

Forecasting Time Series Homework 3

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1) Consider the $MA(1)$ model $x_t = \varepsilon_t + \beta \varepsilon_{t-1}$, where $\{\varepsilon_t\}$ is zero mean white noise.

A) Use the formula $\rho_1 = \text{Corr}(x_t, x_{t-1}) = \beta \frac{\text{var}(\varepsilon_t)}{\text{var}(x_t)}$ to show that $\rho_1 = \frac{\beta}{1+\beta^2}$.

Ans)

$$\rho_1 = \text{Corr}(x_t, x_{t-1}) = \beta \frac{\text{var}(\varepsilon_t)}{\text{var}(x_t)}$$

For $MA(1)$ model,

$$\begin{aligned}\text{var}(x_t) &= \text{var}(\varepsilon_t + \beta \varepsilon_{t-1}) \\ &= \text{var}(\varepsilon_t) + \beta^2 \text{var}(\varepsilon_{t-1}) + 2\beta \text{cov}(\varepsilon_t, \varepsilon_{t-1}) \\ &\quad \underbrace{= \text{var}(\varepsilon_t)}_{= 0} \quad \underbrace{= 0}_{\text{since all } \varepsilon\text{'s are uncorrelated}} \\ &= (1 + \beta^2) \text{var}(\varepsilon_t)\end{aligned}$$

By rewriting the equation, we obtain

$$\begin{aligned}\rho_1 &= \text{Corr}(x_t, x_{t-1}) \\ &= \beta \frac{\text{var}(\varepsilon_t)}{\text{var}(x_t)} \\ &= \beta \frac{\text{var}(\varepsilon_t)}{(1 + \beta^2) \text{var}(\varepsilon_t)} \\ &= \frac{\beta}{1 + \beta^2}\end{aligned}$$

B) Using the result from Part A), determine the maximum possible value for ρ_1 for the MA(1) model. At what value of β is this maximum attained?

Ans) For MA(1) model to converge, the β needs to be between -1 and 1. For ρ_1 to be the maximum using the equation in Part A, the β needs to be 1 and it makes the ρ_1 be $\frac{1}{1+\beta^2} = \frac{1}{2}$. The mathematical proof for this can be taking a derivative of the equation, $\frac{\beta}{1+\beta^2}$, with respect to β and setting it equal to 0. Calculations are below.

To find the maximum,

$$\text{Set } \frac{d}{d\beta} \left(\frac{\beta}{1+\beta^2} \right) = \frac{(1)(1+\beta^2) - \beta(2\beta)}{(1+\beta^2)^2} = 0$$

$$1 + \beta^2 - 2\beta^2 = 0$$

$$1 - \beta^2 = 0$$

$$(1+\beta)(1-\beta) = 0$$

$$\beta = -1 \text{ or } 1$$

Using the first derivative test,

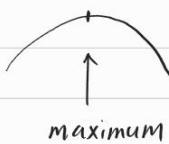
$$\text{At } \beta = -1,$$

$$\begin{array}{c} (-) \\ \hline -1 \end{array}$$



$$\text{At } \beta = 1,$$

$$\begin{array}{c} (+) \\ \hline 1 \end{array}$$



Therefore, the local maximum is at $\beta = 1$.

$$\text{At } \beta = 1, \quad \rho_1 = \frac{\beta}{1+\beta^2} = \frac{1}{2}$$

To check the end behavior of the function, use the Limit Theorem,

$$\lim_{\beta \rightarrow -\infty} \frac{\beta}{1+\beta^2} = 0 \quad \text{and} \quad \lim_{\beta \rightarrow \infty} \frac{\beta}{1+\beta^2} = 0$$

\Rightarrow This shows that $\rho_1 = \frac{1}{2}$ is the maximum at $\beta = 1$.

C) Based on your answer to Part B), is the $MA(1)$ model capable of producing very smooth (i.e., very highly autocorrelated) realizations?

