

Demand Forecasting Using Time Series

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Import dataset

```
dataPath<-"/Users/anupriyathirumurthy/Documents/AnuBackUp/University/MScA_UoC/Courses/TimeSeries/Project1/Books.csv"
dataset <-read.csv(file=paste(dataPath,"Books.csv",sep="/"))
head(dataset)
```

```
##   ID_LABEL1 Date.Ordered ID.. Format Pub.Status Pub.Status.Description
## 1      124    8/24/17     1     C         1         Active Title
## 2      124   11/29/17     1     C         1         Active Title
## 3      124    9/5/18     1     C         1         Active Title
## 4      124    5/21/18     1     C         1         Active Title
## 5      124    6/14/17     1     C         1         Active Title
## 6      124    8/29/18     1     C         1         Active Title
##   SRDP Order.Disc.Class Product.Class Quantity.Ordered Order.Price
## 1    NA          124ND      UCTECH              2           72
## 2    NA          124ND      UCTECH              1           72
## 3    NA          124ND      UCTECH              6           72
## 4    NA          124ND      UCTECH              1           72
## 5    NA          124ND      UCTECH              1           72
## 6    NA          124ND      UCTECH              9           72
##   Disc.Pct Line.Amount
## 1         0         144
## 2        100          0
## 3         0         432
## 4        100          0
## 5        100          0
## 6         0         648
```

```
str(dataset)
```

```
## 'data.frame':   4152 obs. of  13 variables:
## $ ID_LABEL1      : int  124 124 124 124 124 124 124 124 124 124 ...
## $ Date.Ordered   : Factor w/ 683 levels "1/10/17","1/10/18",...: 556 133 670 342 383 576 585 ...
## $ ID..           : int   1 1 1 1 1 1 1 1 1 1 ...
## $ Format          : Factor w/ 5 levels "C","E","O","P",...: 1 1 1 1 1 1 1 1 1 1 ...
## $ Pub.Status     : int   1 1 1 1 1 1 1 1 1 1 ...
## $ Pub.Status.Description: Factor w/ 3 levels "Active Title",...: 1 1 1 1 1 1 1 1 1 1 ...
## $ SRDP           : logi  NA NA NA NA NA NA ...
## $ Order.Disc.Class : Factor w/ 1 level "124ND": 1 1 1 1 1 1 1 1 1 1 ...
## $ Product.Class   : Factor w/ 1 level "UCTECH": 1 1 1 1 1 1 1 1 1 1 ...
## $ Quantity.Ordered : int   2 1 6 1 1 9 -6 1 6 -2 ...
## $ Order.Price     : num   72 72 72 72 72 72 72 72 72 72 ...
## $ Disc.Pct        : int    0 100 0 100 100 0 0 0 0 0 ...
## $ Line.Amount     : Factor w/ 273 levels "-1,080.00","-1,152.00",...: 111 69 196 69 69 232 40 ...
```

Import relevant packages

```
library(forecast)
```

```
## Registered S3 method overwritten by 'xts':
##   method      from
##   as.zoo.xts zoo

## Registered S3 method overwritten by 'quantmod':
##   method      from
##   as.zoo.data.frame zoo

## Registered S3 methods overwritten by 'forecast':
##   method      from
##   fitted.fracdiff   fracdiff
##   residuals.fracdiff fracdiff

library(tseries)
library(lubridate)

##
## Attaching package: 'lubridate'

## The following object is masked from 'package:base':
##
##   date

library(dplyr)

##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:lubridate':
##
##   intersect, setdiff, union

## The following objects are masked from 'package:stats':
##
##   filter, lag

## The following objects are masked from 'package:base':
##
##   intersect, setdiff, setequal, union
```

