

R Textbook Companion for  
Introduction To Time Series And Forecasting  
by Peter J. Brockwell, Richard A. Davis<sup>1</sup>

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December 27, 2025

<sup>1</sup>Funded by a grant from the National Mission on Education through ICT  
- <http://spoken-tutorial.org/NMEICT-Intro>. This Textbook Companion and R  
codes written in it can be downloaded from the "Textbook Companion Project"  
section at the website - <https://r.fossee.in>.

# Book Description

**Title:** Introduction To Time Series And Forecasting

**Author:** Peter J. Brockwell, Richard A. Davis

**Publisher:** Springer-verlag, New York, Usa

**Edition:** 3

**Year:** 2016

**ISBN:** ISBN 0-387-95351-5

R numbering policy used in this document and the relation to the above book.

**Exa** Example (Solved example)

**Eqn** Equation (Particular equation of the above book)

For example, Exa 3.51 means solved example 3.51 of this book. Sec 2.3 means an R code whose theory is explained in Section 2.3 of the book.

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# Chapter 1

## Introduction

**R code Exa 1.1.1** Australian wine sales

```
1 # Page No. 2
2 # Downloading link: https://storage.googleapis.com/springer-extras/zip/2002/978-0-387-21657-7.zip
3 library(ggplot2)
4 wine_data <- read.delim("WINE.TSM", header = FALSE)
5 colnames(wine_data)[1] <- "Sales"
6 ggplot(wine_data, aes(x = seq(as.Date("1980-01-01"),
  as.Date("1991-10-01"), by = "month"), y = Sales)
  ) +
7   geom_point() +
8   geom_line() +
9   labs(title = "Monthly Wine Sales (Jan 1980 – Oct
    1991)",
10         x = "Months",
11         y = "Sales") +
12   theme_minimal()
```

---

**R code Exa 1.1.3** Accidental deaths



```

1 # Page No. 2
2 # Downloading link: https://storage.googleapis.com/
   springer-extras/zip/2002/978-0-387-21657-7.zip
3 library(ggplot2)
4 deaths= read.csv("DEATHS.TSM", header = FALSE)
5 colnames(deaths)[1] <- "deaths"
6 ggplot(deaths, aes(x = seq(as.Date("1973-01-01"), as
   .Date("1978-12-01"), by = "month"), y = deaths))
   +
7   geom_point(shape = 15, size = 1) +
8   geom_line() +
9   labs(title = "Deaths (Jan 1973 - Nov 1978)",
10        x = "Months",
11        y = "Deaths") +
12   theme_minimal()

```

---

#### R code Exa 1.1.4 Signal Detection Problem

```

1 # Page No. 3
2 set.seed(123)
3 t <- 1:200
4 N <- rnorm(200, mean = 0, sd = 0.5)
5 X <- cos(t/10)
6 plot(t, X, type = "l", col = "blue", xlab = "t",
   ylab = "X", main = "Signal plot", lwd=2)
7 points(t, N, pch = 16, col = "black", bg = "black",
   cex = 0.5)

```

---

#### R code Exa 1.1.5 Population of the USA

```

1 # Page No. 4
2 # Downloading link: https://storage.googleapis.com/
   springer-extras/zip/2002/978-0-387-21657-7.zip

```

```

3 library(ggplot2)
4 uspop= read.csv("USPOP.TSM")
5 names(uspop)[names(uspop) == "X3929214"] <- "
  population"
6 start_year=1790
7 num_repeated=20
8 interval=10
9 ggplot(uspop, aes(x=seq_len(num_repeated) * interval
  + start_year, y = population)) +
10   geom_point() +
11   geom_line() +
12   labs(title = "Population",
13         x = "Years",
14         y = "US population") +
15   theme_minimal()

```

---

#### R code Exa 1.1.6 Strikes in USA

```

1 # Page No. 4
2 # Downloading link: https://storage.googleapis.com/springer-extras/zip/2002/978-0-387-21657-7.zip
3 library(ggplot2)
4 strike <- read.delim("STRIKES.TSM", header = FALSE)
5 colnames(strike)[1] <- "Strikes"
6 start_year=1951
7 end_year=1980
8 ggplot(strike, aes(x=seq(start_year, end_year), y =
  Strikes)) +
9   geom_point() +
10   geom_line() +
11   labs(title = "Strikes in US",
12         x = "Years",
13         y = "Strikes") +
14   theme_minimal()

```

---

### R code Exa 1.3.3 Random walk

```
1 # Page no. 7
2 set.seed(123)
3 t <- 200
4 steps <- rnorm(t)
5 random_walk <- cumsum(steps)
6 plot(0:t, c(0, random_walk), type = "l", col = "blue",
7       , xlab = "Time", ylab = "Value", main = "Simple
          Random Walk")
8 points(0:t, c(0, random_walk), col = "red", pch = 1)
```

---

### R code Exa 1.3.4 Regression on population data

```
1 # Page No. 8
2 # Downloading link: https://storage.googleapis.com/springer-extras/zip/2002/978-0-387-21657-7.zip
3 library(ggplot2)
4 uspop= read.delim("USPOP.TSM", header = FALSE)
5 colnames(uspop)[1] <- "population"
6 start_year=1790
7 num_repeated=21
8 interval=10
9 uspop$years <- seq_len(num_repeated) * interval +
  start_year
10 fit<-lm(population ~ poly(years,2,raw = TRUE), data
  = uspop)
11 ggplot(uspop, aes(x=years, y=population)) +
12   geom_point() +
13   geom_smooth(method = "lm", formula = y ~poly(x,2,
  raw=TRUE), se = FALSE) +
```

```

14 labs(title = "US Population",
15       x = "Years",
16       y = "Population") +
17 theme_minimal()

```

---

### R code Exa 1.3.5 Level of Lake Huron

```

1 # Page No. 9
2 # Downloading link: https://storage.googleapis.com/springer-extras/zip/2002/978-0-387-21657-7.zip
3 library(ggplot2)
4 hudson= read.csv("LAKE.TSM", header = FALSE)
5 colnames(hudson)[1] <- "level"
6 start_year=1875
7 end_year=1972
8 hudson$years <-(seq(start_year,end_year))
9 fit<-lm(level~years,data = hudson)
10 residuals <- resid(fit)
11 residual_df <- data.frame(years = hudson$years,
12                            residuals = residuals)
12 par(mfrow=c(1,2))
13 # Figure 1-9
14 plot(hudson$years, hudson$level, type = "o",
15       main = "Lake Hudson", xlab = "Years", ylab = "
16       Water levels", pch = 19)
16 abline(fit, col = "blue",lw=2)
17 # Figure 1-10
18 plot(residual_df$years,residual_df$residuals, type =
19       "o",pch = 19,
20       xlab = "Years", ylab = "Residuals", main = "
21       Residuals plot")
20 abline(h = 0, col = "blue", lw = 2)
21 print(coef(fit))

```

---

### R code Exa 1.3.6 Harmonic regression on accidental deaths

```
1 # Page No. 11
2 # Downloading link: https://storage.googleapis.com/springer-extras/zip/2002/978-0-387-21657-7.zip
3 library(ggplot2)
4 deaths <- read.csv("DEATHS.TSM", header = FALSE)
5 colnames(deaths)[1] <- "deaths"
6 n <- length(deaths$deaths)
7 time <- 1:n
8 f1 <- n / 12
9 f2 <- n / 6
10 fit <- lm(deaths$deaths ~ sin(2 * pi * time / f1) +
            cos(2 * pi * time / f1) +
11            sin(2 * pi * time / f2) + cos(2 * pi *
            time / f2))
12 fitted_values <- predict(fit)
13 plot(time, deaths$deaths, type = "p", col = "black",
        pch = 15, xlab = "Time", ylab = "Value",
14        main = "Harmonic Fit")
15 lines(time, fitted_values, col = "blue", lw = 2)
```

---

### R code Exa 1.4.6 Random noise

```
1 # Page No. 16
2 # Downloading link: https://storage.googleapis.com/springer-extras/zip/2002/978-0-387-21657-7.zip
3 library(ggplot2)
4 set.seed(123)
5 noise <- rnorm(200, mean = 0, sd = 1)
6 df <- data.frame(Index = 1:200, Noise = noise)
7 ggplot(df, aes(x = Index, y = Noise)) +
```

```

8   geom_point()+
9   geom_line() +
10  labs(x = "Index", y = "Noise", title = "Simulated
      N(0,1) Noise")+
11  theme_minimal()
12  acf_result <- acf(noise, plot = FALSE)
13  n <- length(noise)
14  bounds <- 1.96 / sqrt(n)
15  acf_df <- data.frame(Lag = acf_result$lag, ACF = acf
      _result$acf)
16  ggplot(acf_df, aes(x = Lag, y = ACF)) +
17    geom_hline(yintercept = c(-bounds, bounds)) +
18    geom_hline(yintercept = 0) +
19    geom_segment(aes(xend = Lag, yend = 0)) +
20    labs(x = "Lag", y = "ACF", title = "Sample
      Autocorrelation Function (ACF)") +
21    ylim(-1, 1)+
22    theme_minimal()

```

---

### R code Exa 1.5.1 Moving average of strikes

```

1  # Page No. 22
2  # Downloading link: https://storage.googleapis.com/springer-extras/zip/2002/978-0-387-21657-7.zip
3  library(ggplot2)
4  library(zoo)
5  strike<- read.csv("STRIKES.TSM", header =FALSE)
6  colnames(strike)[1] <- "Strikes"
7  start_year=1951
8  end_year=1980
9  window_size <- 5
10 strike$Moving_Avg <- rollmean(strike$Strikes, k =
      window_size, fill = NA)
11 strike$residuals <- strike$Strikes-strike$Moving_Avg
12 # Figure 1-18

```

```

13 ggplot()+
14   geom_line(data=strike, aes(x = seq(start_year, end_
      year), y=Moving_Avg))+
15   geom_point(data=strike, aes(x = seq(start_year, end
      _year), y=strike$ Strikes))+
16   labs(x = "Year", y = "Strikes", title = "Strikes
      Data with Moving Average")+
17   theme_minimal()
18 # Figure 1-19
19 ggplot(data=strike, aes(x = seq(start_year, end_year)
      , y=residuals))+
20   geom_line()+
21   geom_point()+
22   labs(x = "Year", y = "Strikes", title = "Strikes
      Data residuals")+
23   theme_minimal()

```

---

#### R code Exa 1.5.2 Smooth exponential and low pass filter

```

1 # Page No. 24
2 # Downloading link: https://storage.googleapis.com/springer-extras/zip/2002/978-0-387-21657-7.zip
3 library(itsmr)
4 strike<- read.csv("STRIKES.TSM", header = FALSE)
5 colnames(strike)[1] <- "Strikes"
6 # Figure 1-21
7 plot(smooth.exp(ts(strike$Strikes), 0.4))
8 lines(smooth.exp(ts(strike$Strikes), 0.4))
9 # Figure 1-22
10 plot(smooth.fft(ts(strike$Strikes), 0.4))
11 lines(smooth.fft(ts(strike$Strikes), 0.4))

