

TEST #2

STA 4853

Name: \_\_\_\_\_

April 29, 2020

Please read the following directions.

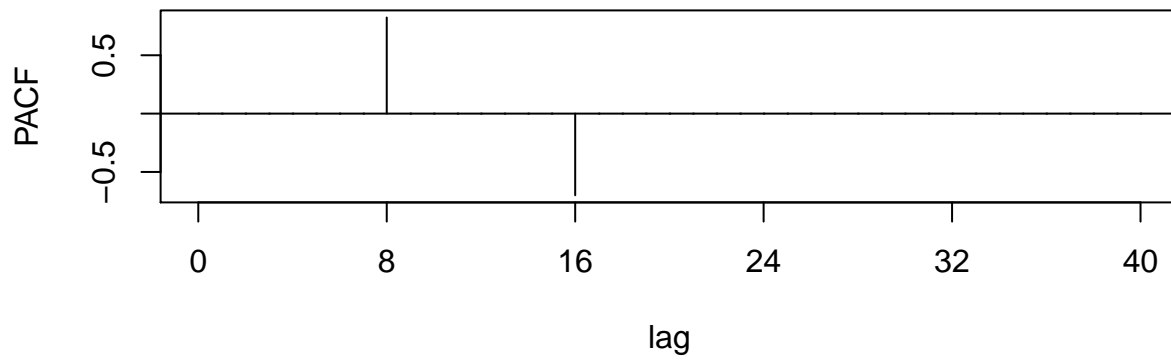
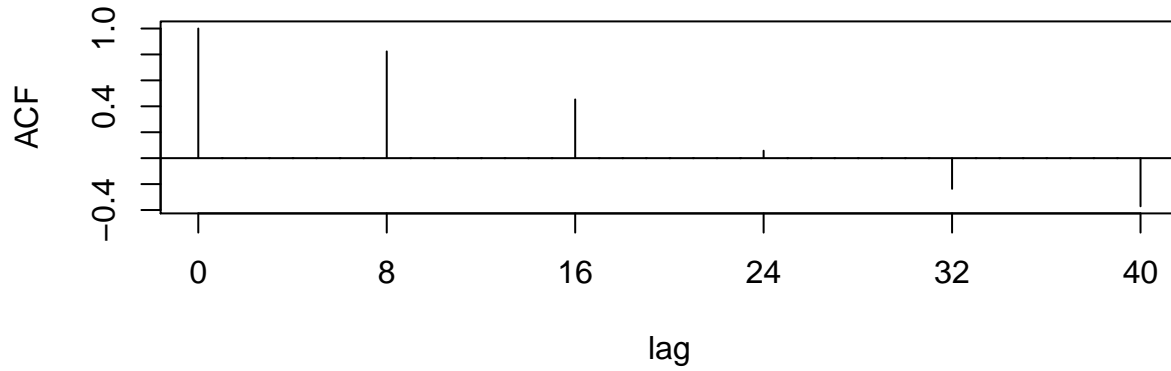
**DO NOT TURN THE PAGE UNTIL INSTRUCTED TO DO SO**

## Directions

- This exam is **closed book** and **closed notes**.
- There are **30** multiple choice questions.
- Select the **single best** answer for each multiple choice question.
- For each question, type the **single lower case letter** of the correct response into the “Fill in the blank” box in Canvas.
- There is no penalty for guessing.
- The exam has **13** pages.
- Each question is worth equal credit.

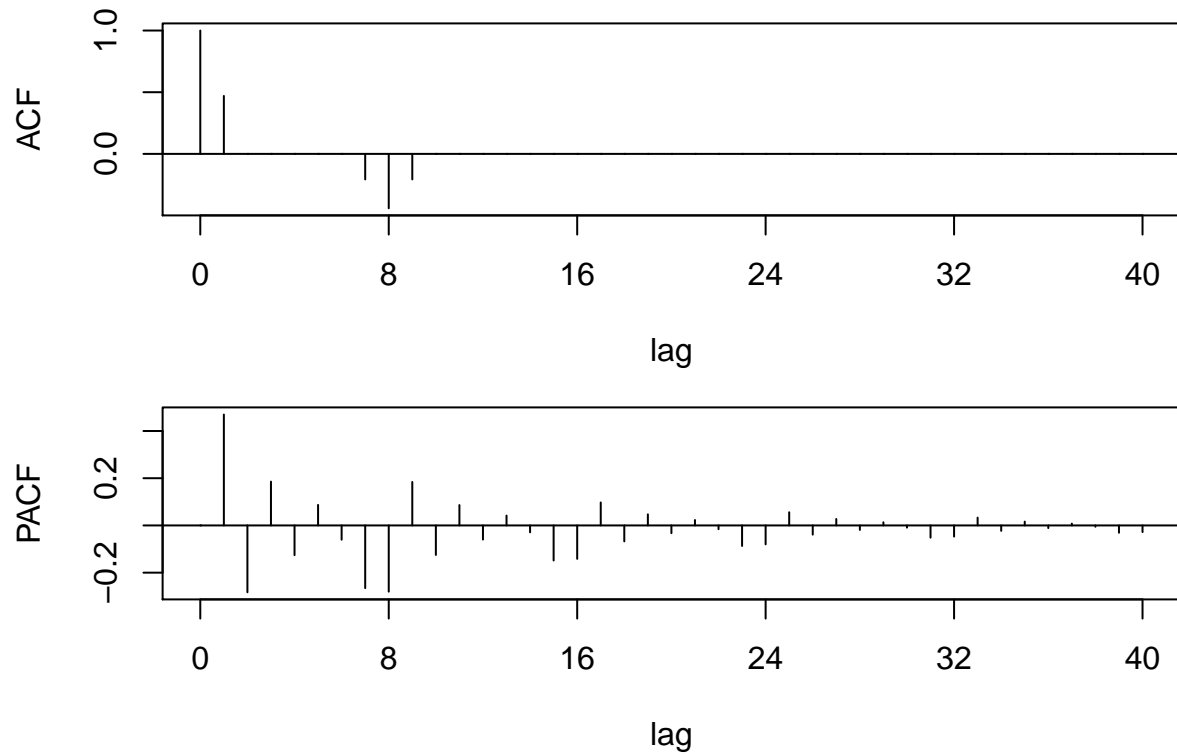
**Problem 1.** The plots below give the theoretical ACF and PACF of an ARMA process. What is this process?