Step 1: Data clean-up

```
#Rename ISBN column
colnames(dataset)[3] <- "ISBN"

#Separate units ordered vs. returned
dataset$Qty_Ordered <- ifelse(dataset$Quantity.Ordered > 0, dataset$Quantity.Ordered, 0)
dataset$Qty_Returned <- ifelse(dataset$Quantity.Ordered < 0, dataset$Quantity.Ordered, 0)

#Create timeframe identifier
Date.Ordered.Year <- year(as.Date(dataset$Date.Ordered, "%m/%d/%Y"))
Date.Ordered.Year <- as.numeric(paste("20", Date.Ordered.Year, sep = ""))
Date.Ordered.Year <- as.data.frame(Date.Ordered.Year, "%Y")

## Warning in as.data.frame.numeric(Date.Ordered.Year, "%Y"): 'row.names' is
## not a character vector of length 4152 -- omitting it. Will be an error!

#df$Fasta.headers = paste(">", df$Fasta.headers, sep = "")
dataset<- cbind(dataset, Date.Ordered.Year)
```

```

max <- tapply(dataset$Date.Ordered.Year, dataset$ISBN, max)
min <- tapply(dataset$Date.Ordered.Year, dataset$ISBN, min)
min_max <- cbind(min, max)
min_max <- as.data.frame(min_max)
min_max <- cbind(newColName = rownames(min_max), min_max)
rownames(min_max) <- 1:nrow(min_max)
colnames(min_max)[1] <- "ISBN"
min_max$combined <- paste(min_max$min, "-", min_max$max)

merged_dataset <- merge(x = dataset, y = min_max, by = "ISBN", all.x = TRUE)

#Eliminate unnecessary columns
final_dataset <- merged_dataset[, -c(2,5:9,12:13,17:18)]
head(final_dataset)

```

```

##   ISBN Date.Ordered Format Quantity.Ordered Order.Price Qty_Ordered
## 1    1    8/24/17      C                2          72           2
## 2    1   11/29/17      C                1          72           1
## 3    1    9/5/18       C                6          72           6
## 4    1   5/21/18       C                1          72           1
## 5    1   6/14/17       C                1          72           1
## 6    1   8/29/18       C                9          72           9
##   Qty_Returned Date.Ordered.Year   combined
## 1             0             2017 2016 - 2019
## 2             0             2017 2016 - 2019
## 3             0             2018 2016 - 2019
## 4             0             2018 2016 - 2019
## 5             0             2017 2016 - 2019
## 6             0             2018 2016 - 2019

```

```
str(final_dataset)
```

```

## 'data.frame':   4152 obs. of  9 variables:
##  $ ISBN          : int  1 1 1 1 1 1 1 1 1 1 ...
##  $ Date.Ordered   : Factor w/ 683 levels "1/10/17","1/10/18",...: 556 133 670 342 383 576 585 423 5...
##  $ Format          : Factor w/ 5 levels "C","E","O","P",...: 1 1 1 1 1 1 1 1 1 1 ...
##  $ Quantity.Ordered : int  2 1 6 1 1 9 -6 1 6 -2 ...
##  $ Order.Price     : num  72 72 72 72 72 72 72 72 72 72 ...
##  $ Qty_Ordered     : num  2 1 6 1 1 9 0 1 6 0 ...
##  $ Qty_Returned    : num  0 0 0 0 0 0 -6 0 0 -2 ...
##  $ Date.Ordered.Year: num  2017 2017 2018 2018 2017 ...
##  $ combined        : chr  "2016 - 2019" "2016 - 2019" "2016 - 2019" "2016 - 2019" ...

```

Step 2: Split test/train data

```

train_data <- final_dataset[final_dataset$Date.Ordered.Year < "2018",]
test_data <- final_dataset[final_dataset$Date.Ordered.Year >= "2018",]
dim(train_data)