Ans) No, based on part B, we expect the maximum value of the autocorrelation coefficient to be $\frac{1}{2}$. This value is not close to 1, meaning that $MA(1)$ model is not capable of producing very smooth, or highly autocorrelated, realizations.

D) What is the correlation between x_t and x_{t-1} if $\{x_t\}$ is the first difference of a white noise series?

Ans) The white noise is already stationary and if we take another difference of stationary series, we are over-differencing it resulting in negative autocorrelation. We get $y_t = e_t - e_{t-1}$, which is an $MA(1)$ series with negative autocorrelation coefficient of -0.5 . ($\beta = -1$, so the correlation between x_t and x_{t-1} is -0.5 based on Part A.)

$$D) x_t = e_t - e_{t-1}$$

This can be interpreted as $MA(1)$ model with $B = -1$

$$(x_t = e_t + \underbrace{B e_{t-1}}_{-1})$$

$$\text{Lag 1 (auto)correlation: } \rho_1 = \frac{B}{1+B^2} = -\frac{1}{2}$$

2) Granger, p. 56, Problem 2

2. You are told that the monthly change in sales of paperback books in a certain store obeys an MA(2) model of the form

$$x_t = \varepsilon_t + 0.6\varepsilon_{t-1} + 0.3\varepsilon_{t-2}$$

and are given the following recent values for x_t : $x_{20} = 180$, $x_{21} = -120$, $x_{22} = 90$, $x_{23} = 10$.

- (a) What forecast would you have made for x_{20} and x_{21} at time $t = 19$ if you had assumed $\varepsilon_{17} = -10$, $\varepsilon_{18} = 30$, $\varepsilon_{19} = 70$?
 (b) Using these same values for ε_{17} , ε_{18} , and ε_{19} , what do you forecast for x_{24} , x_{25} , x_{26} , and x_{27} at time $t = 23$?

2(a) As we are in $t=19$, $\varepsilon_{20} = \varepsilon_{21} = \varepsilon_{22} \dots = 0$

$$-\bar{x}_{20} = \varepsilon_{20} + 0.6\varepsilon_{19} + 0.3\varepsilon_{18} = 0 + 0.6 \times 70 + 0.3 \times 30 \\ \begin{matrix} \uparrow & \uparrow & \uparrow \\ 0 & 70 & 30 \end{matrix} = 51$$

$$-\bar{x}_{21} = \varepsilon_{21} + 0.6\varepsilon_{20} + 0.3\varepsilon_{19} = 0 + 0 + 0.3 \times 70 \\ \begin{matrix} \uparrow & \uparrow & \uparrow \\ 0 & 0 & 70 \end{matrix} = 21$$

$$-\bar{x}_{22} = \varepsilon_{22} + 0.6\varepsilon_{21} + 0.3\varepsilon_{20} = 0 \\ \begin{matrix} \uparrow & \uparrow & \uparrow \\ 0 & 0 & 0 \end{matrix}$$

(b) $\boxed{t=23}$ $x_{20} = 180$, $x_{21} = -120$, $x_{22} = 90$, $x_{23} = 10$

As we are in $t=23$, $\varepsilon_{24} = \varepsilon_{25} = \varepsilon_{26} \dots = 0$

$$\boxed{-\bar{x}_{24}} = \varepsilon_{24} + 0.6\varepsilon_{23} + 0.3\varepsilon_{22} = 0 + (-20.3304) + 54.702 \\ \begin{matrix} \uparrow & \uparrow & \uparrow \\ 0 & 182.34 & 182.34 \end{matrix} = \boxed{34.3716}$$

$$\boxed{-\bar{x}_{25}} = \varepsilon_{25} + 0.6\varepsilon_{24} + 0.3\varepsilon_{23} = \boxed{-10.1652} \\ \begin{matrix} \uparrow & \uparrow & \uparrow \\ 0 & 0 & -20.3304 \end{matrix}$$