- |                                      |                                   |                                   |
|--------------------------------------|-----------------------------------|-----------------------------------|
| a) $\text{ARMA}(2, 0)(0, 0)_8$       | b) $\text{ARMA}(0, 2)(0, 0)_8$    | c) $\text{ARMA}(0, 0)(0, 2)_8$    |
| d) $\star \text{ARMA}(0, 0)(2, 0)_8$ | e) $\text{ARMA}(0, 0)(2, 0)_{16}$ | f) $\text{ARMA}(0, 0)(0, 2)_{16}$ |
| g) $\text{ARMA}(2, 0)(0, 0)_{16}$    | h) $\text{ARMA}(0, 2)(0, 0)_{16}$ | i) $\text{ARMA}(0, 0)(2, 2)_8$    |
| j) $\text{ARMA}(0, 0)(2, 2)_{16}$    | k) $\text{ARMA}(2, 2)(0, 0)_8$    | l) $\text{ARMA}(2, 2)(0, 0)_{16}$ |



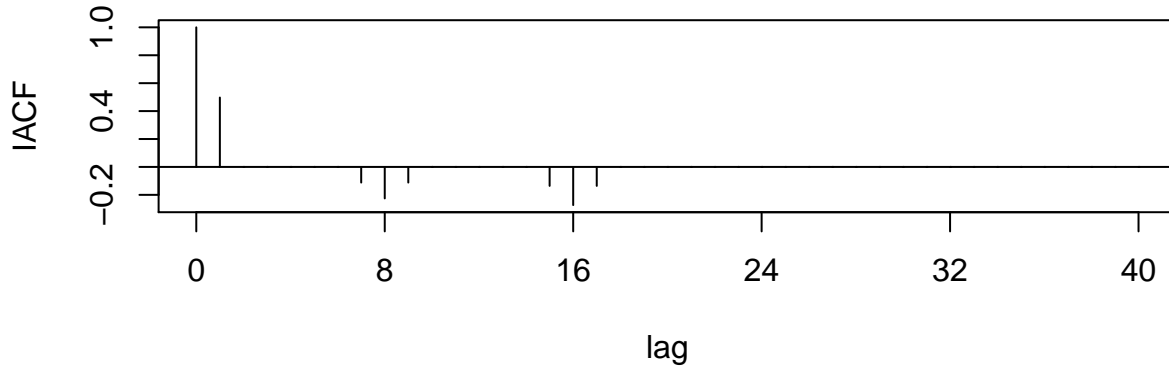
**Problem 2.** The plots below give the theoretical ACF and PACF of another ARMA process. What is this process?

- |                                   |                                   |                                   |
|-----------------------------------|-----------------------------------|-----------------------------------|
| a) $\text{ARMA}(2, 0)(0, 1)_8$    | b) $\text{ARMA}(2, 0)(1, 0)_{16}$ | c) $\text{ARMA}(1, 0)(0, 1)_8$    |
| d) $\text{ARMA}(1, 0)(1, 0)_8$    | e) $\text{ARMA}(0, 1)(0, 1)_{16}$ | f) $\text{ARMA}(0, 1)(1, 0)_{16}$ |
| g) $\text{ARMA}(1, 0)(0, 1)_{16}$ | h) $\text{ARMA}(1, 0)(1, 0)_{16}$ | i) $\text{ARMA}(0, 1)(0, 2)_8$    |
| j) $\text{ARMA}(0, 1)(2, 0)_{16}$ | k) $\text{ARMA}(0, 1)(0, 1)_8$    | l) $\text{ARMA}(0, 1)(1, 0)_8$    |



**Problem 3.** The plots below give the theoretical **IACF** of yet another ARMA process. What is this process?

- |                                   |                                   |                                   |
|-----------------------------------|-----------------------------------|-----------------------------------|
| a) ARMA(2, 0)(1, 0) <sub>8</sub>  | b) ARMA(0, 2)(1, 0) <sub>8</sub>  | c) ARMA(2, 0)(0, 1) <sub>8</sub>  |
| d) ARMA(0, 2)(0, 1) <sub>8</sub>  | e) ARMA(2, 0)(1, 0) <sub>16</sub> | f) ARMA(0, 2)(1, 0) <sub>16</sub> |
| g) ARMA(2, 0)(0, 1) <sub>16</sub> | h)★ ARMA(1, 0)(2, 0) <sub>8</sub> | i) ARMA(0, 1)(2, 0) <sub>8</sub>  |
| j) ARMA(1, 0)(0, 2) <sub>8</sub>  | k) ARMA(0, 1)(0, 2) <sub>8</sub>  | l) ARMA(0, 2)(0, 1) <sub>16</sub> |
| m) ARMA(1, 0)(0, 2) <sub>16</sub> | n) ARMA(0, 1)(0, 2) <sub>16</sub> |                                   |



The following two problems involve this situation:

Suppose  $\{z_t\}$  is a realization of a known ARIMA( $p, d, q$ ) process; we know the orders  $p, d, q$  and the values of all parameters. Suppose we observe the values of  $z_t$  and the random shocks  $a_t$  for all times  $t$  up to time 100. For any time  $t$ , let  $\hat{z}_t$  denote the best forecast for  $z_t$  based on only the given information up to time 100, that is,  $\hat{z} = E(z_t | \mathcal{I}_{100})$  where  $\mathcal{I}_{100}$  denotes the observed information up to time 100.

