



3 Time Series Models

Recall that B is the backshifting operator in the sense that $B^k X_t = X_{t-k}$ for all $k \in \mathbb{N}$.

3.1 Identification of Models

Common Linear Time Series Model

Definition 1. Let $\{Y_t\}$ be a time-series and $\{Z_t\} \sim \text{WN}(0, \sigma^2)$. Then we say

1. **(Autoregressive Model)** $\{Y_t\} \sim \text{AR}(\mathbf{p})$ if $\phi(B)Y_t = Z_t$, i.e.

$$Y_t = \phi_1 Y_{t-1} + \cdots + \phi_p Y_{t-p} + Z_t,$$

where $\phi(x) := 1 - \phi_1 x - \phi_2 x^2 - \cdots - \phi_p x^p$ is the **AR characteristic polynomial**.

2. **(Moving Average Model)** $\{Y_t\} \sim \text{MA}(\mathbf{q})$ if $Y_t = \theta(B)Z_t$, i.e.

$$Y_t = Z_t - \theta_1 Z_{t-1} - \cdots - \theta_q Z_{t-q},$$

where $\theta(x) := 1 - \theta_1 x - \theta_2 x^2 - \cdots - \theta_q x^q$ is the **MA characteristic polynomial**.

3. **(ARMA)** $\{Y_t\} \sim \text{ARMA}(\mathbf{p}, \mathbf{q})$ if $\phi(B)Y_t = \theta(B)Z_t$, i.e.

$$Y_t - \phi_1 Y_{t-1} - \cdots - \phi_p Y_{t-p} = Z_t - \theta_1 Z_{t-1} - \cdots - \theta_q Z_{t-q},$$

where (i). $\phi(1) \neq 0$, (ii). $\phi(\cdot)$ and $\theta(\cdot)$ have NO common root.

4. **(ARIMA)** $\{Y_t\} \sim \text{ARIMA}(\mathbf{p}, \mathbf{d}, \mathbf{q})$ if

$$\phi(B)(1 - B)^d Y_t = \theta(B)Z_t,$$

where (i). $\phi(1) \neq 0$, (ii). $\phi(x)(1 - x)^d$ and $\theta(x)$ have NO common root.

5. **(SARIMA)** $\{Y_t\} \sim \text{SARIMA}(\mathbf{p}, \mathbf{d}, \mathbf{q}) \times (\mathbf{P}, \mathbf{D}, \mathbf{Q})_s$ if

$$\phi(B)\Phi_P(B^s)(1 - B)^d(1 - B^s)^D Y_t = \theta(B)\Theta_Q(B^s)Z_t,$$

where $s > 1$,

$$\Phi_P(B^s) = 1 - \Phi_1 B^s - \cdots - \Phi_P B^{sP} \quad \text{and} \quad \Theta_Q(B^s) = 1 - \Theta_1 B^s - \cdots - \Theta_Q B^{sQ},$$

(i). $\phi(1)$ and $\Phi_P(1)$ are non-zero, (ii). $\phi(x)\Phi_P(x^s)(1 - x)^d(1 - x^s)^D$ and $\theta(x)\Theta_Q(x^s)$ have NO common root.

Remark 1. There are several remarks on the identification of models

- If there is common factor(s) in $\phi(\cdot)$ and $\theta(\cdot)$ [or in $\Phi_P(\cdot)$ and $\Theta_Q(\cdot)$], i.e. say $\phi(x) = (1 - c)\phi'(x)$ and $\theta(x) = (1 - c)\theta'(x)$, we should cancel them out and consider the $\phi'(\cdot)$ and $\theta'(\cdot)$ as the true AR and MA characteristic polynomial instead.
- SARIMA model can be expressed as high-order ARIMA model. However, you are required to write a more informative representation for the assessment. See part b of exercise 1.

The following flowchart summarizes the relationship among the models mentioned above.