$$\boxed{-\bar{x}_{26}} = \varepsilon_{26} + 0.6\varepsilon_{25} + 0.3\varepsilon_{24} = \boxed{0} \\ \begin{matrix} \uparrow & \uparrow & \uparrow \\ 0 & 0 & 0 \end{matrix}$$

$$\boxed{-\bar{x}_{27}} = \varepsilon_{27} + 0.6\varepsilon_{26} + 0.3\varepsilon_{25} = \boxed{0} \\ \begin{matrix} \uparrow & \uparrow & \uparrow \\ 0 & 0 & 0 \end{matrix}$$

$$180 = \bar{x}_{20} = \varepsilon_{20} + 0.6\varepsilon_{19} + 0.3\varepsilon_{18} = \varepsilon_{20} + 0.6 \times 70 + 0.3 \times 30 \\ = \varepsilon_{20} + 42 + 9 \\ \therefore \varepsilon_{20} = 180 - 51 = 129$$

$$\begin{aligned}
 -120 &= \ell_{21} + 0.6\ell_{20} + 0.3\ell_{19} = \ell_{21} + 0.6 \times 129 + 0.3 \times 90 \\
 &= \ell_{21} + 98.4 \\
 \therefore \ell_{21} &= -120 - 98.4 = -218.4
 \end{aligned}$$

$$\begin{aligned}
 90 &= \ell_{22} + 0.6\ell_{21} + 0.3\ell_{20} \\
 &= \ell_{22} + 0.6 \times -218.4 + 0.3 \times 129 \\
 &= \ell_{22} + (-131.04) + 38.7 \\
 &= \ell_{22} - 92.34 \\
 \therefore \ell_{22} &= 182.34
 \end{aligned}$$

$$\begin{aligned}
 10 &= \ell_{23} + 0.6\ell_{22} + 0.3\ell_{21} \\
 &= \ell_{23} + 0.6 \times 182.34 + 0.3 \times (-218.4) \\
 &= \ell_{23} + 109.404 + (-65.52) \\
 &= \ell_{23} + 43.884 \\
 \therefore \ell_{23} &= -33.884
 \end{aligned}$$

3) Granger, p. 56, Problem 3

3. Suppose that you are unsure whether a certain series has been generated by an MA(1) or an MA(2) model. How would the value of the second autocorrelation coefficient ρ_2 help you choose between these alternative models?

Ans) In ACF, if there is a statistical cut-off beyond the lag-1 or the ρ_2 is 0, it can be said that the series has been generated by an MA(1) model. If there is a statistical cut-off beyond the lag-2 or the ρ_2 is not 0, it can be said that the series has been generated by an MA(2) model.

4) Granger, p. 57, Problem 4

4. Prove that the two series x_t and y_t , generated by

$$x_t = \varepsilon_t + 0.8\varepsilon_{t-1}$$

and

$$y_t = \eta_t + 1.25\eta_{t-1},$$

where ε_t , η_t are each zero-mean white noise series and $\text{var}(\varepsilon_t) = 1$, $\text{var}(\eta_t) = 0.64$, have identical variances and autocorrelation sequences ρ_k , $k = 0, 1, 2, \dots$. Prove that if z_t is generated by

$$z_t = \theta_t + a\theta_{t-1} + b\theta_{t-2},$$

where θ_t is white noise, and if $b \neq 0$, then z_t cannot have the same autocorrelation sequence as x_t and y_t .

Answers for this problem continue on the next page.