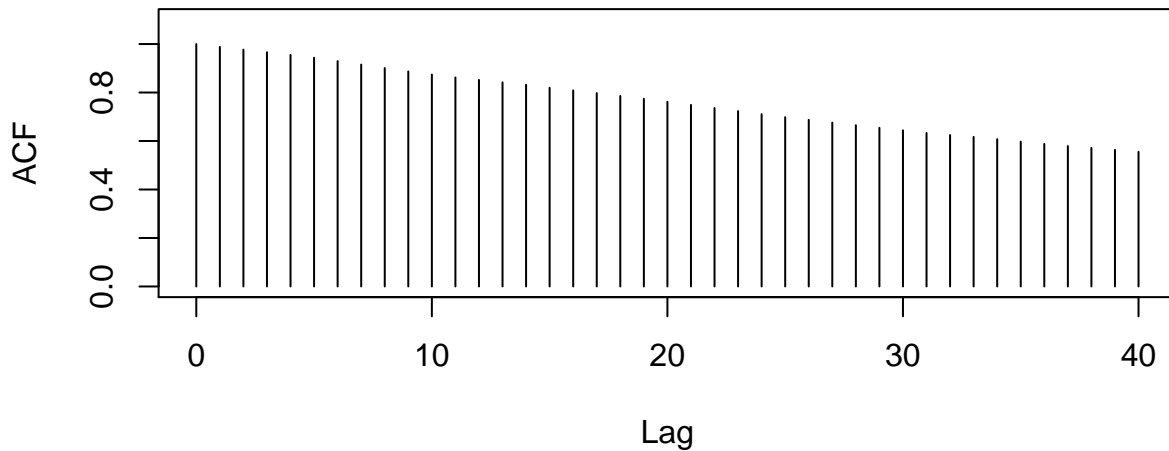
**Problem 4.**  $\hat{z}_{99} = \underline{\hspace{2cm}}$ .

- |                   |                    |                    |                        |
|-------------------|--------------------|--------------------|------------------------|
| a) $a_{99}$       | b) $a_{98}$        | c) $a_{100}$       | d) 0                   |
| e) $\hat{z}_{98}$ | f) $\hat{z}_{100}$ | g)★ $z_{99}$       | h) $z_{98}$            |
| i) $z_{100}$      | j) $\hat{a}_{98}$  | k) $\hat{a}_{100}$ | l) $C + \phi_1 z_{98}$ |

**Problem 5.** The best forecast for  $2z_{102} + 3a_{101} + 5$  is equal to  $\underline{\hspace{2cm}}$ .

- |                          |                                    |                                    |                   |
|--------------------------|------------------------------------|------------------------------------|-------------------|
| a) $2z_{102}$            | b) $2z_{102} + 3$                  | c) $2z_{101} + 3$                  | d) $2z_{100} + 3$ |
| e)★ $2\hat{z}_{102} + 5$ | f) $2\hat{z}_{101} + 3a_{100} + 5$ | g) $2\hat{z}_{100} + 3a_{100} + 5$ |                   |
| h) $2z_{101} + 3a_{100}$ | i) $2z_{100} + 3a_{100}$           |                                    |                   |

**Problem 6.** Suppose we wish to find an ARIMA model for a monthly time series of length  $n = 500$ . The sample ACF of this time series is given below. The appearance of this sample ACF suggests that this time series \_\_\_\_\_.



- a) has non-constant variance and may need a transformation
- b) is non-stationary because it has a non-constant ACF
- c) has a seasonal tendency and may require a model with a seasonal term
- d) has been over-differenced
- e) has a downward trend with a roughly constant slope
- f)★ is non-stationary and may need differencing at lag 1
- g) has a strong seasonal pattern and may need differencing at lag 12

**Problem 7.** A stationary ARMA( $p, q$ ) process  $\{z_t\}$  may be written as

$$\tilde{z}_t = \sum_{k=0}^{\infty} \psi_k a_{t-k}$$

where the  $\psi$ -weights  $\psi_k$  may be found by expanding \_\_\_\_\_ as a series.

- |                                       |                                |                                 |                                       |
|---------------------------------------|--------------------------------|---------------------------------|---------------------------------------|
| a) $\phi(B)\theta(B)$                 | b) $\frac{1}{\phi(B)}$         | c) $\frac{1}{\theta(B)}$        | d) $\frac{\theta(B)}{(1-B)^d\phi(B)}$ |
| e) $\frac{(1-B)^d\theta(B)}{\phi(B)}$ | f) $\frac{\phi(B)}{\theta(B)}$ | g)★ $\frac{\theta(B)}{\phi(B)}$ | h) $\frac{\phi(B)}{(1-B)^d\theta(B)}$ |
| i) $\frac{(1-B)^d\phi(B)}{\theta(B)}$ | j) $(1-B)^d\phi(B)\theta(B)$   |                                 |                                       |

**Problem 8.** Let  $B$  denote the backshift operator. The expression

$$(4B + 2B^3 + 3B^5)Z_t$$

means the same as \_\_\_\_\_

- a)  $4Z_{t+1} + 2Z_{t+3} + 3Z_{t+5}$                       b)★  $4Z_{t-1} + 2Z_{t-3} + 3Z_{t-5}$   
c)  $Z_{t-4} + 3Z_{t-2} + 5Z_{t-3}$                       d)  $Z_{t+4} + 3Z_{t+2} + 5Z_{t+3}$   
e)  $Z_{t-4} + Z_{t-2}^3 + Z_{t-3}^5$                       f)  $Z_{t+4} + Z_{t+2}^3 + Z_{t+3}^5$                       g)  $Z_{t-1}^4 + Z_{t-3}^2 + Z_{t-5}^3$

**Problem 9.** If  $\{z_t\}$  is an ARIMA( $p, d, q$ ) process whose AR coefficients satisfy the stationarity conditions, then \_\_\_\_\_.