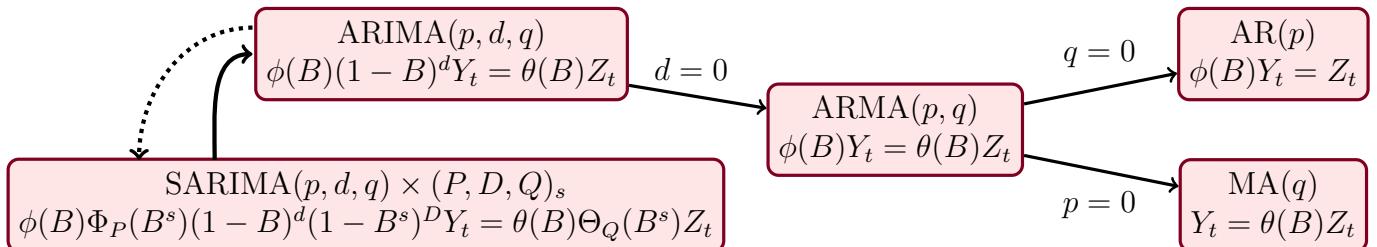


Figure 1: Relationship among models

General Guidance in Identification of Models

For the SARIMA model, we have to notice if there is a common pattern lag among Y'_t s or Z'_t s (eg: $Y_t - 4Y_{t-3} = Z_t + 2Z_{t-3} + 0.5Z_{t-6}$) within the model. If such a lag is not observed, it should be an ARIMA instead. The general strategy for identifying an ARIMA model is as follows:

1. Rearrange the time series model such that it could be written in the form of $\phi_0(B)Y_t = \theta_0(B)Z_t$.
2. (**Identifying MA polynomial θ**) Cancel out common factors of $\phi_0(x)$ and $\theta_0(x)$ (if any) to obtain $\phi_1(x)$ and $\theta(x)$. Then we have $\phi_1(B)Y_t = \theta(B)Z_t$.
3. (**Identifying AR polynomial ϕ**) Write $\phi_1(x) = (1 - x)^d\phi(x)$, where $\phi(1) \neq 0$.

Then the time series $\{Y_t\} \sim \text{ARIMA}(p, d, q)$, where $p = \deg(\phi)$ and $q = \deg(\theta)$.

(★☆☆) Identification of Models

Exercise 1. Identify the time-series model below. Let $\{Y_t\}$ be a time-series and $\{Z_t\} \sim \text{WN}(0, \sigma^2)$.

- (a) $Y_t - 4Y_{t-1} + 5Y_{t-2} - 2Y_{t-3} = Z_t - \frac{8}{3}Z_{t-1} + \frac{4}{3}Z_{t-2}$.
- (b) $Y_t - Y_{t-1} + 0.5Y_{t-4} - 0.5Y_{t-5} = Z_t + 0.25Z_{t-4} + 0.6Z_{t-8}$

Solution

- (a) (i) The model could be rewritten as $(1 - 2B)(1 - B)^2 Y_t = (1 - 2B)(1 - \frac{2}{3}B)Z_t$.
(ii) Cancelling out the common factor gives $(1 - B)^2 Y_t = (1 - \frac{2}{3}B)Z_t$.
(iii) As $\phi(x) = 1$ and $\theta(x) = 1 - 2x/3$, $\{Y_t\} \sim \text{ARIMA}(0, 2, 1)$.

- (b) The model could be written as

$$(1 - B) \underbrace{(1 + 0.5B^4)}_{d=1} \underbrace{Y_t}_{s=4} = \underbrace{(1 + 0.25B^4 + 0.6B^8)}_{s=4} Z_t$$

Hence we have $\{Y_t\} \sim \text{SARIMA}(0, 1, 0) \times (1, 0, 2)_4$, where $\Phi_1(x) = 1 + 0.5x$ and $\Theta_2(x) = 1 + 0.25x + 0.6x^2$ with $s = 4$.

Remark 2. We can also say $\{Y_t\} \sim \text{ARIMA}(4, 1, 8)$. However, $\{Y_t\} \sim \text{SARIMA}(0, 1, 0) \times (1, 0, 2)_4 \Rightarrow \{Y_t\} \sim \text{ARIMA}(4, 1, 8)$ but the converse does not hold, so $\{Y_t\} \sim \text{SARIMA}(0, 1, 0) \times (1, 0, 2)_4$ would be an more appropriate and informative answer.