```

---

#### R code Exa 1.5.3 Differenced series

```

1 # Page No. 11
2 # Downloading link: https://storage.googleapis.com/springer-extras/zip/2002/978-0-387-21657-7.zip
3 library(ggplot2)
4 library(pracma)
5 library(dplyr)
6 uspop= read.delim("USPOP.TSM", header = FALSE)
7 colnames(uspop)[1] <- "population"
8 start_year=1790
9 num_repeated=21
10 interval=10
11 uspop$years <- seq_len(num_repeated) * interval+
    start_year
12 diff2 <- diff(diff(uspop$population))
13 uspop <- slice(uspop, -(1:2))
14 uspop$diff2 <- diff2
15 ggplot(uspop, aes(x = years, y = diff2)) +
16   geom_point()+
17   geom_line() +
18   labs(title = "Second-Order Differences of
    Population Data",
19         x = "Years", y = "Second-Order Differences")+
20   theme_minimal()

```

---

#### R code Exa 1.5.4 Deseasonalization and seasonal component

```

1 # Page No. 28
2 # Downloading link: https://storage.googleapis.com/springer-extras/zip/2002/978-0-387-21657-7.zip
3 library(ggplot2)
4 library(pracma)
5 deaths<-read.delim("DEATHS.TSM", header =FALSE)
6 deaths$years<- seq(as.Date("1973-01-01"), as.Date("
    1978-12-01"), by = "month")
7 period <- 12

```



```

8 colnames(deaths)[1] <- "deaths"
9 decomposition <- decompose(ts(deaths$deaths,
    frequency = period))
10 seasonal_component <- decomposition$seasonal
11 deseasonalized_data <- deaths$deaths - seasonal_
    component
12 deseasonalized_df <- data.frame(years = deaths$years
    , deseasonalized_deaths = deseasonalized_data)
13 seasonal_component_df <- data.frame(years = deaths$
    years, seasonal_component = seasonal_component)
14 # Figure 1-24
15 ggplot(deseasonalized_df, aes(x = years, y =
    deseasonalized_deaths)) +
16   geom_line(color = "blue") +
17   geom_point()+
18   labs(x = "Years", y = "Deseasonalized Deaths",
    title = "Deseasonalized Deaths") +
19   theme_minimal()
20 # Figure 1-25
21 ggplot(seasonal_component_df, aes(x = years, y =
    seasonal_component)) +
22   geom_line(color = "red") +
23   geom_point()+
24   labs(x = "Years", y = "Seasonal Component", title
    = "Seasonal Component") +
25   theme_minimal()

```

---

### R code Exa 1.5.5 Estimation of seasonal component

```

1 # Page No. 28
2 # Downloading link: https://storage.googleapis.com/springer-extras/zip/2002/978-0-387-21657-7.zip
3 library(ggplot2)
4 library(dplyr)
5 deaths= read.delim("DEATHS.TSM", header = FALSE)

```

```

6 colnames(deaths)[1] <- "deaths"
7 deaths$months=seq(as.Date("1973-01-01"), as.Date("
  1978-12-01"),by='month')
8 diff1 <- diff(deaths$deaths, lag = 12)
9 deaths <- slice(deaths, -(1:12))
10 deaths$diff1 <- diff1
11 # Figure 1-26
12 ggplot(deaths, aes(x = months, y = diff1)) +
13   geom_point()+
14   geom_line() +
15   labs(title = "First-Order Differences of deaths
    Data",
16         x = "months", y = "First-Order Differences")+
17   theme_minimal()
18 # Figure 1-27
19 diff2 <- diff(deaths$diff1)
20 deaths <- slice(deaths, -1)
21 deaths$diff2 <- diff2
22 ggplot(deaths, aes(x = months, y = diff2)) +
23   geom_point()+
24   geom_line() +
25   labs(title = "Second-Order Differences of deaths
    Data",
26         x = "months", y = "Second-Order Differences")+
27   +
28   theme_minimal()

```

---

### R code Exa 1.6.1 ACF on signal data

```

1 # Page No. 33
2 # Downloading link: https://storage.googleapis.com/springer-extras/zip/2002/978-0-387-21657-7.zip
3 signal<- read.delim("SIGNAL.TSM", header = FALSE)
4 colnames(signal)[1] <- "signals"
5 acf_values <- acf(signal$signals, plot = FALSE)$acf

```

```
6 n <- length(signal$signals)
7 conf_bound <- 1.96 / sqrt(n)
8 plot(acf_values, ylim = c(-conf_bound, conf_bound),
9       main = "Sample Autocorrelation Function (ACF)",
10      ylab = "ACF", xlab = "Lag", type = "h")
11 abline(h = c(-conf_bound, conf_bound), col = "red",
12        lty = 2)
12 abline(h = 0, lty = 2)
```

---

# Chapter 2

## Stationary Processes

R code Exa 2.4.3 MA1 Process

```
1 # Page No. 53
2 n <- 200
3 set.seed(123)
4 Z <- rnorm(n)
5 X <- numeric(n)
6 X[1] <- Z[1]
7 for (i in 2:n) {
8   X[i] <- Z[i] - 0.8 * Z[i-1]
9 }
10 acf_values <- acf(X, plot = FALSE)$acf
11 plot(0:40, acf_values[1:41], type = "h", ylim = c
      (-1, 1),
12       xlab = "Lag", ylab = "ACF", main = "Sample
      Autocorrelation Function for MA(1)")
13 abline(h = c(-1.96/sqrt(n), 1.96/sqrt(n)), col = "
      red", lty = 2)
14 abline(h = 0, col = "blue", lty = 1)
```

---

R code Exa 2.4.4 AR1 Process

```

1 #..
2 # Page No. 54
3 # Downloading link: https://storage.googleapis.com/springer-extras/zip/2002/978-0-387-21657-7.zip
4 hudson= read.csv("LAKE.TSM")
5 names(hudson)[names(hudson) == "X10.38"] <- "level"
6 start_year=1876
7 end_year=1972
8 hudson$years <- seq(start_year, end_year)
9 fit<-lm(level~years, data = hudson)
10 residuals <- resid(fit)
11 residuals_df <- data.frame(years = hudson$years,
12                             residuals = residuals)
12 n <- nrow(residuals_df)
13 phi <- 0.791
14 model_acf <- function(i) {
15   phi^i
16 }
17 confidence_bounds <- function(i) {
18   1.96 * (n^(-0.5)) * sqrt(((1 - (phi^(2*i))) * (1 +
19     (phi^2))) / (1 - (phi^2)))
20 }
21 acf_values <- acf(residuals_df$residuals, plot =
22   FALSE)$acf
23 upper_conf_bounds <- sapply(1:40, function(i) {
24   confidence_bounds(i) + (phi^i)
25 })
26 lower_conf_bounds <- sapply(1:40, function(i) {
27   (phi^i) - confidence_bounds(i)
28 })
29 plot(0:40, acf_values[1:41], type = "h", ylim = c
30   (-1, 1),
31   xlab = "Lag", ylab = "ACF", main = "Sample
32     Autocorrelation Function of Residuals (AR(1)
33     )")
34 lines(1:40, upper_conf_bounds, col = "red", lty = 2)
35 lines(1:40, lower_conf_bounds, col = "red", lty = 2)
36

```

```

32 # Plot the model ACF
33 points(1:40, sapply(1:40, model_acf), type = "b",
        col = "blue")

```

---

### R code Exa 2.5.5 Durbin Levinson and innovations algorithm

```

1 # Page no. 64
2 compute_autocovariance <- function(phi) {
3   gamma_0 <- 1 + phi^2
4   gamma_1 <- -phi
5   return(list(gamma_0 = gamma_0, gamma_1 = gamma_1))
6 }
7 innovation_algorithm <- function(gamma) {
8   theta_11 <- -gamma$gamma_1 / gamma$gamma_0
9   return(list(theta_11 = theta_11))
10 }
11 durbin_levinson_algorithm <- function(gamma) {
12   phi_11 <- gamma$gamma_1 / gamma$gamma_0
13   sigma_1_squared <- gamma$gamma_0 * (1 - phi_11^2)
14   return(list(phi_11 = phi_11, sigma_1_squared =
15     sigma_1_squared))
16 }
17 phi <- 0.9
18 gamma <- compute_autocovariance(phi)
19 theta <- innovation_algorithm(gamma)
20 phi_result <- durbin_levinson_algorithm(gamma)
21 cat(paste0("theta_11 = ", theta$theta_11, "\n"))
22 cat(paste0("phi_11 = ", phi_result$phi_11, "\n"))

```

---

# Chapter 3

## ARMA Models

R code Exa 3.1.1 ARMA 1 1

```
1 # Page no.76
2 ar_params <- c(0.5)
3 ma_params <- c(0.4)
4 is_invertible <- function(ma_params) {
5   roots <- polyroot(c(1, ma_params))
6   all(abs(roots) > 1)
7 }
8
9 invertibility_status <- is_invertible(ma_params)
10 invertibility_status
```

---

R code Exa 3.1.2 AR2 Process

```
1 # Page no.76
2 # Coefficients of AR(2) model
3 phi1 <- 0.7
4 phi2 <- -0.1
5 poly_coefs <- c(1, -phi1, -phi2)
```

```

6 roots <- polyroot(poly_coefs)
7 cat("Roots of the characteristic polynomial (zeros
    of the AR(2) process):\n")
8 cat(roots, "\n")

```

---

### R code Exa 3.1.3 ARMA 2 1

```

1 # Page no. 77
2 ar_params <- c(-0.75, 0.5625)
3 ma_params <- c(1.25)
4 is_invertible <- function(ma_params) {
5   roots <- polyroot(c(1, ma_params))
6   all(abs(roots) > 1)
7 }
8 invertibility_status <- is_invertible(ma_params)
9 invertibility_status

```

---

### R code Exa 3.2.4 General AR2 process

```

1 # Page No. 80
2 # Figure 3-1
3 library(stats)
4 xi1 <- 2
5 xi2 <- 5
6 phi1 <- 1/xi1 + 1/xi2
7 phi2 <- -(1/xi1) * (1/xi2)
8 set.seed(123)
9 n <- 1000
10 ar_process <- arima.sim(model = list(ar = c(phi1,
    phi2)), n = n)
11 acf(ar_process, main = "Sample ACF of AR(2) Process"
    )
12 # Figure 3-2