```

```
## [1] 3342    9
```

```
dim(test_data)
```

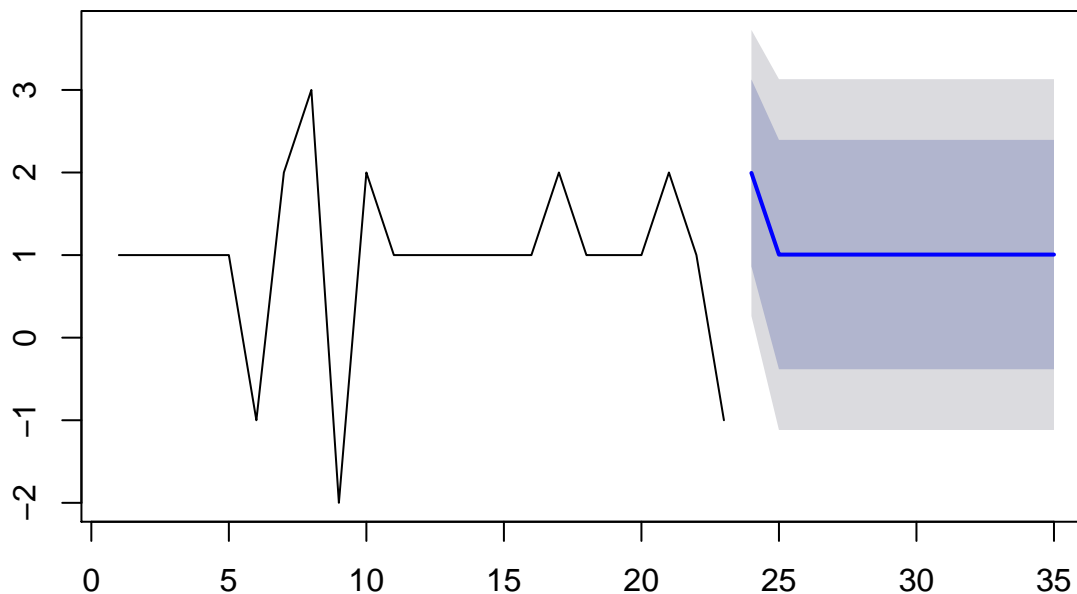
```
## [1] 810    9
```

Step 3: Auto Arima with just one title

```
ISBN_8 <- final_dataset[final_dataset$ISBN == 8,]
train_data_8 <- ISBN_8[ISBN_8$Date.Ordered.Year < "2018",]
test_data_8 <- ISBN_8[ISBN_8$Date.Ordered.Year >= "2018",]

#Arima model
arima_8 <- auto.arima(ISBN_8$Quantity.Ordered)
forecast_8 <- forecast(arima_8, h = 12)
plot(forecast_8)
```

Forecasts from ARIMA(0,0,1) with non-zero mean



```
print(forecast_8)
```

```
##      Point Forecast      Lo 80      Hi 80      Lo 95      Hi 95
## 24      1.994563    0.8620119  3.127114    0.2624756  3.726650
## 25      1.006129   -0.3826485  2.394906   -1.1178229  3.130081
## 26      1.006129   -0.3826485  2.394906   -1.1178229  3.130081
## 27      1.006129   -0.3826485  2.394906   -1.1178229  3.130081
## 28      1.006129   -0.3826485  2.394906   -1.1178229  3.130081
## 29      1.006129   -0.3826485  2.394906   -1.1178229  3.130081
## 30      1.006129   -0.3826485  2.394906   -1.1178229  3.130081
## 31      1.006129   -0.3826485  2.394906   -1.1178229  3.130081
## 32      1.006129   -0.3826485  2.394906   -1.1178229  3.130081
## 33      1.006129   -0.3826485  2.394906   -1.1178229  3.130081
## 34      1.006129   -0.3826485  2.394906   -1.1178229  3.130081
## 35      1.006129   -0.3826485  2.394906   -1.1178229  3.130081
```

```
forecast_8 <- as.vector(forecast_8$mean)
pred <- mean(forecast_8)
pred
```

```
## [1] 1.088498
```

```
test <- mean(test_data_8$Quantity.Ordered)
test
```

```
## [1] 1.4
```

```
smape <- (sum(abs(test-pred)/(abs(test)+abs(pred))))/length(test)
smape
```

```
## [1] 0.1251765
```