3.2 Causality and Invertibility of Models

Causality and Invertibility

Definition 2. Let $\{Y_t\}$ be a time-series and $\{Z_t\} \sim \text{WN}(0, \sigma^2)$. Then we say

1. A model is **causal** if there exists a sequence $\{\psi_k\}_{k=0}^{\infty}$ such that $\sum_{k=0}^{\infty} |\psi_k| < \infty$ with

$$Y_t = \sum_{k=0}^{\infty} \psi_k Z_{t-k},$$

2. A model is **invertible** if there exists a sequence $\{\psi_k\}_{k=0}^{\infty}$ such that $\sum_{k=0}^{\infty} |\psi_k| < \infty$ with

$$Z_t = \sum_{k=0}^{\infty} \psi_k Y_{t-k},$$

Verification for Causality and Invertibility

Theorem 1. An ARMA(p, q) process $\phi(B)Y_t = \theta(B)Z_t$ is

1. **Causal** if and only if roots of $\phi(x) = 0$ are ALL outside the unit circle.
2. **Invertible** if and only if roots of $\theta(x) = 0$ are ALL outside the unit circle.

where the term "x out of the unit circle" means that $|x| > 1$, and for all $x \in \mathbb{C}$, $|x|^2 := \text{Re}(x)^2 + \text{Im}(x)^2$.

(★☆☆) Causality and Invertibility of Models

✉ **Exercise 2.** Let $\{Z_t\} \sim \text{WN}(0, \sigma^2)$. Show if the following time/series are causal or invertible.

- $Y_t + 3Y_{t-1} = 2Z_t - Z_{t-1}$.
- $1.5Y_t - Y_{t-1} = 2Z_t + 3Z_{t-1}$.
- $Y_t = 4Y_{t-1} - 4Y_{t-2} + Z_t - 5Z_{t-1} + 6Z_{t-2}$.

Solution

- Rewrite the model as $(1 + 3B)Y_t = (2 - B)Z_t$. Then

- AR polynomial: $\phi(x) = 1 + 3x$ have root $-1/3$ within unit circle, hence not causal.
- MA polynomial: $\theta(x) = 1 + 3x$ have root 2 outside unit circle, hence invertible.

- Rewrite the model as $(1.5 - B)Y_t = (2 + 3B)Z_t$. Then

- AR polynomial: $\phi(x) = 1.5 - x$ have root 1.5 outside unit circle, hence causal.
- MA polynomial: $\theta(x) = 2 + 3x$ have root $-2/3$ within unit circle, hence not invertible.

- Rewrite the model as $(1-2B)(1-2B)Y_t = (1-2B)(1-3B)Z_t$ and simplify it to $(1-2B)Y_t = (1-3B)Z_t$. Then

- AR polynomial: $\phi(x) = 1 - 2x$ have root $1/2$ within unit circle, hence not causal.
- MA polynomial: $\theta(x) = 1 - 3x$ have root $1/3$ within unit circle, hence not invertible.

Consider the ARMA(p, q) process $\phi(B)Y_t = \theta(B)Z_t$. You might be asked to show whether a model is causal/invertible and write down the corresponding representation.

1. If a model is causal, then we can write the **MA/causal representation** as $Y_t = \phi(B)^{-1}\theta(B)Z_t$.
2. If a model is invertible, then we can write the **AR representation** as $Z_t = \theta(B)^{-1}\phi(B)Y_t$.

In order to evaluate $\phi(B)^{-1}$ or $\theta(B)^{-1}$ explicitly, recall for $|r| < 1$,

$$\frac{a}{1-r} = a \sum_{k=0}^{\infty} r^k$$

and by the fundamental theorem of algebra, we can write any degree- p polynomial $P(x)$ as $P(x) = c \prod_{k=1}^p (x - \xi_k)$ for some $c, \xi_1, \dots, \xi_p \in \mathbb{C}$. Sometimes, the method of partial fraction can help further simplify the calculation. For example, see exercise 8.

(★☆☆) AR and MA representation

 **Exercise 3. (Continuation of Exercise 2)** Let $\{Z_t\} \sim \text{WN}(0, \sigma^2)$. Find the AR and MA representation (if possible) of the following model

- (a) $Y_t + 3Y_{t-1} = 2Z_t - Z_{t-1}$.
- (b) $1.5Y_t - Y_{t-1} = 2Z_t + 3Z_{t-1}$.