```



```

13 xi1 <- 10/9
14 xi2 <- 2
15 phi1 <- 1/xi1 + 1/xi2
16 phi2 <- -(1/xi1) * (1/xi2)
17 ar_process <- arima.sim(model = list(ar = c(phi1,
      phi2)), n = n)
18 acf(ar_process, main = "Sample ACF of AR(2) Process"
    )
19 # Figure 3-3
20 xi1 <- -10/9
21 xi2 <- 2
22 phi1 <- 1/xi1 + 1/xi2
23 phi2 <- -(1/xi1) * (1/xi2)
24 ar_process <- arima.sim(model = list(ar = c(phi1,
      phi2)), n = n)
25 acf(ar_process, main = "Sample ACF of AR(2) Process"
    )
26
27 # Figure 3-4
28 xi1 <- complex(real = 2/3, imaginary = 2*sqrt(3)/3)
29 xi2 <- complex(real = 2/3, imaginary = -2*sqrt(3)/3)
30 phi1 <- Re(1/xi1 + 1/xi2)
31 phi2 <- Re(-(1/xi1) * (1/xi2))
32 ar_process <- arima.sim(model = list(ar = c(phi1,
      phi2)), n = n)
33 acf(ar_process, main = "Sample ACF of AR(2) Process"
    )

```

---

### R code Exa 3.2.8 Overshorts series

```

1 # Page No. 84
2 # Downloading link: https://storage.googleapis.com/springer-extras/zip/2002/978-0-387-21657-7.zip
3 oshorts <- read.csv("OSHORTS.TSM", header = FALSE)
4 colnames(oshorts)[1] <- "overshorts"

```

```

5 oshorts$days <- seq(1,nrow(oshorts))
6 # Figure 3-5
7 plot(oshorts$days,oshorts$overshorts, xlab = "Days",
      ylab = "Overshorts",
8      type = 'o', col = "blue")
9 abline(h=0)
10 # Figure 3-6
11 acf_result <- acf(oshorts$overshorts, plot = FALSE)
12 n <- length(oshorts)
13 bounds <- 1.96 * ((1 + 2 * acf_result$acf[2]^2)^(1/
14 2)) / sqrt(n)
15 plot(acf_result, main = "Sample ACF with Bounds")
16 print(mean(oshorts$overshorts))
17 acvf<-acf(oshorts$overshorts, plot= FALSE, type = '
18 covariance')
19 print(acvf$acf[1])
20 print(acvf$acf[2])

```

---

### R code Exa 3.2.9 The sunspot numbers

```

1 # Page No. 86
2 # Downloading link: https://storage.googleapis.com/springer-extras/zip/2002/978-0-387-21657-7.zip
3 library(ggplot2)
4 spots<- read.csv("SUNSPOTS.TSM",header = FALSE)
5 colnames(spots)[1] <- "sunspots"
6 pacf_result <- pacf(spots, plot = FALSE)
7 bounds <- 1.96 / sqrt(100)
8 plot(pacf_result, main = "Sample PACF")
9 print(pacf_result)
10 acvf<-acf(spots$sunspots, plot= FALSE, type = '
11 covariance')
12 print(acvf$acf[1])
13 print(acvf$acf[2])
14 print(acvf$acf[3])

```

---

### R code Exa 3.3.4 Numerical prediction of ARMA 2 3

```
1 # Page no. 90
2 # Answer may vary due to randomization in simulation
3 library(forecast)
4 ar_params <- c(1,-0.24)
5 ma_params <- c(0.4, 0.2, 0.1)
6 set.seed(46)
7 n <- 10
8 arma_process <- arima.sim(model = list(ar = ar_
    params, ma = ma_params), n = n)
9 print(arma_process)
10 acf_values <- acf(arma_process, type="covariance",
    plot=FALSE)$acf
11 gamma_0 <- acf_values[1]
12 gamma_1 <- acf_values[2]
13 gamma_2 <- acf_values[3]
14 cat("gamma_0 =", gamma_0, "\n")
15 cat("gamma_1 =", gamma_1, "\n")
16 cat("gamma_2 =", gamma_2, "\n")
17 innovations_algorithm <- function(arma_process, n_
    steps) {
18   n <- length(arma_process)
19   predictions <- numeric(n_steps)
20   e <- numeric(n + n_steps)
21   phi <- numeric(n + n_steps)
22   theta <- numeric(n + n_steps)
23   for (i in 1:n_steps) {
24     predictions[i] <- sum(ar_params * arma_process[(
        n-i+1):(n-i+2)])
25     + sum(ma_params * e[(n-i+1):(n-i+3)])
26     e[n+i] <- arma_process[i] - predictions[i]
27   }
28   return(predictions)
```

```

29 }
30 predictions <- innovations_algorithm(arma_process,
    10)
31 print(predictions)

```

---

### R code Exa 3.3.5 h step prediction of ARMA

```

1 # Page no. 91
2 # Downloading link: https://storage.googleapis.com/springer-extras/zip/2002/978-0-387-21657-7.zip
3 library(forecast)
4 ar_params <- c(1, -0.24)
5 ma_params <- c(0.4, 0.2, 0.1)
6 E334 <- read.delim("E334.TSM", header = FALSE)
7 colnames(E334)[1] <- "E"
8 Ets <- ts(E334$E)
9 arma_model <- Arima(Ets, order=c(2, 0, 3))
10 forecasts <- forecast(arma_model, h=10)
11 cat("\nForecasted values for the next 10 steps:\n")
12 print(forecasts$fitted)

```

---

# Chapter 4

## Spectral Analysis

**R code Exa 4.1.2** Linear combination of sinusoids

```
1 # Page no. 101
2 # Answer may vary due to randomization
3 library(ggplot2)
4 k <- 2
5 omega <- seq(pi/4, pi/6, length.out = k)
6 sigma2 <- 9
7 t <- 1:100
8 set.seed(123)
9 A <- rnorm(k, mean = 0, sd = sqrt(sigma2))
10 B <- rnorm(k, mean = 0, sd = sqrt(sigma2))
11 X_t <- sapply(t, function(ti) {
12   sum(A * cos(omega * ti) + B * sin(omega * ti))
13 })
14 df <- data.frame(Time = t, Value = X_t)
15 ggplot(df, aes(x = Time, y = Value)) +
16   geom_line() +
17   geom_point() +
18   ggtitle("Sample Path") +
19   xlab("Time") +
20   ylab("X(t)") +
21   theme_minimal()
```

```

22 F_lambda <- function(lambda, omega, sigma2) {
23   sapply(lambda, function(l) {
24     sum(sigma2 * (0.5 * (1 >= -omega & l < omega) +
25       1.0 * (l >= omega)))
26   })
27 lambda <- seq(-pi, pi, length.out = 1000)
28 F_values <- F_lambda(lambda, omega, sigma2)
29 df_F <- data.frame(Lambda = lambda, F_Lambda = F_
  values)
30 ggplot(df_F, aes(x = Lambda, y = F_Lambda)) +
31   geom_step() +
32   ggtitle("Spectral Distribution Function F( )") +
33   xlab(" ") +
34   ylab("F( )") +
35   theme_minimal()

```

---

#### R code Exa 4.1.4 Spectral density of AR 1

```

1 # Page no. 103
2 library(ggplot2)
3 library(stats)
4 set.seed(123)
5 n <- 1000
6 # Figure 4-3
7 phi <- 0.7
8 sigma2 <- 1
9 density <- function(lambda, phi, sigma2) {
10   1 / (2 * pi) * sigma2 / (1 + phi^2 - 2 * phi * cos
11     (lambda))
12 }
13 lambda <- seq(0, pi, length.out = 1000)
14 values <- density(lambda, phi, sigma2)
15 df_spectral <- data.frame(Lambda = lambda,
  SpectralDensity = values)

```

```

15 ggplot(df_spectral, aes(x = Lambda, y =
    SpectralDensity)) +
16   geom_line() +
17   ggtitle("Spectral Density") +
18   xlab(" ") +
19   ylab("Spectral Density") +
20   theme_minimal()
21 # Figure 4-4
22 phi <- -0.7
23 sigma2 <- 1
24 density <- function(lambda, phi, sigma2) {
25   1 / (2 * pi) * sigma2 / (1 + phi^2 - 2 * phi * cos
    (lambda))
26 }
27 lambda <- seq(0, pi, length.out = 1000)
28 values <- density(lambda, phi, sigma2)
29 df_spectral <- data.frame(Lambda = lambda,
    SpectralDensity = values)
30 ggplot(df_spectral, aes(x = Lambda, y =
    SpectralDensity)) +
31   geom_line() +
32   ggtitle("Spectral Density") +
33   xlab(" ") +
34   ylab("Spectral Density") +
35   theme_minimal()
36 # Figure 4-5
37 phi <- 0.7
38 ar_process <- arima.sim(model = list(ar = c(phi)), n
    = n)
39 acf(ar_process, main = "ACF of AR(1) Process")
40 # Figure 4-6
41 phi <- -0.7
42 ar_process <- arima.sim(model = list(ar = c(phi)), n
    = n)
43 acf(ar_process, main = "ACF of AR(1) Process")

```

---

### R code Exa 4.1.5 Spectral density of MA 1

```
1 # Page no. 105
2 library(ggplot2)
3 theta <- 0.9
4 sigma2 <- 1
5 density <- function(lambda, theta, sigma2) {
6   sigma2 / (2 * pi) * (1 + theta^2 + 2 * theta * cos
7     (lambda))
8 }
9 lambda <- seq(0, pi, length.out = 1000)
10 values <- density(lambda, theta, sigma2)
11 df_spectral <- data.frame(Lambda = lambda,
12   SpectralDensity = values)
13 # Figure 4-7
14 ggplot(df_spectral, aes(x = Lambda, y =
15   SpectralDensity)) +
16   geom_line() +
17   ggtitle("Spectral Density of MA(1) Process") +
18   xlab(expression(lambda)) +
19   ylab(expression(f(lambda))) +
20   theme_minimal()
21 # Figure 4-8
22 theta <- -0.9
23 sigma2 <- 1
24 density <- function(lambda, theta, sigma2) {
25   sigma2 / (2 * pi) * (1 + theta^2 + 2 * theta * cos
26     (lambda))
27 }
28 lambda <- seq(0, pi, length.out = 1000)
29 values <- density(lambda, theta, sigma2)
30 df_spectral <- data.frame(Lambda = lambda,
31   SpectralDensity = values)
32 ggplot(df_spectral, aes(x = Lambda, y =
```



```

    SpectralDensity)) +
28   geom_line() +
29   ggtitle("Spectral Density of MA(1) Process") +
30   xlab(expression(lambda)) +
31   ylab(expression(f(lambda))) +
32   theme_minimal()