- a) differencing  $z_t$   $d$  times produces an overdifferenced series  
b) integrating  $z_t$   $d$  times produces an overdifferenced series  
c) integrating  $z_t$   $d$  times produces a stationary ARMA( $p, q$ ) process  
d)★ differencing  $z_t$   $d$  times produces a stationary ARMA( $p, q$ ) process  
e) the theoretical ACF of  $z_t$  decays rapidly to zero  
f) the theoretical ACF of  $z_t$  has a cutoff after lag  $q$   
g) the theoretical PACF of  $z_t$  has a cutoff after lag  $p$

**Problem 10.** If your goal is to explain a response series  $\{y_t\}$  by a linear regression on two input series  $\{x_{1,t}\}$  and  $\{x_{2,t}\}$ , and the regression errors  $\{\varepsilon_t\}$  are serially correlated and follow a ARMA( $p, q$ ) process

$$\phi(B)\varepsilon_t = \theta(B)a_t,$$

then a good model for  $\{y_t\}$  is given by \_\_\_\_\_ where  $a_t$  is a sequence of random shocks.

- a)  $\phi(B)y_t = \beta_0 + \beta_1x_{1,t} + \beta_2x_{2,t} + \theta(B)a_t$   
b)  $\phi(B)y_t = \beta_0 + \beta_1x_{1,t} + \beta_2x_{2,t} + \theta(B)a_t$   
c)  $y_t = \beta_0 + \beta_1x_{1,t} + \beta_2x_{2,t} + a_t$   
d)  $\phi(B)y_t = a_t + \theta(B)(\beta_0 + \beta_1x_{1,t} + \beta_2x_{2,t})$   
e)  $\theta(B)y_t = a_t + \phi(B)(\beta_0 + \beta_1x_{1,t} + \beta_2x_{2,t})$   
f)  $y_t = \beta_0 + \beta_1x_{1,t} + \beta_2x_{2,t} + \frac{\phi(B)}{\theta(B)}a_t$   
g)★  $y_t = \beta_0 + \beta_1x_{1,t} + \beta_2x_{2,t} + \frac{\theta(B)}{\phi(B)}a_t$

**Problem 11.** Suppose you wish to apply the methods of ARIMA modeling to a time series. If you observe that the variability of the series increases systematically with the level, then what should you do?

- a) Use a seasonal model
- b) Try fitting a trend
- c)★ Try a transformation
- d) Try differencing at lag 1
- e) Try differencing at the seasonal lag
- f) None of the above

**Problem 12.** Suppose  $\{z_t\}$  is an AR(1) process:

$$z_t = C + \phi_1 z_{t-1} + a_t$$

and you have observed all the values  $z_t$  and  $a_t$  up to time  $n$ . What is the best forecast of  $z_{n+1}$ ? (The best forecast of  $z_{n+1}$  is denoted  $\hat{z}_{n+1}$  or  $\hat{z}_n(1)$  in the lecture notes.)

- |                               |                             |                                  |                        |
|-------------------------------|-----------------------------|----------------------------------|------------------------|
| a) $C$                        | b)★ $C + \phi_1 z_n$        | c) $C + \phi_1 C + \phi_1^2 z_n$ | d) $C + \hat{a}_{n+1}$ |
| e) $\mu_z + \phi_1 \hat{z}_n$ | f) $\mu_z \pm 1.96\sigma_z$ | g) $C + \phi_1 z_n + a_{n+1}$    | h) $\mu_z$             |

**Problem 13.** Continuing the previous problem, if you have observed  $z_t$  and  $a_t$  up to time  $n$ , what is the best forecast of  $z_{n+2}$ ? (This forecast is denoted  $\hat{z}_{n+2}$  or  $\hat{z}_n(2)$ .)

- |                                   |                                   |                                   |                         |
|-----------------------------------|-----------------------------------|-----------------------------------|-------------------------|
| a) $\mu_z \pm 1.96\sigma_z$       | b) $C$                            | c) $C + \phi_1 z_n$               | d) $C + \phi_1 z_{n+1}$ |
| e) $\mu_z + \phi_1 \hat{z}_{n+1}$ | f)★ $C + \phi_1 C + \phi_1^2 z_n$ | g) $C + \phi_1 z_{n+1} + a_{n+2}$ | h) $\mu_z$              |
- 

**Problem 14.** The theoretical **Inverse ACF (IACF)** of an **AR**( $p$ ) process ...

- a)★ is the same as the **ACF** of an **MA**( $p$ ) process.
- b) is the same as the **IACF** of an **MA**( $q$ ) process.
- c) is the same as the **PACF** of an **MA**( $p$ ) process.
- d) is the same as the **PACF** of an **AR**( $p$ ) process.
- e) is the same as the **ACF** of an **AR**( $p$ ) process.
- f) is the same as the **IACF** of an **MA**( $p$ ) process.

**Problem 15.** If a time series consists of a repeating seasonal pattern plus a linear trend, then seasonal differencing will ...

- a) remove the linear trend but not the seasonal pattern
- b)★ remove both the seasonal pattern and the linear trend
- c) sometimes fail to remove the linear trend and second differencing is needed
- d) sometimes fail to remove the seasonal pattern and second differencing is needed
- e) remove the seasonal pattern but not the linear trend

**Problem 16.** If you are unable to find a good  $\text{ARIMA}(p, d, q)$  model for a non-stationary time series, one alternative is to \_\_\_\_\_

- a) re-express the model in backshift notation
- b) check that the model satisfies the stationarity conditions
- c) use the Box-Jenkins approach
- d)★ model the series as (Series) = (Trend) + (Stationary Process)
- e) try differencing the series
- f) try including additional AR or MA terms

**Problem 17.** You wish to predict a quantity  $X$  on the basis of information  $\mathcal{I}$ . If you will be forced to pay \$100 unless your prediction  $\hat{X}$  is within  $\varepsilon$  of  $X$  (where  $\varepsilon$  is small), then your best prediction is the \_\_\_\_\_ of the conditional distribution of  $X$  given  $\mathcal{I}$ .