Let $X_t = \varepsilon_t + \theta \varepsilon_{t-1}$ to find the generalized formulas for variance and autocorrelation coefficient for MA(1) model.

$$\begin{aligned}\text{Var}(X_t) &= \text{Var}(\varepsilon_t + \theta \varepsilon_{t-1}) \\ &= \text{Var}(\varepsilon_t) + \theta^2 \text{Var}(\varepsilon_{t-1}) \\ &\quad \text{~~~~~} = \text{Var}(\varepsilon_t) \\ &= (1 + \theta^2) \text{Var}(\varepsilon_t)\end{aligned}$$

$$\rho_0 = \text{corr}(X_t, X_t) = 1$$

$$\rho_1 = \text{corr}(X_t, X_{t+1})$$

$$= \frac{\text{cov}(X_t, X_{t+1})}{\sqrt{\text{Var}(X_t)} \sqrt{\text{Var}(X_{t+1})}}$$

$$= \frac{\text{cov}(\varepsilon_t + \theta \varepsilon_{t-1}, \varepsilon_{t+1} + \theta \varepsilon_t)}{\sqrt{\text{Var}(X_t)} \sqrt{\text{Var}(X_{t+1})}}$$

$$= \frac{\cancel{\text{cov}(\varepsilon_t, \varepsilon_{t+1})} + \cancel{\text{cov}(\varepsilon_t, \theta \varepsilon_t)} + \cancel{\text{cov}(\theta \varepsilon_{t-1}, \varepsilon_{t+1})} + \cancel{\text{cov}(\theta \varepsilon_{t-1}, \theta \varepsilon_t)}}{\sqrt{\text{Var}(X_t)} \sqrt{\text{Var}(X_{t+1})}}$$

$$= \frac{\theta \text{Var}(\varepsilon_t)}{\text{Var}(X_t)}$$

$$= \frac{\theta \text{Var}(\varepsilon_t)}{(1 + \theta^2) \text{Var}(\varepsilon_t)}$$

from calculation above

$$\rho_2 = \text{corr}(X_t, X_{t+2})$$

$$= \frac{\text{cov}(X_t, X_{t+2})}{\sqrt{\text{Var}(X_t)} \sqrt{\text{Var}(X_{t+2})}}$$

$$= \frac{\text{cov}(\varepsilon_t + \theta \varepsilon_{t-1}, \varepsilon_{t+2} + \theta \varepsilon_{t+1})}{\sqrt{\text{Var}(X_t)} \sqrt{\text{Var}(X_{t+2})}}$$

$$= \frac{\cancel{\text{cov}(\varepsilon_t, \varepsilon_{t+2})} + \cancel{\text{cov}(\varepsilon_t, \theta \varepsilon_{t+1})} + \cancel{\text{cov}(\theta \varepsilon_{t-1}, \varepsilon_{t+2})} + \cancel{\text{cov}(\theta \varepsilon_{t-1}, \theta \varepsilon_{t+1})}}{\sqrt{\text{Var}(X_t)} \sqrt{\text{Var}(X_{t+2})}}$$

$$= 0$$

$\rho_3, \rho_4, \rho_5, \dots = 0$ since all covariances $k > 1$ will be 0 using the same logic.

Apply the formulas above to the given equations.

$$\textcircled{1} \quad X_t = \varepsilon_t + 0.8 \varepsilon_{t-1}$$

$$\begin{aligned}\text{Var}(X_t) &= (1 + \theta^2) \text{Var}(\varepsilon_t) \\ &= (1 + 0.8^2)(1) \\ &= 1.64\end{aligned}$$

$$P_0 = 1$$

$$P_1 = \frac{\theta}{1 + \theta^2}$$

$$= \frac{0.8}{1 + 0.8^2}$$

$$= \frac{20}{41} (\approx 0.4878)$$

$$P_2, P_3, P_4, \dots = 0$$

$$\textcircled{2} \quad Y_t = n_t + 1.25 n_{t-1}$$

$$\begin{aligned}\text{Var}(Y_t) &= (1 + \theta^2) \text{Var}(n_t) \\ &= (1 + 1.25^2)(0.64) \\ &= 1.64\end{aligned}$$

$$P_0 = 1$$

$$P_1 = \frac{\theta}{1 + \theta^2}$$

$$= \frac{1.25}{1 + 1.25^2}$$

$$= \frac{20}{41} (\approx 0.4878)$$

$$P_2, P_3, P_4, \dots = 0$$

\Rightarrow Therefore, X_t and Y_t have identical variances
and autocorrelation sequences P_k .