Step 4: Auto-arma with all isbn's

```
# Auto Arima for all the titles
```

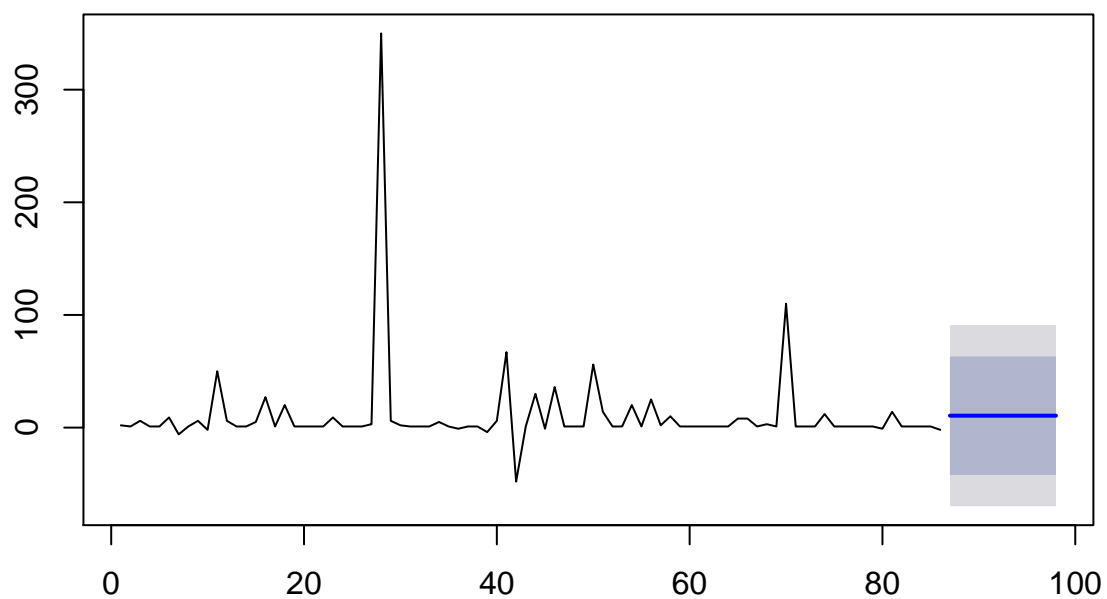
```
isbn_list <- unique(sort(final_dataset$ISBN))
isbn_list
```

```
## [1] 1 2 3 4 5 6 7 8 9 10 11 14 15 16 17 18 19
## [18] 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36
## [35] 37 38 39 40 41 42 43 49 54 56 57 58 59 60 61 62 63
## [52] 86 90 91 92 93 94 95 96 97 103 109 110 128 129 132 165 166
## [69] 172 195 196 197 239 243 244 324 325 364 542
```

```
for (i in isbn_list){
  ISBN <- final_dataset[final_dataset$ISBN == i,]
  train_data_all <- ISBN[ISBN$Date.Ordered.Year < "2018",]
  test_data_all <- ISBN[ISBN$Date.Ordered.Year >= "2018",]
  #Arima model
  arima_all <- auto.arima(ISBN$Quantity.Ordered)
  forecast_all <- forecast(arima_all, h = 12)
  cat("Book ID: ", unique(ISBN$ISBN))
  plot(forecast_all)
  #print(forecast_all)
}
```