- |                       |               |           |             |
|-----------------------|---------------|-----------|-------------|
| a) minimum            | b) $P$ -value | c)★ mode  | d) variance |
| e) standard deviation | f) mean       | g) median |             |

**Problem 18.** If we form a new series  $\{z_t\}$  by differencing the series  $x_t$  3 times at lag 1 and then 4 times at lag 12, we may write \_\_\_\_\_.

- |   |                                       |
|---|---------------------------------------|
| a) $z_t = (1 - B^3)^1(1 - B^4)^{12}x_t$ | b) $z_t = (1 - 3B)^1(1 - 4B)^{12}x_t$ |
| c)★ $z_t = (1 - B)^3(1 - B^{12})^4x_t$  | d) $z_t = (1 - 4B)^1(1 - 3B)^{12}x_t$ |
| e) $z_t = (1 - 3B^1)(1 - 4B^{12})x_t$   | f) $z_t = (1 - 3B^{12})(1 - 4B^1)x_t$ |



**Problem 19.** Suppose you have a monthly time series  $x_t$  with seasonal variation at lag 12, and you wish to find a good  $\text{ARIMA}(p, d, q)(P, D, Q)_{12}$  model for  $x_t$ . After finding reasonable orders of differencing  $d$  and  $D$ , we usually determine plausible initial values for  $p, q, P, Q$  by studying the sample ACF, PACF, and IACF of the \_\_\_\_\_.

- a)★ differenced series, and identifying  $p$  and  $q$  using the pattern along the early non-seasonal lags 1, 2, 3, ..., and  $P$  and  $Q$  from the pattern along the seasonal lags 12, 24, 36, ...
- b) differenced series, and identifying  $p$  and  $q$  using the pattern along the seasonal lags 12, 24, 36, ..., and  $P$  and  $Q$  from the pattern along the early non-seasonal lags 1, 2, 3, ...
- c) original series  $x_t$ , and identifying  $p$  and  $q$  using the pattern along the early non-seasonal lags 1, 2, 3, ..., and  $P$  and  $Q$  from the pattern along the seasonal lags 12, 24, 36, ...
- d) original series  $x_t$ , and identifying  $p$  and  $q$  using the pattern along the seasonal lags 12, 24, 36, ..., and  $P$  and  $Q$  from the pattern along the early non-seasonal lags 1, 2, 3, ...
- e) original series  $x_t$ , and then including all possible terms in the model and dropping the non-significant terms one by one
- f) original series  $x_t$ , and then including all possible terms in the model and dropping the non-significant terms one by one
- g) differenced series, and then including all possible terms in the model and dropping the non-significant terms one by one

**Problem 20.**  $Ba_{t-2} =$  \_\_\_\_\_

- |               |              |              |              |
|---------------|--------------|--------------|--------------|
| a) $a_{t+2}$  | b) $a_{t+1}$ | c) $a_t$     | d) $a_{t-2}$ |
| e)★ $a_{t-3}$ | f) $a_{t-4}$ | g) $a_{t-5}$ | h) $a_{t-1}$ |

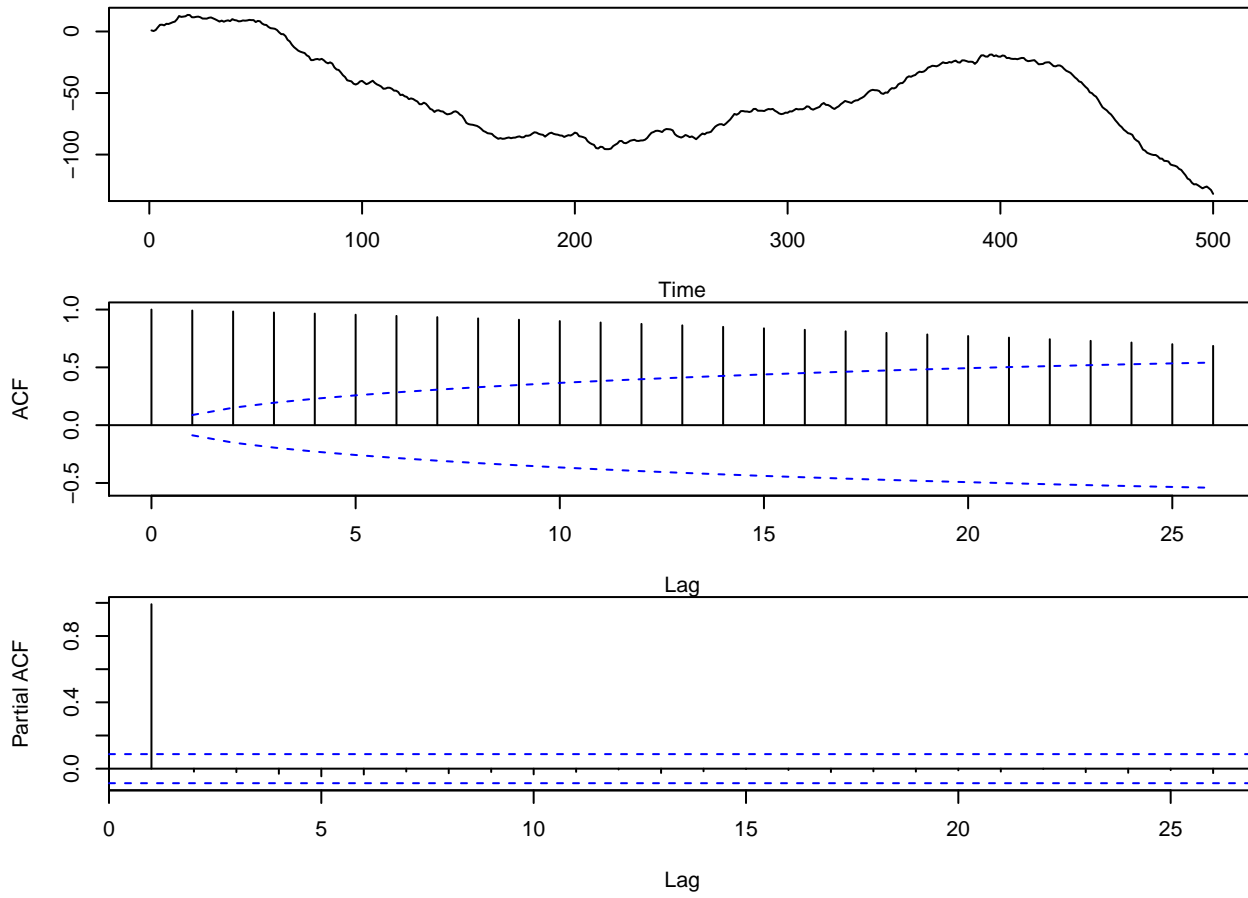
**Problem 21.**  $(1 + 2B^2)(1 + 3B^{12}) =$  \_\_\_\_\_