```

---

### R code Exa 4.2.2 Sunspot numbers spectral density

```

1 # Page No. 110
2 # Downloading link: https://storage.googleapis.com/springer-extras/zip/2002/978-0-387-21657-7.zip
3 library(ggplot2)
4 library(TSA)
5 library(stats)
6 library(itsmr)
7 spots= read.csv("SUNSPOTS.TSM", header =FALSE)
8 colnames(spots)[1]<- "sunspots"
9 periodogram <- spec.pgram(spots, log = "no", plot =
    FALSE)
10 freq <- periodogram$freq
11 spec <- periodogram$spec
12 weights <- rep(1/3, 3)
13 freq <- freq * (2 * pi)
14 smoothed_spec <- stats::filter(spec, filter=weights,
    sides=2)
15 # Figure 4-9
16 p <- periodogram(ts(spots$sunspots), q = 1, opt = 0)
17 plot(p$freq,(p$spec)/(2*pi), type = "o-", pch=19,
    xlab = "frequency", ylab = "spectral density")
18 # Figure 4-10
19 df <- data.frame(freq = freq, smoothed_spec =
    smoothed_spec)
20 ggplot(df, aes(x = freq, y = smoothed_spec)) +
21   geom_line() +

```

```

22   scale_x_continuous(limits = c(0, pi)) +
23   labs(
24     x = expression(lambda),
25     y = expression(hat(f)(lambda)),
26     title = "Spectral Density Estimate"
27   ) +
28   theme_minimal()
29 # Figure 4-11
30 weights <- c(1/15, 2/15, 3/15, 3/15, 3/15, 2/15, 1/
15)
31 smoothed_spec <- stats::filter(spec, filter=weights,
sides=2)
32 df <- data.frame(freq = freq, smoothed_spec =
smoothed_spec)
33 ggplot(df, aes(x = freq, y = smoothed_spec)) +
34   geom_line() +
35   scale_x_continuous(limits = c(0, pi)) +
36   labs(
37     x = expression(lambda),
38     y = expression(hat(f)(lambda)),
39     title = "Spectral Density Estimate"
40   ) +
41   theme_minimal()

```

---

#### R code Exa 4.4.1 Spectral density of AR 2

```

1 # Page 112
2 library(ggplot2)
3 D_q <- function(lambda, q) {
4   if (lambda == 0) {
5     return(1)
6   } else {
7     return(sin((q + 0.5) * lambda) / ((2 * q + 1) *
sin(lambda / 2)))
8   }

```

```

9 }
10 q <- 10
11 lambda <- seq(0, pi, length.out = 1000)
12 D_10 <- sapply(lambda, D_q, q = q)
13 df <- data.frame(lambda = lambda, D_10 = D_10)
14 ggplot(df, aes(x = lambda, y = D_10)) +
15   geom_line() +
16   labs(
17     x = expression(lambda),
18     y = expression(D[10](lambda)),
19     title = "Transfer Function D[10](lambda) for
              Simple Moving-Average Filter"
20   ) +
21   theme_minimal()
22 # Figure 4-13
23 ideal_low_pass <- function(lambda, wc) {
24   ifelse(abs(lambda) <= wc, 1, 0)
25 }
26 wc <- pi / 4
27 q_values <- c(2, 10)
28 ideal_values <- ideal_low_pass(lambda, wc)
29 D_2_values <- sapply(lambda, D_q, q = 2)
30 D_10_values <- sapply(lambda, D_q, q = 10)
31 df <- data.frame(
32   lambda = rep(lambda, 3),
33   value = c(ideal_values, D_2_values, D_10_values),
34   type = factor(rep(c("Ideal", "q = 2", "q = 10"),
                      each = length(lambda)))
35 )
36 ggplot(df, aes(x = lambda, y = value, color = type))
37   +
38   geom_line() +
39   labs(
40     x = expression(lambda),
41     y = "Transfer Function",
42     title = "Transfer Functions: Ideal Low-Pass
              Filter and Truncated Fourier Approximations"
43   ) +

```

```
43   scale_color_manual(values = c("Ideal" = "black", "  
    q = 2" = "blue", "q = 10" = "red")) +  
44   theme_minimal() +  
45   theme(legend.title = element_blank())
```

---

## Chapter 5

# Modeling and Forecasting with ARMA Processes

R code Exa 5.1.1 The Dow Jones Utilities Index

```
1 # Page No. 126
2 # Downloading link: https://storage.googleapis.com/springer-extras/zip/2002/978-0-387-21657-7.zip
3 library(forecast)
4 library(tseries)
5 dow<- read.csv("DOWJ.TSM", header = FALSE)
6 colnames(dow)[1]<- "jones"
7 dowjones <- ts(dow$jones)
8 dowjones_diff <- diff(dowjones, lag = 1)
9 ar_model <- ar(dowjones_diff, order.max = 1, method
  = "yule-walker")
10 sample_autocovariance <- acf(dowjones_diff, plot =
  FALSE, type = 'covariance')
11 ar_coefficient <- ar_model$ar
12 par(mfrow = c(1, 2))
13 acf(dowjones_diff, main = "ACF of Differenced Series
  ")
14 pacf(dowjones_diff, main = "PACF of Differenced
  Series")
```

```
15 print(sample_autocovariance)
16 print(ar_coefficient)
```

---

### R code Exa 5.1.2 MA 1 model forecasting

```
1 # Page No. 128
2 library(forecast)
3 library(tseries)
4 oshorts<- read.csv("OSHORTS.TSM", header = FALSE)
5 colnames(oshorts)[1]<- "overshorts"
6 ots <- ts(oshorts$overshorts)
7 rho_1 <- acf(ots, plot=FALSE)$acf[2]
8 gamma <- acf(ots, plot = FALSE, type = 'covariance')
9           $acf[1]
10
11 if (abs(rho_1) > 0.5) {
12   theta_hat <- rho_1/abs(rho_1)
13 } else {
14   theta_hat <- (rho_1) * sqrt(4 * rho_1^2 - 4 * rho_
15     1) / (2 * abs(rho_1))
16 }
17 sigma2_hat <- gamma / (1 + theta_hat^2)
18 cat("Estimated theta_hat:", theta_hat, "\n")
19 cat("Estimated sigma2_hat:", sigma2_hat, "\n")
```

---

### R code Exa 5.1.3 Dow jones utilities index using burg model

```
1 # Page No. 131
2 # Downloading link: https://storage.googleapis.com/springer-extras/zip/2002/978-0-387-21657-7.zip
3 library(tseries)
4 library(itsmr)
5 dow<- read.csv("DOWJ.TSM", header = FALSE)
```

```

6 colnames(dow)[1] <- "jones"
7 time_series <- ts(dow$jones)
8 Y_t <- diff(time_series, lag=1)
9 ar_order <- 1
10 burg_model <- burg(Y_t, ar_order)
11 ar_param <- burg_model$phi
12 stderr <- (burg_model$se.phi)
13 aicc <- burg_model$aicc
14 cat("AR(1) model parameter:", ar_param, "\n")
15 cat("AICC:", aicc, "\n")
16 find_conf <- function(param, stderr){
17   low <- param - (stderr*1.96)
18   high <- param + (stderr*1.96)
19   x <- c(low, high)
20   return (x)
21 }
22 confs <- find_conf(ar_param, stderr)
23 cat("95% Confidence Bounds: ", confs)

```

---

#### R code Exa 5.1.4 Modeling on Lake data

```

1 # Page No. 131
2 # Downloading link: https://storage.googleapis.com/springer-extras/zip/2002/978-0-387-21657-7.zip
3 library(tseries)
4 library(itsmr)
5 huron <- read.csv("LAKE.TSM", header=FALSE)
6 colnames(huron)[1] <- 'water'
7 time_series <- ts(huron$water)
8 Y_t <- time_series
9 X_t <- Y_t - 9.0041
10 par(mfrow = c(1, 2))
11 # Figure 5-3
12 acf(X_t, main = "ACF")
13 # Figure 5-4

```

```

14 pacf(X_t, main = "PACF")
15 ar_order <-2
16
17 # Burg model
18 burg_model <- burg(X_t, ar_order)
19 arb_param <- burg_model$phi
20 stderr <- (burg_model$se.phi)
21 aicc <- burg_model$aicc
22 conf_lower <- arb_param - (stderr*1.96)
23 conf_upper <- arb_param + (stderr*1.96)
24 print(" For burg model: ")
25 cat("AR(1) model parameter:", arb_param, "\n")
26 cat("AICC:", aicc, "\n")
27 cat("95% Confidence Bounds: (", conf_lower, ", ", ", ",
      conf_upper, ")\n")
28
29 # Yule walker model
30 yw_model <- yw(X_t, ar_order)
31 ary_param <- yw_model$phi
32 stderr <- (yw_model$se.phi)
33 aicc <- yw_model$aicc
34 conf_lower <- ary_param - (stderr*1.96)
35 conf_upper <- ary_param + (stderr*1.96)
36 print(" For yule walker model: ")
37 cat("AR(1) model parameter:", ary_param, "\n")
38 cat("AICC:", aicc, "\n")
39 cat("95% Confidence Bounds: (", conf_lower, ", ", ", ",
      conf_upper, ")\n")

```

---

#### R code Exa 5.1.5 Estimations on Dow jones utilities index

```

1 # Page No. 134
2 # Downloading link: https://storage.googleapis.com/springer-extras/zip/2002/978-0-387-21657-7.zip
3 library(tseries)

```



```

4 library(itsmr)
5 dow<- read.csv("DOWJ.TSM", header = FALSE)
6 colnames(dow)[1] <- "jones"
7 time_series <- ts(dow$jones)
8 Y_t <- diff(time_series, lag=1)
9 ma_order <- 2
10 inno_model <- ia(Y_t, ma_order, m = 17)
11 ma_param <- inno_model$theta
12 stderr <- (inno_model$se.theta)
13 aicc <- inno_model$aicc
14 stddev_1 <- ma_param[1]/(1.96*stderr[1])
15 stddev_2 <- ma_param[2]/(1.96*stderr[2])
16 wnvar <- inno_model$sigma2
17 cat("MA(2) model parameter:", ma_param, "\n")
18 cat("AICC:", aicc, "\n")
19 print("Standard deviations for first two MA
      parameters:")
20 print(stddev_1);print(stddev_2)
21 cat("White noise variance: ", wnvar)

```

---

#### R code Exa 5.1.6 Estimations on Lake data

```

1 # Page No. 137
2 library(itsmr)
3 library(tseries)
4 huron<- read.csv("LAKE.TSM", header = FALSE)
5 colnames(huron)[1] <- 'water'
6 Y_t <- ts(huron$water)
7 X_t <- Y_t - mean(Y_t)
8 arma_model <- arma(X_t, p=1, q=1)
9 ma_param <- arma_model$theta
10 ar_param <- arma_model$phi
11 stderr_phi <- arma_model$se.phi
12 stderr_theta <- arma_model$se.theta
13 aicc <- arma_model$aicc