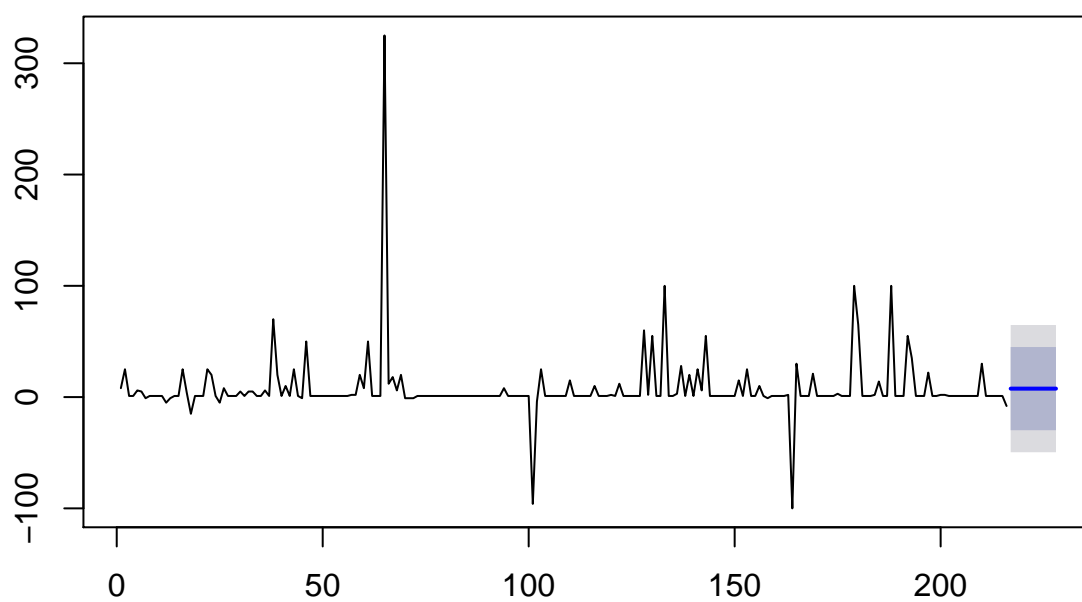
```
## Book ID: 1
```

Forecasts from ARIMA(0,0,0) with non-zero mean



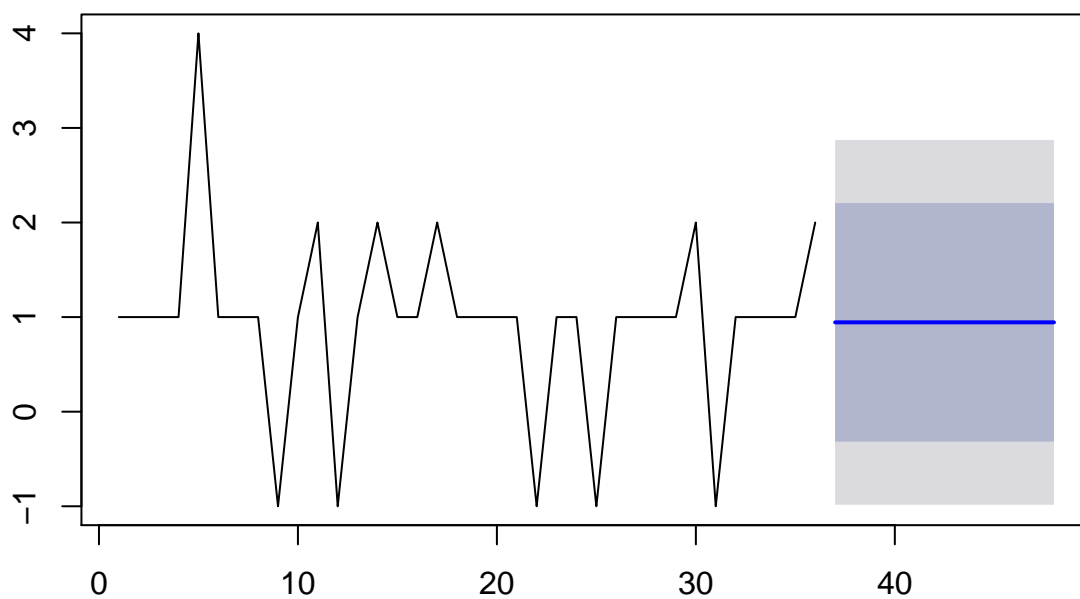
Book ID: 2

Forecasts from ARIMA(0,0,0) with non-zero mean