- |                         |                                   |                                    |
|-------------------------|-----------------------------------|------------------------------------|
| a) $1 + 6B^{24}$        | b) $2 + 3B^2 + 4B^{12} + 5B^{14}$ | c)★ $1 + 2B^2 + 3B^{12} + 6B^{14}$ |
| d) $2 + 2B^2 + 3B^{12}$ | e) $2 + 2B^2 + 3B^{12} + 6B^{24}$ | f) $1 + 3B^2 + 4B^{12} + 5B^{24}$  |

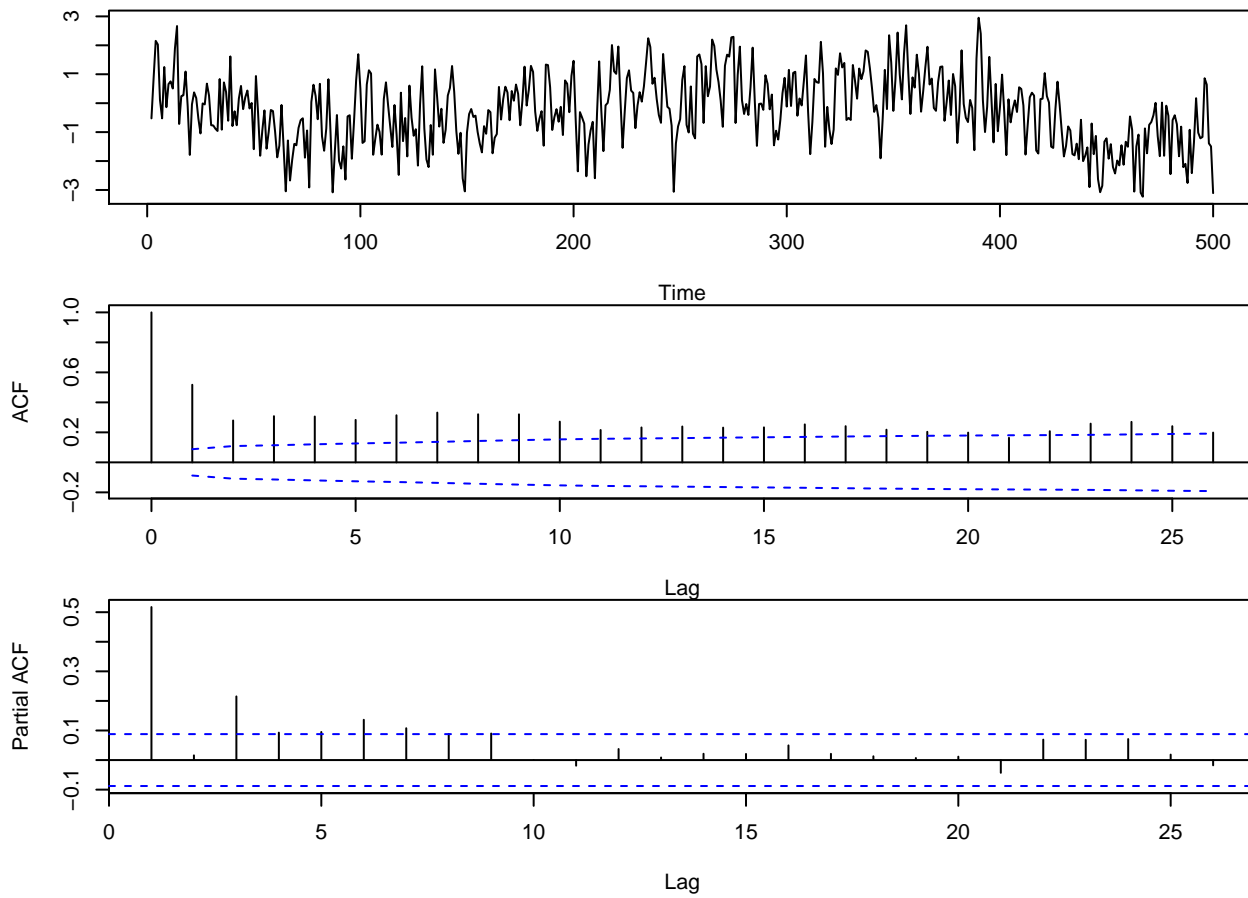
**Problem 22.** This problem uses the graphs on the next two pages. These graphs give the time series plot, the sample ACF, and the sample PACF for a series  $z_t$  of length  $n = 500$ , and also similar plots for the differences at lag 1 ( $\nabla z_t$ ) and for the second differences ( $\nabla^2 z_t$ ). Using these plots, select a good ARIMA model for the series  $z_t$ .