Solution

- (a) This model is only invertible, where the AR representation is given by

$$\begin{aligned} Z_t &= (2 - B)^{-1}(1 + 3B)Y_t = 0.5 \left(\sum_{k=0}^{\infty} 0.5^k B^k \right) (1 + 3B)Y_t \\ &= 0.5 \left(\sum_{k=0}^{\infty} 0.5^k B^k + 3 \sum_{k=0}^{\infty} 0.5^k B^{k+1} \right) Y_t = \left[0.5 + 0.5 \left(\sum_{k=1}^{\infty} 0.5^k B^k + 3 \sum_{k=1}^{\infty} 0.5^{k-1} B^k \right) \right] Y_t \\ &= \left[0.5 + \left(\sum_{k=1}^{\infty} [0.5^{k+1} + 3(0.5)^k] B^k \right) \right] Y_t = \left[0.5 + \sum_{k=1}^{\infty} 3.5(0.5)^k B^k \right] Y_t \end{aligned}$$

Hence $Z_t = \sum_{k=0}^{\infty} \psi_k Y_{t-k}$, where $\psi_0 = 0.5$ and $\psi_k = 3.5(0.5)^k$ for $k \geq 1$.

- (b) This model is only causal, where the MA representation is given by

$$\begin{aligned} Y_t &= (1.5 - B)^{-1}(2 + 3B)Y_t = \frac{2}{3} \left(\sum_{k=0}^{\infty} \left(\frac{2}{3}\right)^k B^k \right) (2 + 3B)Z_t \\ &= \frac{2}{3} \left(\sum_{k=0}^{\infty} 2 \left(\frac{2}{3}\right)^k B^k + \sum_{k=0}^{\infty} 3 \left(\frac{2}{3}\right)^k B^{k+1} \right) Z_t \\ &= \frac{2}{3} \left[\frac{4}{3} + \left(\sum_{k=1}^{\infty} \left[2 \left(\frac{2}{3}\right)^k + 3 \left(\frac{2}{3}\right)^{k-1} \right] B^k \right) \right] Z_t = \left[\frac{8}{9} + \sum_{k=1}^{\infty} \frac{13}{3} \left(\frac{2}{3}\right)^k B^k \right] Z_t \end{aligned}$$

Hence $Y_t = \sum_{k=0}^{\infty} \psi_k Z_{t-k}$, where $\psi_0 = 8/9$ and $\psi_k = (13/3)(2/3)^k$ for $k \geq 1$.

 **Takeaway 1.** For a sequence $\{a_n\}$, $\sum_{k=L}^U a_k = \sum_{k=L-s}^{U-s} a_{k+s}$.

3.3 Stationarity of Models

In this subsection, we will answer the following questions

1. How to check the stationarity of a given time-series model?
2. If a time-series is stationary, how to find its ACVF $\gamma(\cdot)$

We then answer the first question.

Stationarity of Models

Theorem 2. Consider a time series $\{Y_t\}$.

1. If $\{Y_t\} \sim \text{ARIMA}(p, d, q)$ with $d \geq 1$, then $\{Y_t\}$ is NOT weakly-stationary.
2. If $\{Y_t\} \sim \text{ARMA}(p, q)$, then $\{Y_t\}$ is weakly-stationary if NO root of $\phi(x) = 0$ is **on** the unit circle, i.e. if $\phi(x) = 0$, $|x| \neq 1$.

❶ **Remark 3.** There are several implications due to the theorem above.

- $\{Y_t\} \sim \text{MA}(q) \Rightarrow \text{Causal} \Rightarrow \text{Weakly-Stationary.}$
- For $\{Y_t\} \sim \text{ARMA}(p, q)$ being stationary, $E(Y_t) = 0$.

(★☆☆) Verification of Stationarity

❷ **Exercise 4.** Show whether the following time-series is weakly-stationary.

- (a) $Y_t + Y_{t-2} = 3Z_t - Z_{t-1}$.
- (b) $Y_t - Y_{t-1} = Z_t - 1.5Z_{t-1}$.
- (c) $Y_t = 0.5Y_{t-1} + 0.5Y_{t-2} + Z_t - 1.2Z_{t-1} + 0.2Z_{t-2}$.