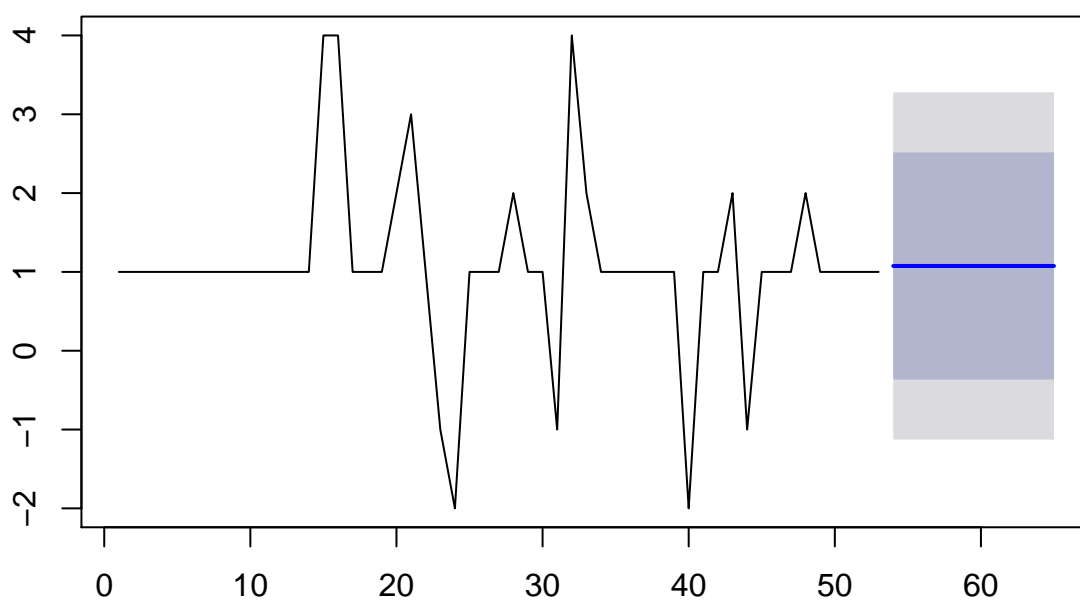
Book ID: 3

Forecasts from ARIMA(0,0,0) with non-zero mean



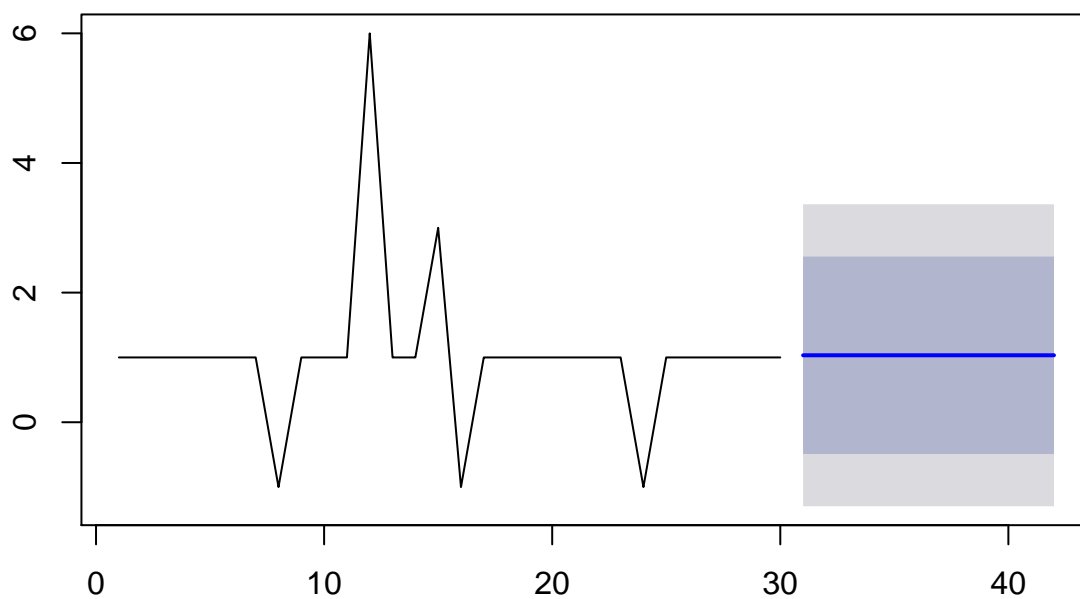
Book ID: 4

Forecasts from ARIMA(0,0,0) with non-zero mean



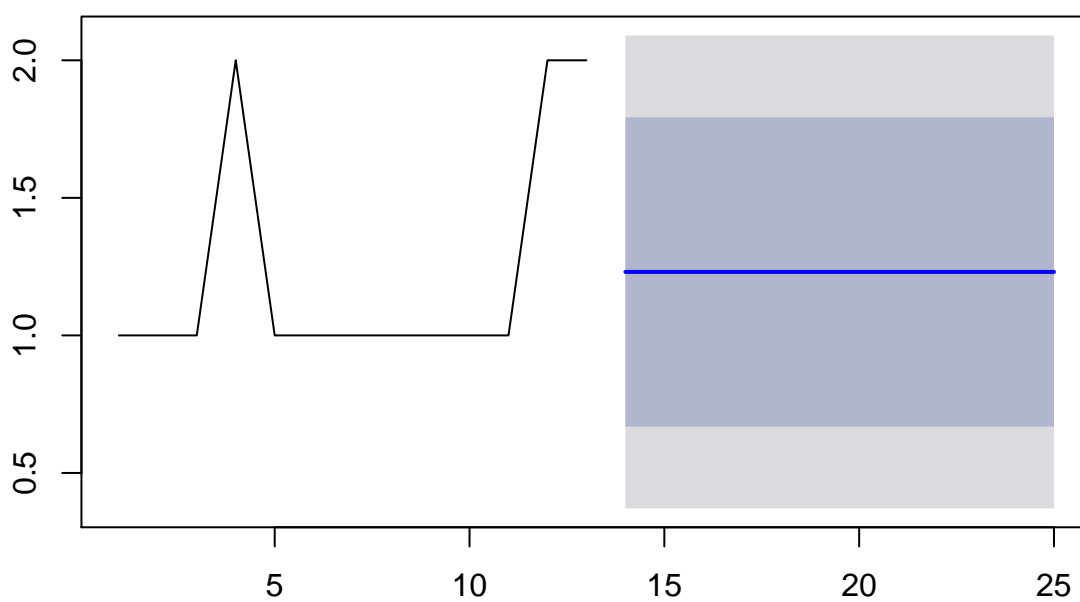
