t-1})}_{\mu} + \underbrace{E(\varepsilon_t)}_{=0}$$

$$\mu - \phi \mu = 0$$

$$\mu = \frac{0}{1-\phi} = 0$$

Problem 6.2

X_t IS A NON-STATIONARY SERIES

$Z_t = X_t - X_{t-1}$ IS THE STATIONARY FIRST DIFFERENCE
WHICH FITS AN AR(1) MODEL

$$Z_t = 2 + 0.4 Z_{t-1} + \varepsilon_t$$

- FORECAST X_{t+1} AND X_{t+2}

FIRSTLY WE COMPUTE THE 1-STEP AHEAD
FORECAST OF Z_t

$$\hat{Z}_t(1) = E[Z_{t+1} | F_t] = [Z_{t+1}]$$

SINCE PARAMETER CONSTANCY OVER TIME IS ASSUMED,
THEN $Z_{t+1} = 2 + 0.4 Z_t + \varepsilon_{t+1}$

So

$$\begin{aligned}\hat{Z}_t(1) &= [Z_{t+1}] \\ &= [2 + 0.4 Z_t + \varepsilon_{t+1}] \\ &= 2 + 0.4 \underbrace{[Z_t]}_{Z_t} + \underbrace{[\varepsilon_{t+1}]}_{= 0 = E[\varepsilon_{t+1} | F_t]}\end{aligned}$$

we know Z at time t .

$$\hat{z}_t(1) = 2 + 0.4 (z_t)$$

$$= 2 + 0.4 (x_t - x_{t-1})$$

THE 2-STEP AHEAD FORECAST FOR z_t IS:

$$\hat{z}_t(2) = [z_{t+2}]$$

$$= [2 + 0.4 z_{t+1} + \varepsilon_{t+2}]$$

$$= 2 + 0.4 [z_{t+1}] + [\varepsilon_{t+2}]$$

↓

$= 0$

THIS IS THE
1-STEP AHEAD FORECAST

$$[z_{t+1}] = \hat{z}_t(1) = 2 + 0.4 z_t$$

$$= 2 + 0.4 \hat{z}_t(1)$$

$$= 2 + 0.4 (2 + 0.4 z_t)$$

$$= 2 + 0.8 + 0.16 z_t$$

$$= 2.8 + 0.16 z_t$$

$$= 2.8 + 0.16 (x_t - x_{t-1})$$

THEN WE COMPUTE $\hat{X}_t(1)$ USING THE EQUALITY

$$Z_{t+1} = X_{t+1} - X_t \quad \Leftrightarrow$$

$$X_{t+1} = X_t + Z_{t+1}$$

So

$$\hat{X}_t(1) = [X_{t+1}]$$

$$= [X_t + Z_{t+1}]$$

$$= \underbrace{[X_t]}_{=X_t} + \underbrace{[Z_{t+1}]}_{\hat{Z}_t(1)}$$

$$= X_t + \hat{Z}_t(1)$$

$$= X_t + \underbrace{2 + 0.4(X_t - X_{t-1})}_{\hat{Z}_t(1)}$$

$$= X_t + 2 + 0.4X_t - 0.4X_{t-1}$$

$$= 2 + 1.4X_t - 0.4X_{t-1}$$

WE NOW COMPUTE $\hat{X}_t(2)$

NOTE THAT
 $X_{t+2} = X_{t+1} + Z_{t+2}$

$$\hat{X}_t(2) = [X_{t+2}]$$

$$= [X_{t+1} + Z_{t+2}]$$

$$= [X_{t+1}] + [Z_{t+2}]$$

$$= \hat{X}_t(1) + \hat{Z}_t(2)$$

$$= \{2 + 1.4X_t - 0.4X_{t-1}\} + \{2.8 + 0.16(X_t - X_{t-1})\}$$

$$= \underline{2} + \underline{1.4X_t} - \underline{0.4X_{t-1}} + \underline{2.8} + \underline{0.16X_t} - \underline{0.16X_{t-1}}$$

$$= 4.8 + 1.56X_t - 0.56X_{t-1}$$

Exercise 6.3

CONSIDER MA(2) MODEL

$$X_t = C_0 + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2}$$

where ε_t is WN $(0, \sigma_\varepsilon^2)$

1) FIND 1-STEP, 2-STEP, 3-STEP AHEAD FORECAST.

BECAUSE OF THE ASSUMPTION OF PARAMETER STABILITY, IF THIS RELATIONSHIP HOLDS FOR THE SERIES X AT TIME t , IT IS ALSO ASSUMED TO HOLD FOR X AT TIME $t+1, t+2, \dots$

$$X_{t+1} = C_0 + \varepsilon_{t+1} + \theta_1 \varepsilon_t + \theta_2 \varepsilon_{t-1}$$

$$X_{t+2} = C_0 + \varepsilon_{t+2} + \theta_1 \varepsilon_{t+1} + \theta_2 \varepsilon_t$$

$$X_{t+3} = C_0 + \varepsilon_{t+3} + \theta_1 \varepsilon_{t+2} + \theta_2 \varepsilon_{t+1}$$

$$\hat{X}_t(1) = E[X_{t+1} | F_t] = [X_{t+1}]$$

$$= [C_0 + \varepsilon_{t+1} + \theta_1 \varepsilon_t + \theta_2 \varepsilon_{t-1}]$$

THE 1-STEP AHEAD FORECAST FOR X IS GIVEN BY THE LINEAR COMBINATIONS OF THE DISTURBANCE TERMS. NOTE THAT IT WOULD NOT BE APPROPRIATE TO SET THE VALUES OF THESE DISTURBANCE TERMS TO THEIR UNCONDITIONAL MEAN OF ZERO. THIS ~~ARISES~~ BECAUSE IT IS THE CONDITIONAL EXPECTATION OF THEIR VALUES THAT IS OF INTEREST. GIVEN THAT ALL INFORMATION IS KNOWN UP TO INCLUDING AT THE TIME t IS AVAILABLE, THE VALUES OF THE ERROR TERMS UP TO TIME t ARE KNOWN. BUT ε_{t+1} IS NOT KNOWN AT TIME t AND THEREFORE $E(\varepsilon_{t+1} | F_t) = 0$.