Solution

- (a) We have $\phi(x) = 1 + x^2$, i.e. AR roots are i and $-i$, while $|i| = 1$ lies on the unit circle. Hence $\{Y_t\}$ is NOT stationary.
- (b) As $\{Y_t\} \sim \text{ARIMA}(0, 1, 1)$, $\{Y_t\}$ is NOT stationary. (it is wrong to write $\phi(x) = 1 - B!$).
- (c) The model is equivalent to $(1 + 0.5B)(1 - B)Y_t = (1 - 0.2B)(1 - B)Z_t$, simplifying the common factor gives $(1 + 0.5B)Y_t = (1 - 0.2B)Z_t$. Then we have $\phi(x) = 1 + 0.5x$ with AR root 2 outside the circle, hence $\{Y_t\}$ is weakly-stationary.

We then discuss the evaluation of ACVF $\gamma(\cdot)$. As the ARIMA(p, d, q) model with $d \geq 1$ is always non-stationary, we restrict our focus of study to be the ARMA(p, q) model. There are two common ways to complete the task. The first approach requires finding the MA representation of a time-series.

Evaluation of ACVF - Method (I) - MA representation

Theorem 3. For **causal** ARMA process $\phi(B)Y_t = \theta(B)Z_t$, we can write the MA representation $Y_t = \sum_{i=0}^{\infty} \psi_i Z_{t-i}$ with $\sum_{i=0}^{\infty} |\psi_i| < \infty$ and ACVF

$$\gamma(k) = \sigma^2 \sum_{i=0}^{\infty} \psi_i \psi_{i+k}.$$

Remark 4. For **stationary** ARMA process (NOT necessarily causal), we can represent Y_t by $Y_t = \sum_{i=-\infty}^{\infty} \psi_i Z_{t-i}$ with $\sum_{i=-\infty}^{\infty} |\psi_i| < \infty$ and ACVF $\gamma(k) = \sigma^2 \sum_{i=-\infty}^{\infty} \psi_i \psi_{i+k}$.

(★☆☆) Application of Method I

Exercise 5. Consider the process $Y_t = 0.8Y_{t-1} + Z_t$, where $\{Z_t\} \sim \text{WN}(0, \sigma^2)$.

- (a) Is the process $\{Y_t\}$ weakly stationary?
- (b) Find the mean and ACVF $\gamma(\cdot)$ of $\{Y_t\}$ by Theorem 3.

Solution

- (a) Rewrite the model as $(1 - 0.8B)Y_t = Z_t$, as the AR root 1.25 lies out of the unit circle, it is causal and also stationary.
- (b) We first find the MA representation of the model.

$$Y_t = (1 - 0.8B)^{-1}Z_t = \sum_{i=0}^{\infty} 0.8^i B^i Z_t = \sum_{i=0}^{\infty} 0.8^i Z_{t-i}.$$

Hence $Y_t = \sum_{i=0}^{\infty} \psi_i Z_{t-i}$, where $\psi_i = 0.8^i$ for all $i \in \mathbb{N}_0$. As $\sum_{i=0}^{\infty} |\psi_i| < \infty$, we have

$$E(Y_t) = E\left(\sum_{i=0}^{\infty} 0.8^i Z_{t-i}\right) = \sum_{i=0}^{\infty} 0.8^i E(Z_{t-i}) = 0$$

Alternatively, you can obtain the same result by using the second bullet of remark 3. Then by Theorem 3, the ACVF is given by

$$\gamma(k) = \sigma^2 \sum_{i=0}^{\infty} \psi_i \psi_{i+k} = \sigma^2 \sum_{i=0}^{\infty} (0.8)^i (0.8)^{i+k} = \sigma^2 (0.8)^k \sum_{i=0}^{\infty} (0.8)^{2i} = \sigma^2 \frac{0.8^k}{1 - 0.8^2} = \frac{25}{9} \left(\frac{4}{5}\right)^k \sigma^2.$$

for all $k \in \mathbb{N}$, i.e.,

$$\gamma(k) = \sigma^2 \frac{0.8^{|k|}}{1 - 0.8^2} = \frac{25}{9} \left(\frac{4}{5}\right)^{|k|} \sigma^2.$$

Evaluation of ACVF - Method (II) - Yule-Walker Equations

Theorem 4. *The general procedure is as follow: For **stationary** ARMA(p, q) model*

1. Consider the set of linear equations (i.e. the Yule-Walker Equations)

$$\gamma(k) = \text{Cov}(Y_t, Y_{t-k}), \quad \text{for } k = 0, \dots, p$$

to solve for value of $\gamma(0), \dots, \gamma(p)$.