Book ID: 5

Forecasts from ARIMA(0,0,0) with non-zero mean



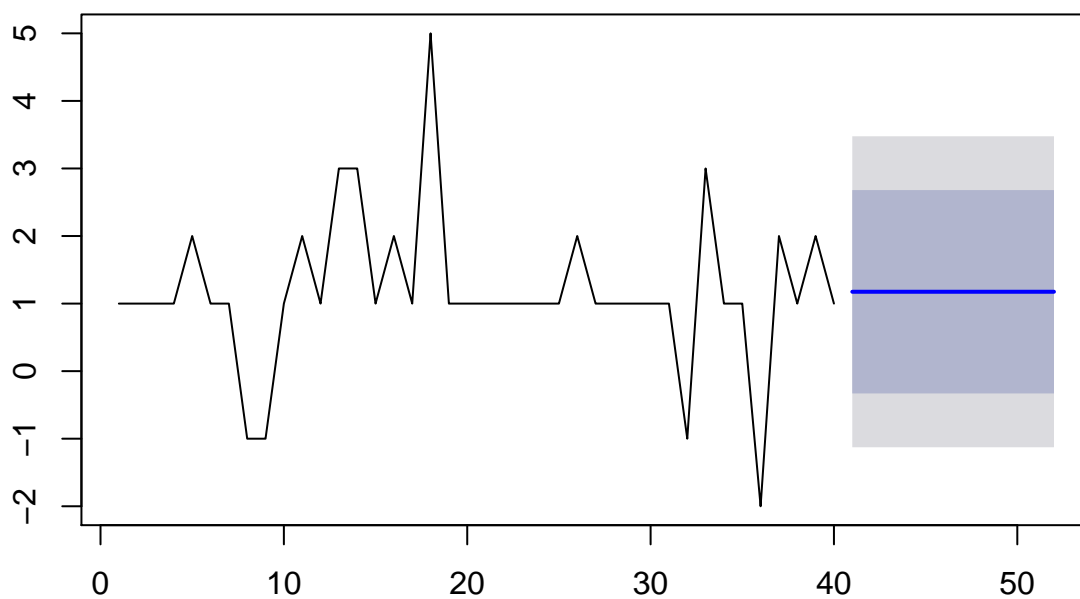
Book ID: 6

Forecasts from ARIMA(0,0,0) with non-zero mean



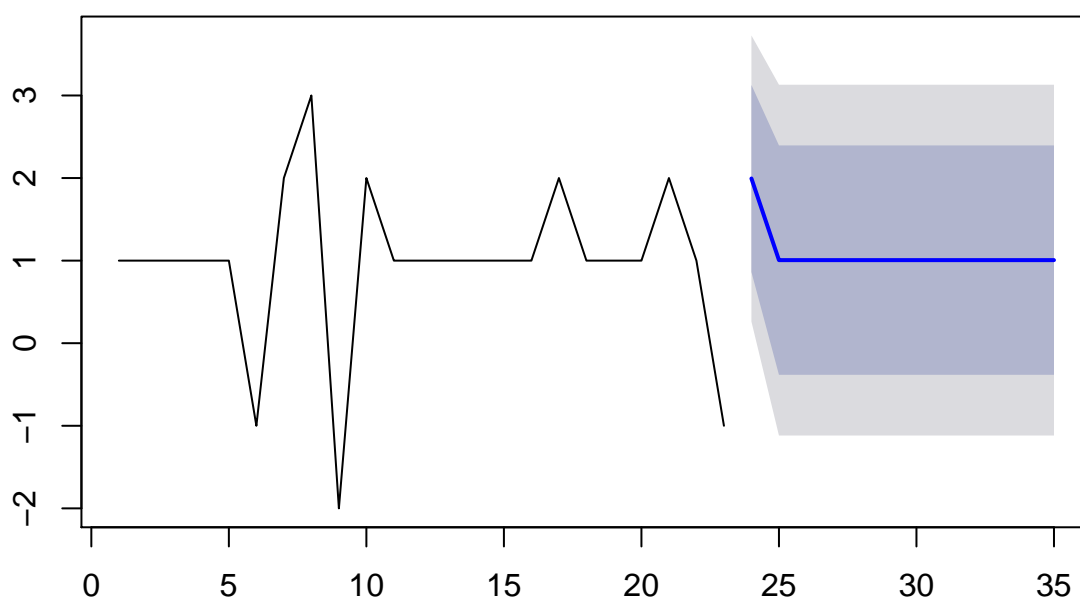
Book ID: 7