$$z_t = \theta_t + a\theta_{t-1} + b\theta_{t-2} : \theta \text{ is white noise, } b \neq 0$$

To prove that z_t cannot have the same autocorrelation sequence as MA(1) model, we focus on the ρ_2 .

$$\rho_2 = \text{corr}(z_t, z_{t+2})$$

$$= \frac{\text{cov}(z_t, z_{t+2})}{\sqrt{\text{Var}(z_t)} \sqrt{\text{Var}(z_{t+2})}}$$

rewriting numerator

$$\begin{aligned} &= \text{cov}(\theta_t + a\theta_{t-1} + b\theta_{t-2}, \theta_{t+2} + a\theta_{t+1} + b\theta_t) \\ &= \cancel{\text{cov}(\theta_t, \theta_{t+2})} + \cancel{\text{cov}(\theta_t, a\theta_{t+1})} + \cancel{\text{cov}(\theta_t, b\theta_t)} \\ &\quad + \cancel{\text{cov}(a\theta_{t-1}, \theta_{t+2})} + \cancel{\text{cov}(a\theta_{t-1}, a\theta_{t+1})} + \cancel{\text{cov}(a\theta_{t-1}, b\theta_t)} \\ &\quad + \cancel{\text{cov}(b\theta_{t-2}, \theta_{t+2})} + \cancel{\text{cov}(b\theta_{t-2}, a\theta_{t+1})} + \cancel{\text{cov}(b\theta_{t-2}, b\theta_t)} \\ &= \text{cov}(\theta_t, b\theta_t) \\ &= b^2 \text{var}(\theta_t) \end{aligned}$$

$$= \frac{b^2 \text{var}(\theta_t)}{\sqrt{\text{Var}(z_t)} \sqrt{\text{Var}(z_{t+2})}}$$

$= \text{Var}(z_t)$

$$= \frac{b^2 \text{var}(\theta_t)}{\text{Var}(z_t)}$$

rewriting denominator

$$\begin{aligned} \text{Var}(z_t) &= \text{Var}(\theta_t + a\theta_{t-1} + b\theta_{t-2}) \\ &= \text{Var}(\theta_t) + a^2 \text{Var}(\theta_{t-1}) + b^2 \text{Var}(\theta_{t-2}) \\ &\quad \cancel{= \text{Var}(\theta_t)} \quad \cancel{= \text{Var}(\theta_t)} \\ &= (1 + a^2 + b^2) \text{var}(\theta_t) \end{aligned}$$

$$\begin{aligned} &= \frac{b^2 \text{var}(\theta_t)}{(1 + a^2 + b^2) \text{var}(\theta_t)} \\ &= \frac{b^2}{1 + a^2 + b^2} \end{aligned}$$

$\neq 0$ since $b \neq 0$ by given

\Rightarrow Therefore, z_t (MA(2) model) cannot have the same autocorrelation sequence as x_t and y_t (MA(1) model)

5) Granger, p. 62, Problem 2

2. A company economist believes that a rival firm's quarterly advertising expenditures obey the AR(3) model

$$x_t = 0.2x_{t-1} + 0.6x_{t-2} - 0.3x_{t-3} + \varepsilon_t.$$

If the values for the last three quarters are $x_{10} = 180$, $x_{11} = 140$, and $x_{12} = 200$, forecast expenditures for the next three quarters, $t = 13$, 14, and 15.