2. For $k > p$, compute $\gamma(k) = \text{Cov}(Y_t, Y_{t-k})$ based on value of $\gamma(0), \dots, \gamma(p)$.

Lemma 1. *The following are the Yule-Walker Equations of some particular models.*

1. For $\{Y_t\} \sim \text{AR}(p)$ being causal with $Z_t \sim \text{WN}(0, \sigma^2)$, the Yule-Walker Equations are

$$\begin{cases} \gamma(0) = \phi_1\gamma(1) + \phi_2\gamma(2) + \dots + \phi_p\gamma(p) + \sigma^2 \\ \gamma(1) = \phi_1\gamma(0) + \phi_2\gamma(1) + \dots + \phi_p\gamma(p-1) \\ \gamma(2) = \phi_1\gamma(1) + \phi_2\gamma(0) + \dots + \phi_p\gamma(p-2) \\ \vdots = \vdots \\ \gamma(p) = \phi_1\gamma(p-1) + \phi_2\gamma(p-2) + \dots + \phi_p\gamma(0). \end{cases}$$

and for $k > p$, $\gamma(k) = \phi_1\gamma(k-1) + \dots + \phi_p\gamma(k-p)$.

2. For $\{Y_t\} \sim \text{ARMA}(p, q)$, i.e. $\phi(B)Y_t = \theta(B)Z_t$ with $Z_t \sim \text{WN}(0, \sigma^2)$, the Yule-Walker Equations are

$$\begin{cases} \gamma(0) = \phi_1\gamma(1) + \phi_2\gamma(2) + \dots + \phi_p\gamma(p) + \text{Cov}(Y_t, \theta(B)Z_t) \\ \gamma(1) = \phi_1\gamma(0) + \phi_2\gamma(1) + \dots + \phi_p\gamma(p-1) + \text{Cov}(Y_{t-1}, \theta(B)Z_t) \\ \gamma(2) = \phi_1\gamma(1) + \phi_2\gamma(0) + \dots + \phi_p\gamma(p-2) + \text{Cov}(Y_{t-2}, \theta(B)Z_t) \\ \vdots = \vdots \\ \gamma(p) = \phi_1\gamma(p-1) + \phi_2\gamma(p-2) + \dots + \phi_p\gamma(0) + \text{Cov}(Y_{t-p}, \theta(B)Z_t). \end{cases}$$

and for $k > p$, $\gamma(k) = \phi_1\gamma(k-1) + \dots + \phi_p\gamma(k-p)$.

! Remark 5. *The causality assumption is important for deriving the Yule-Walker equations. Recall that causality is equivalent to require $Y_t \perp\!\!\!\perp Z_{t+k}$ for all $k > 0$.*

- For the first equation in the Yule-Walker equation of causal AR(p) model, the term σ^2 arises as

$$\text{Cov}(Z_t, Y_t) = \text{Cov}(Z_t, \phi_1Y_{t-1} + \dots + \phi_pY_{t-p} + Z_t) = \text{Cov}(Z_t, Z_t) = \sigma^2.$$

However for non-causal model, $\text{Cov}(Y_{t-k}, Z_t) \neq 0$ in general for $k \geq 1$.

- The Yule-Walker equation derived for ARMA(p, q) does not require causality in general. However, the evaluation of the term $\text{Cov}(Y_{t-k}, \theta(B)Z_t)$ would be complicated.

Hence, please ensure whether the model is causal before applying the method of Yule-Walker equation.

(★☆☆) Application of Method II

✉ Exercise 6. (*Continuation of Exercise 5*) Consider the process $Y_t = 0.8Y_{t-1} + Z_t$, where $\{Z_t\} \sim \text{WN}(0, \sigma^2)$. Find the mean and ACVF $\gamma(\cdot)$ of $\{Y_t\}$ by Theorem 4.