```

```

14 stddev_phi <- ar_param/(1.96*stderr_phi)
15 stddev_theta <- ma_param/(1.96*stderr_theta)
16 cat("Estimated AR coefficient: ", ar_param, "\n")
17 cat("Estimated MA coefficient: ", ma_param, "\n")
18 cat("AICC: ", aicc, "\n")
19 cat(" Standard deviations: ", stddev_phi, " ",
      stddev_theta)
20 find_conf <- function(param, stderr){
21   low <- param - (stderr*1.96)
22   high <- param + (stderr*1.96)
23   x <- c(low, high)
24   return (x)
25 }
26 conf_phi <- find_conf(ar_param, stderr_phi)
27 cat("95% Confidence Bounds for phi: ", conf_phi)
28 conf_theta <- find_conf(ma_param, stderr_theta)
29 cat("95% Confidence Bounds for theta: ", conf_theta)

```

---

### R code Exa 5.1.7 Lake data analysis using Hannan algorithm

```

1 # Page No. 138
2 # Downloading link: https://storage.googleapis.com/springer-extras/zip/2002/978-0-387-21657-7.zip
3 library(itsmr)
4 library(tseries)
5 huron<- read.csv("LAKE.TSM", header = FALSE)
6 colnames(huron)[1] <- 'water'
7 time_series <- ts(huron$water)
8 Y_t <- time_series
9 X_t <- Y_t - mean(Y_t)
10 p <- 1
11 q <- 1
12 h_model <- hannan(X_t, p, q)
13 ar_param <- h_model$phi
14 ma_param <- h_model$theta

```

```

15 aicc <- h_model$aicc
16 stderr_phi <- h_model$se.phi
17 stderr_theta <- h_model$se.theta
18 stddev_phi <- ar_param/(1.96*stderr_phi)
19 stddev_theta <- ma_param/(1.96*stderr_theta)
20 cat("Estimated AR coefficient: ", ar_param, "\n")
21 cat("Estimated MA coefficient: ", ma_param, "\n")
22 cat("AICC: ", aicc, "\n")
23 cat(" Standard deviations , phi and theta
      respectively: ", stddev_phi, stddev_theta)
24 find_conf <- function(param, stderr){
25   low <- param - (stderr*1.96)
26   high <- param + (stderr*1.96)
27   x <- c(low, high)
28   return (x)
29 }
30 confs_phi <- find_conf(ar_param,stderr_phi)
31 cat("95% Confidence Bounds for phi: ",confs_phi)
32 confs_theta <- find_conf(ma_param,stderr_theta)
33 cat("95% Confidence Bounds for theta: ",confs_theta)

```

---

#### R code Exa 5.2.4 Burg and yule walker model comparison

```

1 # Page No. 143
2 # Downloading link: https://storage.googleapis.com/springer-extras/zip/2002/978-0-387-21657-7.zip
3 library(itsmr)
4 library(tseries)
5 dow<- read.csv("DOWJ.TSM", header = FALSE)
6 colnames(dow)[1]<- "jones"
7 dowjones <- ts(dow$jones)
8 dowjones_diff <- diff(dowjones, lag = 1)
9 dow_mean_diff <- dowjones_diff - mean(dowjones_diff)
10 p <- 1; q <- 0; n <- length(dow_mean_diff)
11 ywmodel <- yw(dow_mean_diff, p)

```

```

12 bmodel <- burg(dow_mean_diff, p)
13 model <- autofit(dow_mean_diff, p=0:5, q=0:5)
14 aicc <- model$aicc
15 aicc_yw <- ywmodel$aicc
16 aicc_b <- bmodel$aicc
17 LL_yw <- aicc_yw - (2*(p+q+1)*n/(n-p-q-2))
18 LL_b <- aicc_b - (2*(p+q+1)*n/(n-p-q-2))
19 LL <- aicc - (2*(p+q+1)*n/(n-p-q-2))
20 b_param <- bmodel$phi
21 stderr <- model$se.phi
22 ar_param <- model$phi
23 find_conf <- function(param, stderr){
24   low <- param - (stderr*1.96)
25   high <- param + (stderr*1.96)
26   x <- c(low, high)
27   return (x)
28 }
29 confs <- find_conf(ar_param, stderr)
30
31 cat("Minimum AICC:", aicc, "\n")
32 cat("Standard error:", stderr, "\n")
33 cat("95% Confidence Bounds: ", confs)
34 cat("Log likelihood for autofit:", LL, "\n")
35 cat("Parameters in burg model:", b_param, "\n")
36 cat("Log likelihood for yule walker:", LL_yw, "\n")
37 cat("Log likelihood for burg:", LL_b, "\n")

```

---

### R code Exa 5.2.5 Autofit on Lake data

```

1 # Page No. 144
2 # Downloading link: https://storage.googleapis.com/springer-extras/zip/2002/978-0-387-21657-7.zip
3 library(itsmr)
4 library(tseries)
5 hudson <- read.csv("LAKE.TSM", header = FALSE)

```

```

6 colnames(hudson)[1] <- "level"
7 Y_t <- ts(hudson$level)
8 X_t <- Y_t - mean(Y_t)
9 arma_model <- autofit(X_t, p=0:5, q=0:5)
10 aicc <- arma_model$aicc
11 ar_param <- arma_model$phi
12 ma_param <- arma_model$theta
13 stderr_phi <- arma_model$se.phi
14 stderr_theta <- arma_model$se.theta
15 stddev_phi <- ar_param/(1.96*stderr_phi)
16 stddev_theta <- ma_param/(1.96*stderr_theta)
17 find_conf <- function(param, stderr){
18   low <- param - (stderr*1.96)
19   high <- param + (stderr*1.96)
20   x <- c(low, high)
21   return (x)
22 }
23 confs_phi <- find_conf(ar_param, stderr_phi)
24 confs_theta <- find_conf(ma_param, stderr_theta)
25 cat("AICC:", aicc, "\n")
26 cat("AR Parameter:", ar_param, "\n")
27 cat("MA Parameter", ma_param, "\n")
28 cat("Standard deviations for phi and theta:", stddev_
    phi, stddev_theta, "\n")
29 print("95% Confidence intervals:")
30 cat("for phi:", confs_phi, "\n")
31 cat("for theta:", confs_theta, "\n")

```

---

#### R code Exa 5.4.1 Forecasts on overshorts data

```

1 # Page No. 147
2 # Downloading link: https://storage.googleapis.com/springer-extras/zip/2002/978-0-387-21657-7.zip
3 # Answer may vary due to randomization
4 library(tseries)

```

```

5 library(forecast)
6 oshorts<- read.csv("OSHORTS.TSM",header = FALSE)
7 colnames(oshorts)[1]<- "overshorts"
8 Xts <- ts(oshorts$overshorts)
9 best_model <- auto.arima(Xts,max.order = 1, stepwise
    = FALSE, approximation = FALSE)
10 best_model$coef
11 ma_model <- arima(Xts, order = c(0, 0, 1))
12 predictions <- predict(ma_model,7)
13 mean_Xts <- mean(Xts)
14 predicted_values <- as.numeric(predictions$pred)
15 mse <- sqrt(mean((Xts - mean_Xts)^2 ))
16 cat(" Predicted Values:\n")
17 print(predicted_values)
18 cat("Mean Squared Error (MSE):\n")
19 print(mse)

```

---

#### R code Exa 5.5.1 FPE based selection of an AR model for Lake data

```

1 # Page No. 150
2 # Downloading link: https://storage.googleapis.com/springer-extras/zip/2002/978-0-387-21657-7.zip
3 library(tseries)
4 library(itsmr)
5 huron<- read.csv("LAKE.TSM", header = FALSE)
6 colnames(huron)[1] <- 'water'
7 Y_t <- ts(huron$water)
8 X_t <- Y_t - mean(Y_t)
9 ar_orders <- 1:10
10 fpe_values <- numeric(length(ar_orders))
11 sigma_squared_values <- numeric(length(ar_orders))
12 for (p in ar_orders) {
13   ar_model <- arma(X_t, p=p, q=0)
14   n <- length(X_t)
15   sigma_squared <- ar_model$sigma2

```

```

16   fpe_values[p] <- (n + p) / (n - p) * sigma_squared
17   sigma_squared_values[p] <- sigma_squared
18 }
19 for (p in ar_orders) {
20   cat("Order", p, "- FPE:", fpe_values[p], "Sigma^2:",
21       ", sigma_squared_values[p], "\n")
22 }

```

---

### R code Exa 5.5.2 AICC based model selection

```

1 # Page No. 153
2 # Downloading link: https://storage.googleapis.com/springer-extras/zip/2002/978-0-387-21657-7.zip
3 library(forecast)
4 library(tseries)
5 huron<- read.csv("LAKE.TSM", header=FALSE)
6 colnames(huron)[1] <- 'water'
7 Y_t <- ts(huron$water)
8 X_t <- Y_t - mean(Y_t)
9 p <- 1 ; q <- 1
10 best_model2 <- arma(X_t, p=p, q=q)
11 cat("Best ARIMA model based on AICC:\n")
12 print(best_model2$aicc)
13 p <- 2; q <- 0
14 best_model1 <- arma(X_t, p=p, q=q)
15 cat("Best ARIMA model based on AICC:\n")
16 print(best_model1$aicc)

```

---

## Chapter 6

# Nonstationary and Seasonal time series models

R code Exa 6.1.1 ARIMA 1 1 0 Process

```
1 # Page No. 159
2 # Answer may vary due to randomization
3 library(forecast)
4 library(ggplot2)
5 phi <- 0.8
6 sigma2 <- 1
7 n <- 200
8 set.seed(123)
9 Xt <- arima.sim(model = list(order = c(1,1,0), ar =
    phi), n = n, sd = sqrt(sigma2))
10 # Figure 6-1
11 autoplot(Xt) +
12   ggtitle("ARIMA(1,1,0)") +
13   geom_point() +
14   xlab("Time") +
15   ylab("Xt") +
16   theme_minimal()
17 # Figure 6-2
18 acf_plot <- ggAcf(Xt) +
```



```

19 ggtitle("Sample ACF") +
20   theme_minimal()
21 print(acf_plot)
22 # Figure 6-3
23 pacf(Xt, main = "Sample PACF")
24 # Figure 6-4
25 Yt <- diff(Xt)
26 plot(Yt)