- |                             |                             |
|-----------------------------|-----------------------------|
| a) $\text{ARIMA}(8, 2, 0)$  | b)★ $\text{ARIMA}(0, 2, 2)$ |
| c) $\text{ARIMA}(8, 2, 2)$  | d) $\text{ARIMA}(8, 2, 3)$  |
| e) $\text{ARIMA}(1, 0, 0)$  | f) $\text{ARIMA}(2, 0, 0)$  |
| g) $\text{ARIMA}(1, 0, 26)$ | h) $\text{ARIMA}(0, 0, 26)$ |
| i) $\text{ARIMA}(2, 1, 0)$  | j) $\text{ARIMA}(8, 1, 0)$  |
| k) $\text{ARIMA}(8, 1, 1)$  | l) $\text{ARIMA}(0, 1, 1)$  |

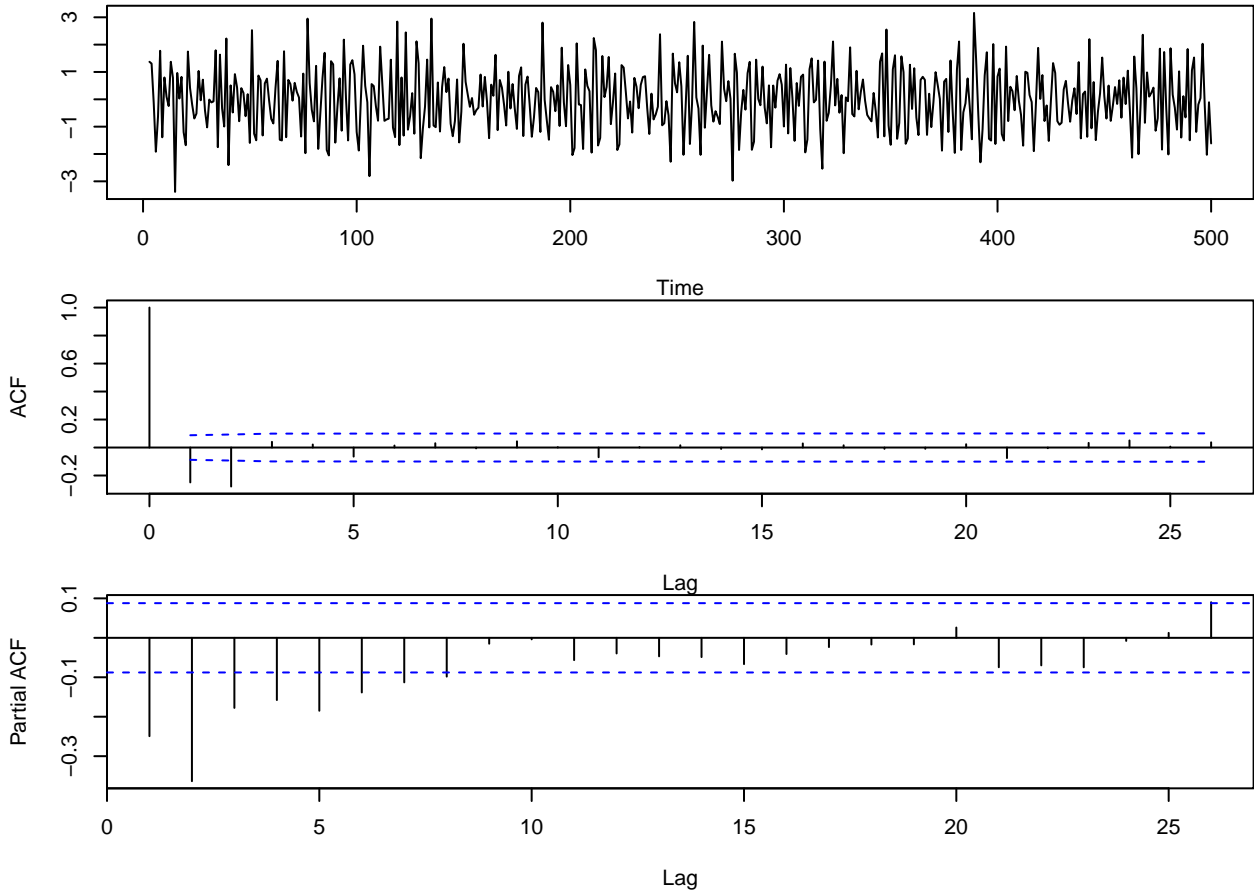
Original Series



Differencing Once at Lag 1



### Differencing Twice at Lag 1



**Problem 23.** The backshift expression  $B(C + \phi_1 z_{t-1} + a_t - \theta_1 a_{t-1})$  is equal to \_\_\_\_\_

- a)  $C + \phi_1 z_{t-2} + a_{t-1} - \theta_1 a_{t-2}$
- b)  $C_{t-1} + \phi_0 z_{t-2} + a_{t-1} - \theta_0 a_{t-2}$
- c)  $C_{t+1} + \phi_2 z_t + a_{t+1} - \theta_2 a_t$
- d)  $C + \phi_2 z_{t-2} + a_{t-1} - \theta_2 a_{t-2}$
- e)  $0 + \phi_1 z_{t-2} + a_{t-1} - \theta_1 a_{t-2}$
- f)  $0 + \phi_0 z_{t-2} + a_{t-1} - \theta_0 a_{t-2}$
- g)  $0 + \phi_2 z_{t+1} + a_{t+1} - \theta_2 a_{t+2}$

**Problem 24.** Suppose we start with the series  $x_t$ , then calculate  $y_t = \nabla x_t$ , and then  $z_t = \nabla_s y_t$ . We find that  $z_t =$  \_\_\_\_\_.