Solution

From Exercise 5, we know $\{Y_t\}$ is stationary. Hence

$$\mathbb{E}(Y_t) = 0.8\mathbb{E}(Y_{t-1}) + \mathbb{E}(Z_t) = 0.8\mathbb{E}(Y_t) \Rightarrow \mathbb{E}(Y_t) = 0.$$

Noticing that the model is indeed causal AR(1) model. Then consider the Yule-Walker equation:

$$\begin{aligned}\gamma(0) &= \text{Cov}(Y_t, Y_t) = \text{Cov}(0.8Y_{t-1} + Z_t, Y_t) = 0.8\gamma(1) + \sigma^2 \\ \gamma(1) &= \text{Cov}(Y_t, Y_{t-1}) = \text{Cov}(0.8Y_{t-1} + Z_t, Y_{t-1}) = 0.8\gamma(0)\end{aligned}$$

On solving, we have $\gamma(0) = (9/25)\sigma^2$ and $\gamma(1) = (4/5)\gamma(0) = (36/125)\sigma^2$. For $k > 1$, we have $\gamma(k) = 0.8\gamma(k-1)$. Hence in general, we have

$$\gamma(k) = \frac{25}{9} \left(\frac{4}{5}\right)^k \sigma^2.$$

for all $k \in \mathbb{N}$, which is consistent with the solution in Exercise 5.

3.4 Chapter Summary

In this subsection, we make a brief summary to this chapter

Model	Causality	Invertibility	Stationarity	ACVF
SARIMA	✗	MA root > 1	✗	\
ARIMA	✗	MA root > 1	✗	\
ARMA	AR root > 1	MA root > 1	AR root ≠ 1	Both OK
AR	AR root > 1	✓	AR root ≠ 1	Yule-Walker
MA	YES	MA root > 1	✓	MA-representation

3.5 Additional Exercises

(★★☆) ACF of AR(2) Model

✉ **Exercise 7.** Consider causal AR(2) model $Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + Z_t$, where $\{Z_t\} \sim \text{WN}(0, \sigma^2)$.

- (a) Find $\rho(1)$ and $\rho(2)$ in terms of ϕ_1 and ϕ_2 .
- (b) Express $\gamma(0)$ in terms of ϕ_1, ϕ_2 and σ^2 .

Solution

(a) Recall by causality assumption, $\text{Cov}(Y_t, Z_{t+k}) = 0$ for all $k \geq 1$. Hence

- $\text{Cov}(Z_t, Y_t) = \text{Cov}(Z_t, \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + Z_t) = \text{Cov}(Z_t, Z_t) = \sigma^2$.
- $\text{Cov}(Z_t, Y_{t-k}) = 0$

Then we consider taking the following operation to both side of the AR(2) model:

- $\text{Cov}(\cdot, Y_{t-1}) : \gamma(1) = \phi_1 \gamma(0) + \phi_2 \gamma(1) + \text{Cov}(Z_t, Y_{t-1}) = \phi_1 \gamma(0) + \phi_2 \gamma(1)$
- $\text{Cov}(\cdot, Y_{t-2}) : \gamma(2) = \phi_1 \gamma(1) + \phi_2 \gamma(0) + \text{Cov}(Z_t, Y_{t-2}) = \phi_1 \gamma(1) + \phi_2 \gamma(0)$

Divide both sides by $\gamma(0)$ gives

$$\rho(1) = \phi_1 + \phi_2 \rho(1) \quad \Rightarrow \quad \rho(1) = \frac{\phi_1}{1 - \phi_2}$$

and

$$\rho(2) = \phi_1 \rho(1) + \phi_2 = \frac{\phi_1^2}{1 - \phi_2} + \phi_2$$

(b) Consider $\gamma(k) = \rho(k)\gamma(0)$, taking covariance with Y_t to the AR(2) model gives

$$\gamma(0) = \phi_1 \gamma(1) + \phi_2 \gamma(2) + \sigma^2 = \phi_1 \rho(1)\gamma(0) + \phi_2 \rho(2)\gamma(0) + \sigma^2$$