```

---

### R code Exa 6.2.1 Burg model on Australian wine data

```

1 # Page no. 168
2 # Downloading link: https://storage.googleapis.com/springer-extras/zip/2002/978-0-387-21657-7.zip
3 # Answer may vary due to specific software features
4 library(forecast)
5 library(tseries)
6 library(itsmr)
7 wine_data <- read.csv("WINE.TSM", header = FALSE)
8 colnames(wine_data)[1] <- 'Sales'
9 winedata <- ts(wine_data$Sales)
10 M <- c("season",12, "trend",1)
11 newwine <- Resid(winedata,M)
12 plot(newwine, type='l')
13 M <- c("log","diff",12)
14 newwine <- Resid(winedata,M)
15 plot(newwine, type='l')
16 acf(newwine)
17 pacf(newwine)
18 Wts <- newwine - mean(newwine)
19 burg_model <- burg(Wts, p=12)
20 print(burg_model)
21 arma_model <- autofit(Wts, p=0:15, q=0)
22 print(arma_model)

```

---

### R code Exa 6.2.2 Autofit for minimum AICC model

```
1 # Page No. 169
2 library(tseries)
3 library(itsmr)
4 huron<- read.csv("LAKE.TSM", header=FALSE)
5 colnames(huron)[1] <- 'water'
6 Y_t <- ts(huron$water)
7 X_t <- Y_t - mean(Y_t)
8 model <- autofit(X_t,p=0:2,q=0:2)
9 cat("Phi:\n", model$phi)
10 cat("Theta:\n", model$theta)
11 cat("Variance:\n", model$sigma2)
12 cat("AICC:\n", model$aicc)
```

---

### R code Exa 6.3.1 Test statistic on simulated data

```
1 # Page no. 171
2 # Answer may vary due to randomization
3 library(forecast)
4 library(tseries)
5 phi <- 0.8
6 sigma2 <- 1
7 n <- 200
8 set.seed(123)
9 X0 <- 0
10 Xt <- arima.sim(model = list(order = c(1,1,0), ar =
    phi), n = n, sd = sigma2)
11 Xt <- c(X0, Xt)
12 dXt <- diff(Xt)
13 Xt_lag1 <- lag(Xt, 1)
14 dXt_lag1 <- lag(dXt, 1)
```

```

15 dXt_lag2 <- lag(dXt, 2)
16 valid_indices <- 4:200
17 reg_data <- data.frame(
18   dXt = dXt[valid_indices - 1],
19   Xt_lag1 = Xt[valid_indices - 1],
20   dXt_lag1 = dXt[valid_indices - 2],
21   dXt_lag2 = dXt[valid_indices - 3]
22 )
23 reg_model <- lm(dXt ~ Xt_lag1 + dXt_lag1 + dXt_lag2,
24   data = reg_data)
24 coeff_Xt_lag1 <- summary(reg_model)$coefficients["Xt_
25   _lag1", "Estimate"]
25 se_Xt_lag1 <- summary(reg_model)$coefficients["Xt_
26   lag1", "Std. Error"]
26 test_statistic <- coeff_Xt_lag1 / se_Xt_lag1
27 cat("Test statistic for unit root:", test_statistic,
28   "\n")

```

---

### R code Exa 6.3.2 Model parameters for overshorts data

```

1 # Page No. 173
2 # Downloading link: https://storage.googleapis.com/springer-extras/zip/2002/978-0-387-21657-7.zip
3 library(tseries)
4 library(forecast)
5 oshorts= read.csv("OSHORTS.TSM", header = FALSE)
6 colnames(oshorts)[1] <- 'overshorts'
7 Xts <- ts(oshorts$overshorts)
8 Y_t <- Xts + 4.035
9 best_model <- auto.arima(Y_t, stepwise = FALSE,
10   approximation = FALSE)
10 print(best_model$coef)
11 print((-2)*logLik(best_model))

```

---

### R code Exa 6.4.1 ARIMA 1 1 0 model on Dow jones utilities index

```
1 # Page No. 176
2 # Downloading link: https://storage.googleapis.com/springer-extras/zip/2002/978-0-387-21657-7.zip
3 library(itsmr)
4 library(tseries)
5 dow<- read.csv("DOWJ.TSM", header = FALSE)
6 colnames(dow)[1]<- "jones"
7 dowjones <- ts(dow$jones)
8 dowjones_diff <- diff(dowjones, lag = 1)
9 M = c("diff", 1)
10 dowj <- Resid(dowjones,M)
11 dowj <- dowj - mean(dowj)
12 p <- 1; q <- 0;
13 bmodel <- burg(dowj, p)
14 cat("Mean squared error",bmodel$sigma2)
15 print(bmodel)
```

---

### R code Exa 6.5.2 ACF of seasonal MA model

```
1 # Page no. 178
2 # Answer may vary due to randomization
3 library(forecast)
4 set.seed(123)
5 n <- 500
6 U_t <- rnorm(n)
7 lag <- 12
8 X_t <- U_t
9 X_t[(lag + 1):n] <- U_t[(lag + 1):n] - 0.4 * U_t[1:(
  n - lag)]
10 acf(X_t, main="ACF")
```

---

**R code Exa 6.5.3** ACF of seasonal AR model

```
1 # Page no. 179
2 # Answer may vary due to randomization
3 library(forecast)
4 set.seed(123)
5 n <- 500
6 U_t <- rnorm(n)
7 X_t <- numeric(n)
8 X_t[1:12] <- U_t[1:12]
9 for (t in (12 + 1):n) {
10   X_t[t] <- U_t[t] + 0.7 * X_t[t - 12]
11 }
12 acf(X_t, main="ACF")
```

---

**R code Exa 6.5.4** ACF of monthly accidental deaths data

```
1 # Page no. 180
2 # Downloading link: https://storage.googleapis.com/springer-extras/zip/2002/978-0-387-21657-7.zip
3 # Answer may vary due to specific software features.
4 library(forecast)
5 library(astsa)
6 library(itsmr)
7 deaths = read.csv("DEATHS.TSM", header = FALSE)
8 colnames(deaths)[1] <- "deaths"
9 deaths$months = seq(as.Date("1973-01-01"), as.Date("1978-12-01"), by = 'month')
10 diff1 <- diff(deaths$deaths, lag = 12)
11 Yt <- ts(diff1, frequency = 12)
12 # Figure 6-17
```

```

13 acf(Yt, main="ACF")
14 best_model <- auto.arima(Yt, seasonal=TRUE, stepwise
    = FALSE, approximation = FALSE)
15 print(best_model)
16 sarima_model <- Arima(Yt, order = c(0, 1, 1),
    seasonal = c(0, 1, 1))
17 model_params <- sarima_model$coef
18 print(model_params)

```

---

#### R code Exa 6.5.5 Forecasting monthly accidental deaths

```

1 # Page no. 180
2 # Answer may vary due to specific software features.
3 library(forecast)
4 library(itsmr)
5 deaths= read.csv("DEATHS.TSM", header = FALSE)
6 dts <- ts(deaths, frequency = 12)
7 dts_diff_12 <- diff(dts, lag = 12)
8 dts_diff_12_1 <- diff(dts_diff_12, lag = 1)
9 dts_mean_corrected <- dts_diff_12_1 - mean(dts_diff_
    12_1)
10 fit <- arma(dts_mean_corrected, p=0, q=13)
11 M <- c("diff", 12, "diff", 1)
12 forecast_values <- forecast(dts, M, fit, h = 6)

```

---

#### R code Exa 6.6.1 GLS based Model parameter estimation

```

1 # Page no. 187
2 # Downloading link: https://storage.googleapis.com/springer-extras/zip/2002/978-0-387-21657-7.zip
3 library(itsmr)
4 library(nlme)
5 oshorts= read.csv("OSHORTS.TSM", header = FALSE)

```

```

6 colnames(oshorts)[1] <- "overshorts"
7 oshorts$time <- seq(1,length(oshorts$overshorts))
8 ots <- ts(oshorts$overshorts)
9 ots <- ots-mean(ots)
10 oshorts$overshorts <- oshorts$overshorts-mean(
    oshorts$overshorts)
11 a <- autofit(ots, p=0, q=1)
12 print(a$theta)
13 cat("OLS beta:",mean(oshorts$overshorts))
14 acv <- acf(oshorts$overshorts,type = 'covariance',
    plot=FALSE)
15 cat("Estimator for beta: ",acv$acf[1]/length(ots))
16 model_formula <- overshorts ~ time
17 gls_model <- gls(model_formula, data = oshorts)
18 summary(gls_model)

```

---

#### R code Exa 6.6.2 Model parameters estimation for Lake data

```

1 # Page no. 189
2 library(forecast)
3 library(nlme)
4 hudson<- read.csv("LAKE.TSM", header = FALSE)
5 colnames(hudson)[1] <- 'level'
6 hudson$t <- seq(1, length(hudson$level))
7 ols_model <- lm(hudson$level ~ hudson$t)
8 ols_residuals <- residuals(ols_model)
9 beta1_hat <- coef(ols_model)[1]
10 cat("OLS estimate of beta1:", beta1_hat, "\n")
11 ar2_model <- Arima(ols_residuals, order=c(2,0,0))
12 phi1_hat <- coef(ar2_model)["ar1"]
13 phi2_hat <- coef(ar2_model)["ar2"]
14 sigma2_hat <- ar2_model$sigma2
15 cat("phi1:",phi1_hat)
16 cat("phi2:",phi2_hat)
17 cat("std. dev.:",sigma2_hat)

```

```
18 glsEstimate() <- gls(lm(level~t),data = hudson)
```

---

### R code Exa 6.6.3 Seat belt legislation

```
1 # Page no. 189
2 # Downloading link: https://storage.googleapis.com/springer-extras/zip/2002/978-0-387-21657-7.zip
3 library(itsmr)
4 library(nlme)
5 library(ggplot2)
6 seat<- read.csv("SBL.TSM", header = FALSE)
7 gt <- read.csv("SBLDIN.TSM", header = FALSE)
8 colnames(gt)[1] <- 'Y'
9 colnames(seat)[1] <- "acc"
10 seat$Years <- seq(as.Date("1975-01-01"), as.Date("1984-12-01"), by = "month")
11 ggplot(seat, aes(x = Years, y = acc)) +
12   geom_point(shape = 15, size = 1) +
13   geom_line() +
14   labs(title = "Road injuries (Jan 1975 - Dec 1984)"
15         ,
16         x = "Months",
17         y = "Injuries") +
18   theme_minimal()
19 # Prediction may differ due to specific software methods
20 Yt <- ts(seat$acc)
21 Xt <- Yt-diff(Yt,lag = 12)
22 data <- data.frame(X = Xt,Y = gt)
23 gls_model <- gls(X~Y, data = data)
24 fitted_values <- fitted(gls_model)
25 seat <-seat[-c(1:12), ]
26 seat$fit <- fitted_values
27 plot(seat$Years,seat$acc, main = "Original Data and Fitted GLS Line",
```



```
27     xlab = "Time", ylab = "Value", type = "o-")
28 lines(seat$Years, fitted_values, col = "red", lwd =
    2)
```