- a)  $x_{t-1} + x_t - x_{t+s+1} + x_{t+s}$
- b)  $x_t + x_{t+1} - x_{t+s} - x_{t+s+1}$
- c)  $x_{t-1} - x_t - x_{t-s-1} + x_{t-s}$
- d)  $x_t + x_{t-1} - x_{t-s} - x_{t-s-1}$
- e)  $x_t - x_{t-1} - x_{t-s} + x_{t-s-1}$
- f)  $x_t - x_{t+1} - x_{t+s} + x_{t+s+1}$

**Problem 25.** The process

$$z_t = \phi_1 z_{t-1} + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \theta_3 a_{t-3}$$

can be written in backshift form as \_\_\_\_\_

- a)★  $(1 - \phi_1 B)z_t = (1 - \theta_1 B - \theta_2 B^2 - \theta_3 B^3)a_t$
- b)  $(1 - \phi_1 B)z_t = (1 + \theta_1 B + \theta_2 B^2 + \theta_3 B^3)a_t$
- c)  $(1 - \theta_1 B - \theta_2 B^2 - \theta_3 B^3)z_t = (1 - \phi_1 B)a_t$
- d)  $(1 - \theta_1 B - \theta_2 B^2 - \theta_3 B^3)z_t = (1 + \phi_1 B)a_t$
- e)  $(1 + \theta_1 B + \theta_2 B^2 + \theta_3 B^3)z_t = (1 - \phi_1 B)a_t$
- f)  $(1 + \theta_1 B + \theta_2 B^2 + \theta_3 B^3)z_t = (1 + \phi_1 B)a_t$
- g)  $(1 + \phi_1 B)z_t = (1 - \theta_1 B - \theta_2 B^2 - \theta_3 B^3)a_t$
- h)  $(1 + \phi_1 B)z_t = (1 + \theta_1 B + \theta_2 B^2 + \theta_3 B^3)a_t$

**Problem 26.** A realization from a process with a **non**-stationary mean will usually \_\_\_\_\_.

- a) have a sample PACF which decays very slowly to zero
- b) have a sample IACF which decays very slowly to zero
- c) require a log transformation
- d) require a square root transformation
- e) require a square transformation
- f) require a reciprocal transformation
- g) require a large AR order  $p$  in its model
- h) require a large MA order  $q$  in its model
- i) require large values of both  $p$  and  $q$  in its model
- j)★ have a sample ACF which decays very slowly to zero

**Problem 27.** Which of the following statements is true for an  $\text{ARIMA}(0, 0, 0)(0, 0, 3)_{12}$  process?

- a) The PACF will be zero at lags 12, 24, 36.
- b) The IACF will be zero at lags 12, 24, 36.
- c) The first three MA coefficients will be zero.
- d) The first three AR coefficients will be zero.
- e) The ACF will decay rapidly along the early lags (1, 2, 3, ...).
- f) The PACF will decay rapidly along the early lags (1, 2, 3, ...).
- g)★ The ACF will be zero everywhere except at lags 12, 24, 36.
- h) The PACF will be zero everywhere except at lags 12, 24, 36.
- i) The ACF will be zero at lags 12, 24, 36.

The next two questions concern the following situation:

Suppose you are using `proc arima` to fit a  $\text{ARIMA}(0,1,2)(1,1,0)_{12}$  model to the time series  $z_t$ . The SAS code for this will require an `identify` statement and an `estimate` statement.

**Problem 28.** Which one of the following is a correct way to write the required `identify` statement?

- |   |   |
|---|---|
| a)★ <code>identify var=z(1,12) ;</code>   | b) <code>identify var=z(1,1) ;</code>         |
| c) <code>identify var=z(12,12) ;</code>   | d) <code>identify var=z(2) ;</code>           |
| e) <code>identify var=z d=1 D=1 ;</code>  | f) <code>identify var=z d=1 D=12 ;</code>     |
| g) <code>identify var=z d=12 D=1 ;</code> | h) <code>identify var=z d=1 D=1 s=12 ;</code> |

**Problem 29.** Which one of the following is a correct way to write the necessary `estimate` statement?

- |   |  |
|---|--|
| a) <code>estimate q=(2) p=(12) ;</code>   | b) <code>estimate q=(2) P=(1) ;</code>     |
| c) <code>estimate q=2 P=(1) ;</code>      | d)★ <code>estimate q=(1,2) p=(12) ;</code> |
| e) <code>estimate p=(1,2) q=(12) ;</code> | f) <code>estimate p=(1,2)(12) ;</code>     |
| g) <code>estimate p=(2)(12) ;</code>      | h) <code>estimate q=(2)(12) ;</code>       |
- 

**Problem 30.** Suppose you are using `proc arima` to fit a  $\text{ARIMA}(3,0,0)(2,0,0)_{12}$  model to the time series  $z_t$ . Which one of the following is a correct way to write the necessary `estimate` statement?

- |  |  |
|--|--|
| a) <code>estimate p=3 q=(12,24) ;</code>   | b) <code>estimate p=(1,2,3) P=(12,24) ;</code> |
| c) <code>estimate q=(3)(2) ;</code>        | d) <code>estimate q=3 Q=2 ;</code>             |
| e) <code>estimate p=(3) Q=(12,24) ;</code> | f)★ <code>estimate p=(1,2,3)(12,24) ;</code>   |
| g) <code>estimate p=(3)(2) ;</code>        | h) <code>estimate p=3 P=2 ;</code>             |