WE CAN WRITE:

$$\hat{X}_t(1) = [C_0 + \varepsilon_{t+1} + \theta_1 \varepsilon_t + \theta_2 \varepsilon_{t-1}]$$

$$= \underbrace{[C_0]}_{= C_0} + \underbrace{[\varepsilon_{t+1}]}_{= E[\varepsilon_{t+1} | F_t] = 0} + \theta_1 \underbrace{[\varepsilon_t]}_{\varepsilon_t} + \theta_2 \underbrace{[\varepsilon_{t-1}]}_{= \varepsilon_{t-1}}$$

SO $\hat{X}_t(1) = C_0 + \theta_1 \varepsilon_t + \theta_2 \varepsilon_{t-1}$

$$\begin{aligned}
 \hat{X}_t(2) &= [C_0 + \varepsilon_{t+2} + \theta_1 \varepsilon_{t+1} + \theta_2 \varepsilon_t] \\
 &= C_0 + \underbrace{[\varepsilon_{t+2}]}_{=0} + \theta_1 \underbrace{[\varepsilon_{t+1}]}_{=0} + \theta_2 \underbrace{[\varepsilon_t]}_{\varepsilon_t} \\
 &= C_0 + \theta_2 \varepsilon_t
 \end{aligned}$$

$$\begin{aligned}
 \hat{X}_t(3) &= [C_0 + \varepsilon_{t+3} + \theta_1 \varepsilon_{t+2} + \theta_2 \varepsilon_{t+1}] \\
 &= C_0 + \underbrace{[\varepsilon_{t+3}]}_{=0} + \theta_1 \underbrace{[\varepsilon_{t+2}]}_{=0} + \theta_2 \underbrace{[\varepsilon_{t+1}]}_{=0} \\
 &= C_0
 \end{aligned}$$

2) SHOW THAT THE FORECAST REVERTS TO THE MEAN AT STEP $k=2$

AS THE MA(2) PROCESS HAS A MEMORY OF ONLY TWO PERIODS, ALL FORECASTS THREE OR MORE STEP AHEAD COLLAPSE TO THE MEAN.

3) FIND THE FORECAST ERRORS.

$$\begin{aligned}
 \bullet e_t(1) &= X_{t+1} - \hat{X}_t(1) \\
 &= \{ \cancel{\mu_0} + \cancel{\varepsilon_{t+1}} + \cancel{\theta_1 \varepsilon_t} + \cancel{\theta_2 \varepsilon_{t-1}} \} - \{ \cancel{\mu_0} + \cancel{\theta_1 \varepsilon_t} + \cancel{\theta_2 \varepsilon_{t-1}} \} \\
 &= \varepsilon_{t+1}
 \end{aligned}$$

$$\text{Var}(e_t(1)) = \text{Var}(\varepsilon_{t+1}) = \sigma_\varepsilon^2$$

$$\begin{aligned}
 \bullet e_t(2) &= X_{t+2} - \hat{X}_t(2) \\
 &= \{ \cancel{\mu_0} + \cancel{\varepsilon_{t+2}} + \cancel{\theta_1 \varepsilon_{t+1}} + \cancel{\theta_2 \varepsilon_t} \} - \{ \cancel{\mu_0} - \cancel{\theta_2 \varepsilon_t} \} \\
 &= \varepsilon_{t+2} + \theta_1 \varepsilon_{t+1}
 \end{aligned}$$

$$\begin{aligned}
 \text{Var}(e_t(2)) &= \text{Var}(\varepsilon_{t+2} + \theta_1 \varepsilon_{t+1}) \\
 &= \underbrace{\text{Var}(\varepsilon_{t+2})}_{\sigma_\varepsilon^2} + \theta_1^2 \underbrace{\text{Var}(\varepsilon_{t+1})}_{\sigma_\varepsilon^2} \\
 &= \sigma_\varepsilon^2 + \theta_1^2 \sigma_\varepsilon^2 = (1 + \theta_1^2) \sigma_\varepsilon^2
 \end{aligned}$$

$$\bullet e_t(3) = X_{t+3} - \hat{X}_t(3) =$$

$$= \{C_0 + \varepsilon_{t+3} + \theta_1 \varepsilon_{t+2} + \theta_2 \varepsilon_{t+1}\} - \{C_0\}$$

$$= \varepsilon_{t+3} + \theta_1 \varepsilon_{t+2} + \theta_2 \varepsilon_{t+1}$$

$$\text{Var}(e_t(3)) = \text{Var}(\varepsilon_{t+3} + \theta_1 \varepsilon_{t+2} + \theta_2 \varepsilon_{t+1})$$

$$= \underbrace{\text{Var}(\varepsilon_{t+3})}_{=\sigma_\varepsilon^2} + \theta_1^2 \underbrace{\text{Var}(\varepsilon_{t+2})}_{=\sigma_\varepsilon^2} + \theta_2^2 \underbrace{\text{Var}(\varepsilon_{t+1})}_{=\sigma_\varepsilon^2}$$

$$= \sigma_\varepsilon^2 + \theta_1^2 \sigma_\varepsilon^2 + \theta_2^2 \sigma_\varepsilon^2$$

$$= (1 + \theta_1^2 + \theta_2^2) \sigma_\varepsilon^2$$