---

# Chapter 7

## Time Series Models for Financial Data

R code Exa 7.2.1 ARCH 1 Series

```
1 # Page no. 199
2 # Answer may vary due to randomization
3 alpha0 <- 1
4 alpha1 <- 0.5
5 n <- 1000
6 set.seed(123)
7 epsilon <- rnorm(n)
8 sigma2 <- numeric(n)
9 y <- numeric(n)
10 for (t in 2:n) {
11   sigma2[t] <- alpha0 + alpha1 * y[t-1]^2
12   y[t] <- sqrt(sigma2[t]) * epsilon[t]
13 }
14 plot(y, type = "l", main = "Simulated ARCH(1)
   Process", xlab = "Time", ylab = "Value")
15 acf(y)
```

---

### R code Exa 7.2.2 Fitting GARCH models to stock data

```
1 # Page No. 201
2 # Downloading link: https://storage.googleapis.com/springer-extras/zip/2002/978-0-387-21657-7.zip
3 library(itsmr)
4 library(tseries)
5 library(rugarch)
6 E1032<- read.csv("E1032.TSM")
7 char_array <- E1032[39:193,]
8 matches <- gregexpr("-?[0-9.]+(?:\\s*[Ee][+-]?[0-9]+)?", char_array)
9 stock <- ts(as.numeric(unlist(regmatches(char_array,
    matches))))
10 garch_spec <- ugarchspec(mean.model = list(armaOrder
    = c(0,0)),
11                           variance.model = list(model
    = "sGARCH", garchOrder
    = c(1,1)))
12 garch_fit <- ugarchfit(data = stock, spec = garch_
    spec)
13 sigma <- sigma(garch_fit)
14 par(mfrow=c(2,1))
15 plot(stock,type = 'l', col = 'blue',ylab = '
    percentage returns')
16 plot(sigma, type = 'l', col = 'red', ylab = '
    Volatility')
```

---

### R code Exa 7.2.3 Fitting ARMA Models Driven by GARCH Noise

```
1 # Page No. 203
2 # Downloading link: https://storage.googleapis.com/springer-extras/zip/2002/978-0-387-21657-7.zip
3 library(itsmr)
4 # Answer may vary due to software specifications
```

```

5 library(forecast)
6 library(tseries)
7 library(rugarch)
8 sunspot<- read.csv("SUNSPOTS.TSM")
9 colnames(sunspot)[1]<- "spots"
10 sunspots<- ts(sunspot$spots)
11 sunspots_mean_corrected <- sunspots - mean(sunspots,
      na.rm = TRUE)
12 fit_arima <- Arima(sunspots_mean_corrected, order =
      c(4,0,3))
13 print(fit_arima)
14 residuals_arima <- fit_arima$residuals
15 p <- 1
16 q <- 1
17 spec <- ugarchspec(variance.model = list(model = "
      sGARCH", garchOrder = c(p, q)),
18                   mean.model = list(armaOrder = c
      (4, 3), include.mean = TRUE),
19                   distribution.model = "norm")
20 fit_garch <- ugarchfit(spec = spec, data = residuals
      _arima)
21 print(fit_garch)
22 n <- as.numeric(length(sunspots_mean_corrected))
23 aicc <- (((-2)*(fit_garch@fit$LLH))*(n/(n-p)))+ (((p
      +q+2)*(2*n))/(n-p-q-2))
24 print(paste("AICC value for the GARCH model:", aicc)
      )
25 print("Parameters of the GARCH(1,1) model:")
26 print(coef(fit_garch))

```

---

### R code Exa 7.5.1 Brownian motion

```

1 # Page no. 213
2 # Answer may vary due to randomization
3 T <- 10; n <- 1000; dt <- T / n

```

```

4 time_points <- seq(0, T, by = dt)
5 set.seed(123)
6 increments <- rnorm(n, mean = 0, sd = sqrt(dt))
7 B_t <- c(0, cumsum(increments))
8 plot(time_points, B_t, type = "l",
9       main = "Standard Brownian Motion B(t)",
10      xlab = "Time", ylab = "B(t)",
11      col = "blue", lwd = 2)

```

---

#### R code Exa 7.5.2 Poisson process

```

1 # Page no. 214
2 lambda <- 5
3 T <- 10
4 set.seed(123)
5 jump_times <- cumsum(rexp(100, rate = lambda))
6 jump_times <- jump_times[jump_times <= T]
7 N_t <- seq_along(jump_times)
8 jump_times <- c(0, jump_times)
9 N_t <- c(0, N_t)
10 plot(jump_times, N_t, type = "s",
11      main = "Poisson Process N(t)",
12      xlab = "Time", ylab = "N(t)",
13      col = "blue", lwd = 2)

```

---

#### R code Exa 7.5.3 Compound Poisson Process

```

1 # Page no. 214
2 lambda <- 5; T <- 10; mu <- 0; sigma <- 1
3 set.seed(123)
4 jump_times <- cumsum(rexp(100, rate = lambda))
5 jump_times <- jump_times[jump_times <= T]

```

```
6 jump_sizes <- rnorm(length(jump_times), mean = mu,
  sd = sigma)
7 X_t <- cumsum(jump_sizes)
8 jump_times <- c(0, jump_times)
9 X_t <- c(0, X_t)
10 plot(jump_times, X_t, type = "s",
11       main = "Compound Poisson Process X(t)",
12       xlab = "Time", ylab = "X(t)",
13       col = "blue", lwd = 2)
```

---

# Chapter 8

## Multivariate Time Series

**R code Exa 8.1.1** Dow Jones and All Ordinaries Indices

```
1 # Page No. 229
2 # Downloading link: https://storage.googleapis.com/springer-extras/zip/2002/978-0-387-21657-7.zip
3 library(forecast)
4 library(tseries)
5 dow<- read.csv("DJO2.TSM", header = FALSE)
6 pc <- read.csv("DJAOPC2.TSM", header = FALSE)
7 colnames(pc)[1]<- "stocks"
8 char_array <- dow[,1]
9 matches <- gregexpr("\\b\\d{3,}\\b", char_array)
10 stock <- as.numeric(unlist(regmatches(char_array,
    matches)))
11 dowjones <- ts(stock[c(TRUE, FALSE)])
12 Aus <- ts(stock[c(FALSE, TRUE)])
13 index <- seq_along(dowjones)
14 plot(index, dowjones, type = 'l', col = 'blue', lwd
    = 2, ylim = range(c(dowjones,1000)),
15      xlab = 'Index', ylab = 'Values', main = 'Dow
    jones and Australian ordinary')
16 lines(index, Aus, col = 'red', lwd = 2)
17
```

```

18 pcs <- separate(pc, col = 1, into = c("dow", "aus"),
    sep = "\\s+")
19 dowjones1 <- ts(as.numeric(pcs$dow))
20 Aus1 <- ts(as.numeric(pcs$aus))
21 acf(dowjones1, main = "Series 1")
22 acf(Aus1, main = "Series 2")
23 ccf1 <- ccf(dowjones1, Aus1, plot = FALSE)
24 positive_lag1 <- ccf1$lag >= 0
25 plot(ccf1$lag[positive_lag1], ccf1$acf[positive_lag1
    ], type = "h",
26     main = "Series 1 * Series 2",
27     xlab = "Lag", ylab = "CCF")
28 abline(h = 0)
29 ccf2 <- ccf(Aus1, dowjones1, plot = FALSE)
30 positive_lag2 <- ccf2$lag >= 0
31 plot(ccf2$lag[positive_lag2], ccf2$acf[positive_lag2
    ], type = "h",
32     main = "Series 2 * Series 1",
33     xlab = "Lag", ylab = "CCF")
34 abline(h = 0)
35 plot(lag(dowjones1, -1), Aus1, main="Scatterplot",
36     xlab="Lagged TS1", ylab="TS2", pch=19)

```

---

### R code Exa 8.1.2 Sales with a leading indicator

```

1 # Page No. 230
2 # Downloading link: https://storage.googleapis.com/springer-extras/zip/2002/978-0-387-21657-7.zip
3 library(forecast)
4 library(tseries)
5 sales<- read.delim("SALES.TSM", header = FALSE)
6 leads<- read.delim("LEAD.TSM", header = FALSE)
7 colnames(sales)[1]<- "sale"
8 colnames(leads)[1]<- "lead"
9 ls2 <- cbind(sales, leads)

```



```

10 lst <- ts(ls2)
11 lst <- diff(lst)
12 par(mfrow = c(2, 2))
13 acf(lst[, 2], main = "Series 1")
14 acf(lst[, 1], main = "Series 2")
15 ccf1 <- ccf(lst[, 1], lst[, 2], plot = FALSE)
16 positive_lag1 <- ccf1$lag >= 0
17 plot(ccf1$lag[positive_lag1], ccf1$acf[positive_lag1
    ], type = "h",
18       main = "Series 2 * Series 1",
19       xlab = "Lag", ylab = "CCF")
20 abline(h = 0)
21 ccf2 <- ccf(lst[,2],lst[,1], plot = FALSE)
22 positive_lag2 <- ccf2$lag >= 0
23 plot(ccf2$lag[positive_lag2], ccf2$acf[positive_lag2
    ], type = "h",
24       main = "Series 1 * Series 2",
25       xlab = "Lag", ylab = "CCF")
26 abline(h = 0)

```

---

### R code Exa 8.3.1 Sample correlations

```

1 # Page No. 239
2 # Downloading link: https://storage.googleapis.com/springer-extras/zip/2002/978-0-387-21657-7.zip
3 library(forecast)
4 library(tseries)
5 E731 <- read.delim("E731A.TSM", header=FALSE)
6 Ets <- ts(E731)
7 par(mfrow = c(2, 2))
8 acf(Ets[, 2], main = "Series 1")
9 acf(Ets[, 1], main = "Series 2")
10 ccf1 <- ccf(Ets[, 1], Ets[, 2], plot = FALSE)
11 positive_lag1 <- ccf1$lag >= 0
12 plot(ccf1$lag[positive_lag1], ccf1$acf[positive_lag1

```

```

      ], type = "h",
13     main = "Series 1 * Series 2",
14     xlab = "Lag", ylab = "CCF")
15 abline(h = 0)
16 ccf2 <- ccf(Ets[,2],Ets[,1],plot = FALSE)
17 positive_lag2 <- ccf2$lag >= 0
18 plot(ccf2$lag[positive_lag2], ccf2$acf[positive_lag2
      ], type = "h",
19     main = "Series 2 * Series 1",
20     xlab = "Lag", ylab = "CCF")
21 abline(h = 0)