ANS) $x_{13} = 70$, $x_{14} = 92$, $x_{15} = 0.4$

$$x_t = 0.2x_{t-1} + 0.6x_{t-2} - 0.3x_{t-3} + \varepsilon_t$$

$$t=13 \quad x_{13} = 0.2x_{12} + 0.6x_{11} - 0.3x_{10} + \varepsilon_{13}$$

0

$$= 0.2(200) + 0.6(140) - 0.3(180)$$

$$= 40 + 84 - 54$$

$$= 70$$

$$t=14 \quad x_{14} = 0.2x_{13} + 0.6x_{12} - 0.3x_{11} + \varepsilon_{14}$$

↑
^
 x_{13}

0

$$= 0.2(70) + 0.6(200) - 0.3(140)$$

$$= 14 + 120 - 42$$

$$= 92$$

$$t=15 \quad x_{15} = 0.2x_{14} + 0.6x_{13} - 0.3x_{12} + \varepsilon_{15}$$

↑
^
 x_{14}

0

$$= 0.2(92) + 0.6(70) - 0.3(200)$$

$$= 18.4 + 42 - 60$$

$$= 0.4$$

6) Granger, p. 63, Problem 3

3. A time series is constructed on a computer by an AR(1) model. You are told that the series has zero mean, that the second autocorrelation is $\rho_2 = 0.64$, and that $x_{50} = 10$. Forecast x_{51} and x_{52} . Why would knowing the value of ρ_3 help forecast x_{51} but not x_{52} ?

Ans)

$$b. - \text{AR}(1) \text{ model: } \hat{x}_{t+1} = B x_t + \hat{\epsilon}_{t+1}$$

$$\text{At time } t, \quad \hat{x}_{t+1} = \underline{\hat{x}_{t+1}} = B \underline{x_t} \quad (\hat{\epsilon}_{t+1} = 0)$$

$$\hat{x}_{t+2} = B \hat{x}_{t+1} + \hat{\epsilon}_{t+2}$$

$$= B(Bx_t + \hat{\epsilon}_{t+1}) + \hat{\epsilon}_{t+2}$$

$$= B^2 x_t + B \underline{\hat{\epsilon}_{t+1}} + \underline{\hat{\epsilon}_{t+2}}$$

$$\text{At time } t, \quad \underline{\hat{x}_{t+2}} = B^2 x_t$$

$$- \text{cov}(x_t, \hat{x}_{t+2}) = \text{cov}(x_t, B^2 x_t + B \underline{\hat{\epsilon}_{t+1}} + \underline{\hat{\epsilon}_{t+2}})$$

$$= \text{cov}(x_t, B^2 x_t) + \frac{\text{cov}(x_t, B \underline{\hat{\epsilon}_{t+1}})}{= 0} + \frac{\text{cov}(x_t, \underline{\hat{\epsilon}_{t+2}})}{= 0}$$

$$= B^2 \text{Var}(x_t)$$

$$- \rho^2 = \frac{\text{cov}(x_t, \hat{x}_{t+2})}{\sqrt{\text{Var}(x_t)} \sqrt{\text{Var}(\hat{x}_{t+2})}} = \frac{\text{cov}(x_t, \hat{x}_{t+2})}{\text{Var}(x_t)} = B^2 = 0.64$$

$$- \text{As } B^2 = 0.64, \quad B = \pm 0.8$$

$$\begin{cases} \hat{x}_{t+1} = B x_t \Leftrightarrow \hat{x}_{51} = B x_{50} = \pm 0.8 \times 10 = \pm 8 \\ \hat{x}_{t+2} = B^2 x_t \Leftrightarrow \hat{x}_{52} = B^2 x_{50} = 0.64 \times 10 = 6.4 \end{cases}$$

Also, if we know $\rho_3 = B^3$, we can identify plus or minus sign of value B. In this example, if $B^3 > 0$, then $B > 0$ and therefore $\hat{x}_{51} = 8$, which helps to forecast \hat{x}_{51} .

(however, \hat{x}_{52} is calculated by B^2 , so knowing B^3 doesn't help to forecast \hat{x}_{52} .)

7) Granger, p. 63, Problem 4

4. If a series x_t is generated by

$$x_t = 0.8x_{t-1} + \varepsilon_t,$$

where ε_t is zero-mean white noise with variance 25, find the variances of the one-, two-, and three-step forecast errors, i.e., $\text{var}(e_{n,h})$, $h = 1, 2$, and 3.