It follows that

$$\gamma(0) = \frac{\sigma^2}{1 - \phi_1 \rho(1) - \phi_2 \rho(2)} = \frac{(1 - \phi_2)\sigma^2}{1 - \phi_2 - \phi_1^2 - \phi_2^2 - \phi_1^2 \phi_2 + \phi_2^3}$$

(★★★) Comprehensive Exercise

 **Exercise 8.** Consider $Y_t - 3.5Y_{t-1} + 3Y_{t-2} = 2Z_t - Z_{t-1}$, where $\{Z_t\} \sim WN(0, \sigma^2)$.

- Is the model causal or invertible? If yes, find its corresponding MA and AR representation.
- Is the model stationary?
- Write $Y_t = \sum_{i=-\infty}^{\infty} \psi_i Z_{t-i}$. Find the ACVF of $\gamma(\cdot)$. (Optional!)

Solution

(a) Rewrite the model as $(1 - 1.5B)(1 - 2B)Y_t = (2 - B)Z_t$. Then

- $\phi(x) = (1 - 1.5x)(1 - 2x)$ have AR roots $2/3$ and $1/2$, which are inside the unit circle. Hence NOT causal.
- $\theta(x) = 2 - x$ have MA root 2 , which is outside the unit circle . Hence invertible.

The AR representation is given by

$$\begin{aligned} Z_t &= 0.5 \left(\sum_{k=0}^{\infty} (0.5)^k B^k \right) (1 - 3.5B + 3B^2) Y_t \\ &= 0.5 \left(\sum_{k=0}^{\infty} (0.5)^k B^k - \sum_{k=0}^{\infty} 3.5(0.5)^k B^{k+1} + \sum_{k=0}^{\infty} 3(0.5)^k B^{k+2} \right) Y_t \\ &= 0.5 \left(\left[1 + 0.5B + \sum_{k=2}^{\infty} (0.5)^k B^k \right] - \left[3.5B + \sum_{k=1}^{\infty} 3.5(0.5)^k B^{k+1} \right] + \sum_{k=0}^{\infty} 3(0.5)^k B^{k+2} \right) Y_t \\ &= 0.5 \left(1 - 3B + \sum_{k=2}^{\infty} (0.5)^k B^k + \sum_{k=2}^{\infty} 3.5(0.5)^{k-1} B^k + \sum_{k=2}^{\infty} 3(0.5)^{k-2} B^k \right) Y_t \\ &= \left(0.5 - 1.5B + 10 \sum_{k=2}^{\infty} (0.5)^k B^k \right) Y_t. \end{aligned}$$

(b) As the AR root $2/3$ and $1/2$ do not lies on the unit circle, the process is stationary.

(c) We only give a drafted solution here. You may try to work out the remaining steps. Recall

$$3B^2 \left(1 - \frac{1}{1.5B} \right) \left(1 - \frac{1}{2B} \right) Y_t = (1 - 1.5B)(1 - 2B)Y_t = (2 - B)Z_t.$$

It follows that

$$\begin{aligned} 3Y_{t-2} &= \left(1 - \frac{1}{1.5B} \right)^{-1} \left(1 - \frac{1}{2B} \right)^{-1} (2 - B)Z_t = \left(\frac{4}{1 - \frac{2}{3}B^{-1}} + \frac{3}{1 - \frac{1}{2}B^{-1}} \right) (2 - B)Z_t \\ &= \sum_{k=0}^{\infty} \left[4 \left(\frac{2}{3} \right)^k + 3 \left(\frac{1}{2} \right)^k \right] B^{-k} (2 - B) = -7Z_{t-1} + \sum_{k=0}^{\infty} \left[\left(\frac{32}{3} \right) \left(\frac{2}{3} \right)^k + \left(\frac{15}{2} \right) \left(\frac{1}{2} \right)^k \right] Z_{t+k}. \end{aligned}$$

Hence

$$Y_t = -\frac{7}{3}Z_{t-1} + \sum_{k=0}^{\infty} \left[\left(\frac{32}{9} \right) \left(\frac{2}{3} \right)^k + \left(\frac{5}{2} \right) \left(\frac{1}{2} \right)^k \right] Z_{t+k+2}.$$

You may attempt to evaluate the ACVF through Theorem 3.