```

---

#### R code Exa 8.6.1 Multivariate models fitted on stock data

```

1 # Page No. 249
2 # Downloading link: https://storage.googleapis.com/springer-extras/zip/2002/978-0-387-21657-7.zip
3 # Answer may vary to unspecified function in problem
4 library(tidyr)
5 library(vars)
6 pc <- read.csv("DJAOPC2.TSM", header = FALSE)
7 pcs <- separate(pc, col = 1, into = c("dow", "aus"),
      sep = "\\s+")
8 pcs$dow <- as.numeric(pcs$dow)
9 pcs$aus <- as.numeric(pcs$aus)
10 pcs_ts <- ts(pcs)
11 var_model <- VAR(pcs_ts,p=1,type = "none")
12 summary(var_model)

```

---

#### R code Exa 8.6.2 Multivariate models fitted on sales data

```

1 # Page No. 249

```

```

2 # Downloading link: https://storage.googleapis.com/
  springer-extras/zip/2002/978-0-387-21657-7.zip
3 library(vars)
4 library(tidyr)
5 library(stringr)
6 library(dplyr)
7 ls <- read.csv("LS2.TSM", header = FALSE)
8 colnames(ls)[1] <- "l1"
9 ls$l1 <- trimws(ls$l1, which = "left")
10 lts <- separate(ls, col = l1, into = c("ld", "sales"
    ), sep = "\\s+")
11 lts$ld <- as.numeric(lts$ld)
12 lts$sales <- as.numeric(lts$sales)
13 lts <- ts(lts)
14 ltds <- diff(lts, lag = 1)
15 lag <- VARselect(lts, lag.max=10)
16 optimal <- lag$selection
17 estim <- VAR(ltds, p=5, type = "none")
18 summary(estim)
19 estim$varresult

```

---

### R code Exa 8.6.3 VAR 1 model on stock data

```

1 # Page No. 251
2 # Downloading link: https://storage.googleapis.com/
  springer-extras/zip/2002/978-0-387-21657-7.zip
3 library(tidyr)
4 library(itsmr)
5 library(vars)
6 pc <- read.csv("DJAOPC2.TSM", header = FALSE)
7 pcs <- separate(pc, col = 1, into = c("dow", "aus"),
    sep = "\\s+")
8 pcs$dow <- as.numeric(pcs$dow)
9 pcs$aus <- as.numeric(pcs$aus)
10 pcs_ts <- ts(pcs)

```

```
11 var_model <- VAR(pcs_ts,p=1,type = "none")
12 summary(var_model)
13 k <- 9
14 n <- length(pcs_ts)
15 log_likelihood <- LogLik(var_model)
16 aicc <- -2 * log_likelihood + 2 * k + (2 * k * (k +
    1)) / (n - k - 1)
17 arm <- autofit(ts(pcs$aus),p=0:2,q=0)
18 print(arm)
```

---

# Chapter 9

## State Space Models

**R code Exa 9.2.1** Random walk plus noise model

```
1 # Page no.261
2 # Answer varies due to randomness
3 set.seed(46)
4 n <- 100
5 sigma_v <- 4
6 sigma_w <- 8
7 M <- cumsum(rnorm(n, mean = 0, sd = sqrt(sigma_w)))
8 W <- rnorm(n, mean = 0, sd = sqrt(sigma_v))
9 Y <- M + W
10 plot(1:n, M, type = "l", col = "blue", xlab = "Time"
      , ylab = "Value",
11       main = "Random Walk Plus Noise Model")
12 points(1:n, Y, pch = 15, col = "red")
13 acf(diff(Y), lag.max = 20)
```

---

**R code Exa 9.5.2** International airline passengers

```
1 # Page No. 278
```

```

2 # Downloading link: https://storage.googleapis.com/
  springer-extras/zip/2002/978-0-387-21657-7.zip
3 # Adequate data not provided in example
4 library(ggplot2)
5 library(MASS)
6 library(KFAS)
7 airpass <- read.csv("AIRPASS.TSM", header = FALSE)
8 colnames(airpass)[1] <- "pass"
9 ggplot(airpass, aes(x = seq(as.Date("1949-01-01"),
  as.Date("1960-12-01"), by = "month"), y = pass))
  +
10   geom_point() +
11   geom_line() +
12   labs(title = "Air passengers (Jan 1949 - Dec 1960)"
  ,
13         x = "Time",
14         y = "Passengers") +
15   theme_minimal()
16 pass <- ts(airpass$pass)

```

---

### R code Exa 9.8.3 Polio in the USA

```

1 # Page No. 292
2 # Downloading link: https://storage.googleapis.com/
  springer-extras/zip/2002/978-0-387-21657-7.zip
3 library(ggplot2)
4 library(dplyr)
5 polio <- read.csv("POLIO.TSM", header = FALSE)
6 colnames(polio)[1] <- "pol"
7 ggplot(polio, aes(x = seq(as.Date("1970-01-01"), as.
  Date("1983-12-01"), by = "month"), y = pol)) +
8   geom_point() +
9   geom_line() +
10   labs(title = "Polio in US (Jan 1970 - Dec 1983)",
11         x = "Time",

```

```

12     y = "Polio cases") +
13     theme_minimal()
14 polio$Month <- 1:length(polio$pol)
15 polio <- polio %>%
16     mutate(
17         t = Month,
18         u1 = 1,
19         u2 = t / 1000,
20         u3 = cos(2 * pi * t / 12),
21         u4 = sin(2 * pi * t / 12),
22         u5 = cos(2 * pi * t / 6),
23         u6 = sin(2 * pi * t / 6)
24     )
25 model <- lm(pol ~ u1 + u2 + u3 + u4 + u5 + u6, data
26             = polio)
27 polio$Trend <- fitted(model)
28 ggplot(polio, aes(x = Month)) +
29     geom_point(aes(y = pol, color = "Actual Cases")) +
30     geom_line(aes(y = Trend, color = "Trend Estimate")
31              ) +
32     labs(
33         title = "Trend Estimate for Monthly U.S. Polio
34                 Cases",
35         x = "Month",
36         y = "Number of Cases",
37         color = "Legend"
38     ) +
39     scale_color_manual(values = c("Actual Cases" = "
40                                   blue", "Trend Estimate" = "red")) +
41     theme_minimal()

```

---

### R code Exa 9.8.7 Goals Scored by England Against Scotland

```

1 # Page No. 299
2 # Downloading link: https://storage.googleapis.com/

```

```

    springer-extras/zip/2002/978-0-387-21657-7.zip
3 # Answer varies due to inadequate data
4 library(ggplot2)
5 library(tidyr)
6 library(itsmr)
7 goals <- read.table("GOALS.TSM", header = FALSE)
8 colnames(goals)[1] <- "goal"
9 colnames(goals)[2] <- "Year"
10 # Figure 9-8
11 ggplot(goals, aes(x = Year, y = goal)) +
12   geom_point() +
13   geom_line(col='blue') +
14   labs(title = "Goals by England",
15        x = "Years",
16        y = "Goals") +
17   theme_minimal()
18 # Figure 9-9
19 ggplot(na.omit(goals), aes(x = factor(goal))) +
20   geom_bar() +
21   xlab("Goals") +
22   ylab("Count") +
23   ggtitle("Histogram of Goals") +
24   theme_minimal()
25
26 data <- na.omit(goals)
27 delta_hat <- 0.844
28 alpha_0 <- 0.154
29 lambda_0 <- delta_hat / (1 - delta_hat)
30 n <- nrow(data)
31 alpha <- numeric(n); lambda <- numeric(n); pred <-
    numeric(n)
32 alpha[1] <- alpha_0
33 lambda[1] <- lambda_0
34 for (t in 2:n) {
35   alpha[t] <- alpha[t-1] + delta_hat * (data$goal[t
    -1] - alpha[t-1])
36   lambda[t] <- lambda[t-1] + delta_hat * (1 - lambda
    [t-1])

```



```
37   pred[t] <- alpha[t] / (1 + lambda[t])
38 }
39
40 ggplot(data.frame(Time = data$Year, pred = pred),
41        aes(x = Time, y = pred)) +
42   geom_line(color = "blue") +
43   geom_point(data = data, aes(x = Year, y = goal),
44             color = "red") +
45   xlab("Year") +
46   ylab("Goals") +
47   ggtitle("One-Step Predictors for Goals Data") +
48   theme_minimal()
```

---

# Chapter 10

## Forecasting Techniques

**R code Exa 10.1.1** Predicted deaths by ARAR algorithm

```
1 # Page No. 312
2 # Downloading link: https://storage.googleapis.com/springer-extras/zip/2002/978-0-387-21657-7.zip
3 library(itsmr)
4 library(forecast)
5 deaths <- read.csv("DEATHS.TSM", header = FALSE)
6 colnames(deaths)[1] <- "death"
7 dts <- ts(deaths$death)
8 arar_model <- arar(dts, h=24, opt=2)
```

---

**R code Exa 10.2.1** Holt Winters non seasonal forecast

```
1 # Page No. 316
2 # Answer may vary due to the nature of forecast function.
3 # Downloading link: https://storage.googleapis.com/springer-extras/zip/2002/978-0-387-21657-7.zip
4 library(forecast)
```

```

5 deaths <- read.csv("DEATHS.TSM", header = FALSE)
6 colnames(deaths)[1] <- "death"
7 dts <- ts(deaths$death, freq=12, start = 1973)
8 hw_model <- HoltWinters(dts, gamma = FALSE)
9 forecast_values <- forecast::forecast(hw_model, n.
    steps=2)
10 plot(forecast_values, main="Holt-Winters Forecast",
    xlab="Time", ylab="Values")
11 lines(dts, col="blue")

```

---

### R code Exa 10.3.1 Holt Winters seasonal forecast

```

1 # Page No. 316
2 # Downloading link: https://storage.googleapis.com/springer-extras/zip/2002/978-0-387-21657-7.zip
3 library(forecast)
4 deaths <- read.delim("DEATHS.TSM", header = FALSE)
5 colnames(deaths)[1] <- "death"
6 dts <- ts(deaths$death, freq=12, start = 1973)
7 hw_model <- HoltWinters(dts)
8 forecast_values <- forecast::forecast(hw_model, h
    =24)
9 plot(forecast_values, main="Holt-Winters Forecast",
    xlab="Time", ylab="Values")
10 lines(dts, col="blue")

```

---

# Chapter 11

## Further Topics

**R code Exa 11.4.1** Annual Minimum Water Levels in the Nile

```
1 # Page No. 340
2 # Downloading link: https://storage.googleapis.com/springer-extras/zip/2002/978-0-387-21657-7.zip
3 library(ggplot2)
4 nile <- read.csv("NILE.TSM", header = FALSE)
5 colnames(nile)[1] <- "water"
6 plot(nile$water, xlab="time", ylab="water level", main="
  Nile river", type = 'l')
7 acf(nile$water, main="ACF")
8 best_model <- auto.arima(nile$water, stepwise =
  FALSE, ic="aicc", approximation = FALSE)
9 print(best_model$aicc)
10 best_arfima <- arfima(nile$water, model = best_model)
11 print(best_arfima$aicc)
```

---