1. $x_t = 0.8x_{t-1} + \varepsilon_t, E[\varepsilon_t] = 0, \text{Var}(\varepsilon_t) = 25$

- One-step forecast: $\hat{x}_{t+1} = 0.8x_t$
- Two-step forecast: $\hat{x}_{t+2} = (0.8)^2 x_t$
- Three-step forecast: $\hat{x}_{t+3} = (0.8)^3 x_t, \text{ where } \varepsilon_{t+1} = \varepsilon_{t+2} = \dots = 0 \text{ at time } t.$

- One-step forecast error

$$\underline{x_{t+1} - \hat{x}_{t+1}} = 0.8x_t + \varepsilon_{t+1} - 0.8x_t = \varepsilon_{t+1}$$

$$\boxed{\text{Var}(x_{t+1} - \hat{x}_{t+1}) = \text{Var}(\varepsilon_{t+1}) = \text{Var}(\varepsilon_t) = 25}$$

- Two-step forecast error

$$\begin{aligned} \underline{x_{t+2} - \hat{x}_{t+2}} &= 0.8x_t + \varepsilon_{t+1} - (0.8)^2 x_t \\ &= 0.8(0.8x_t + \varepsilon_t) + \varepsilon_{t+1} - (0.8)^2 x_t \\ &= (0.8)^2 x_t + 0.8\varepsilon_t + \varepsilon_{t+1} - (0.8)^2 x_t \\ &= 0.8\varepsilon_t + \varepsilon_{t+1} \end{aligned}$$

$$\begin{aligned} \boxed{\text{Var}(x_{t+2} - \hat{x}_{t+2})} &= \text{Var}(0.8\varepsilon_t + \varepsilon_{t+1}) \\ &= 0.64 \text{Var}(\varepsilon_t) + \text{Var}(\varepsilon_{t+1}) + 2 \cdot 0.8 \text{Cov}(\varepsilon_t, \varepsilon_{t+1}) \\ &= 0.64 \times 25 + 25 \\ &= 1.64 \times 25 = \boxed{41} \end{aligned}$$

- Three-step forecast error

$$\begin{aligned} \underline{x_{t+3} - \hat{x}_{t+3}} &= 0.8x_{t+2} + \varepsilon_{t+2} - (0.8)^3 x_t \\ &= 0.8(0.8x_t + \varepsilon_t) + \varepsilon_{t+2} - (0.8)^3 x_t \\ &= 0.8(0.8(0.8x_t + \varepsilon_t) + \varepsilon_{t+1}) + \varepsilon_{t+2} - (0.8)^3 x_t \\ &= 0.8^3 x_t + 0.8^2 \varepsilon_t + 0.8 \varepsilon_{t+1} + \varepsilon_{t+2} - (0.8)^3 x_t \\ &= (0.8)^3 x_t + (0.8)^2 \varepsilon_t + 0.8 \varepsilon_{t+1} + \varepsilon_{t+2} - (0.8)^3 x_t \end{aligned}$$

$$\begin{aligned} \boxed{\text{Var}(x_{t+3} - \hat{x}_{t+3})} &= \text{Var}((0.8)^3 \varepsilon_t + 0.8 \varepsilon_{t+1} + \varepsilon_{t+2}) \\ &\quad (\text{Cov}(\varepsilon_t, \varepsilon_{t+1}) = \text{Cov}(\varepsilon_{t+1}, \varepsilon_{t+2}) = \text{Cov}(\varepsilon_t, \varepsilon_{t+2}) = 0) \\ &= (0.8)^6 \text{Var}(\varepsilon_t) + (0.8)^2 \text{Var}(\varepsilon_{t+1}) + \text{Var}(\varepsilon_{t+2}) \\ &= (0.8)^6 \times 25 + (0.8)^2 \times 25 + 25 \\ &= ((0.8)^6 + (0.8)^2 + 1) \times 25 = \boxed{51.24} \end{aligned}$$