Forecasts from ARIMA(0,0,0) with non-zero mean



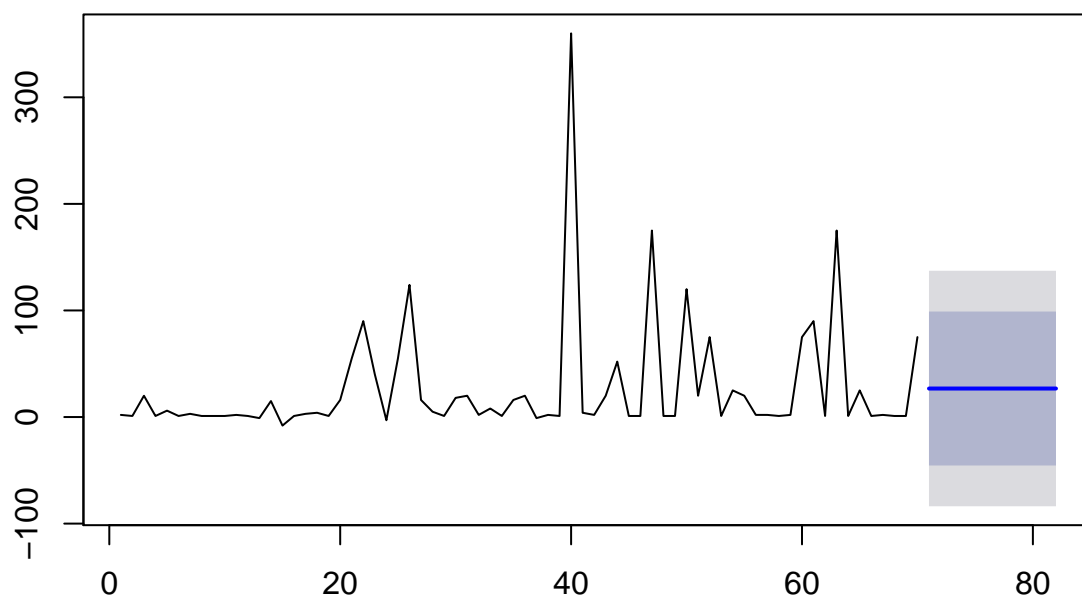
Book ID: 8

Forecasts from ARIMA(0,0,1) with non-zero mean



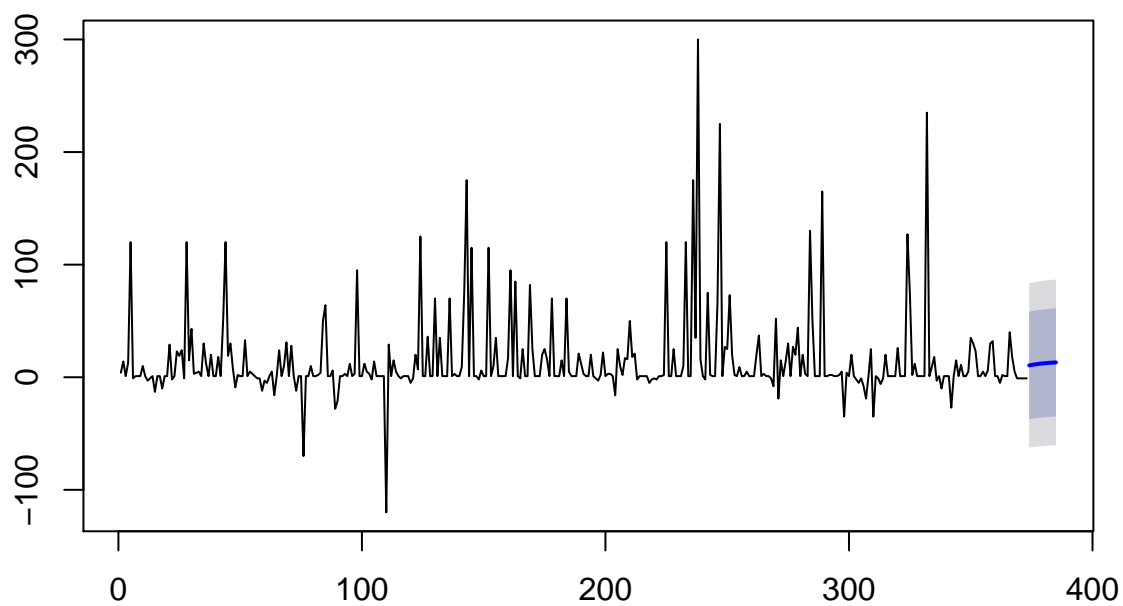
Book ID: 9

Forecasts from ARIMA(0,0,0) with non-zero mean



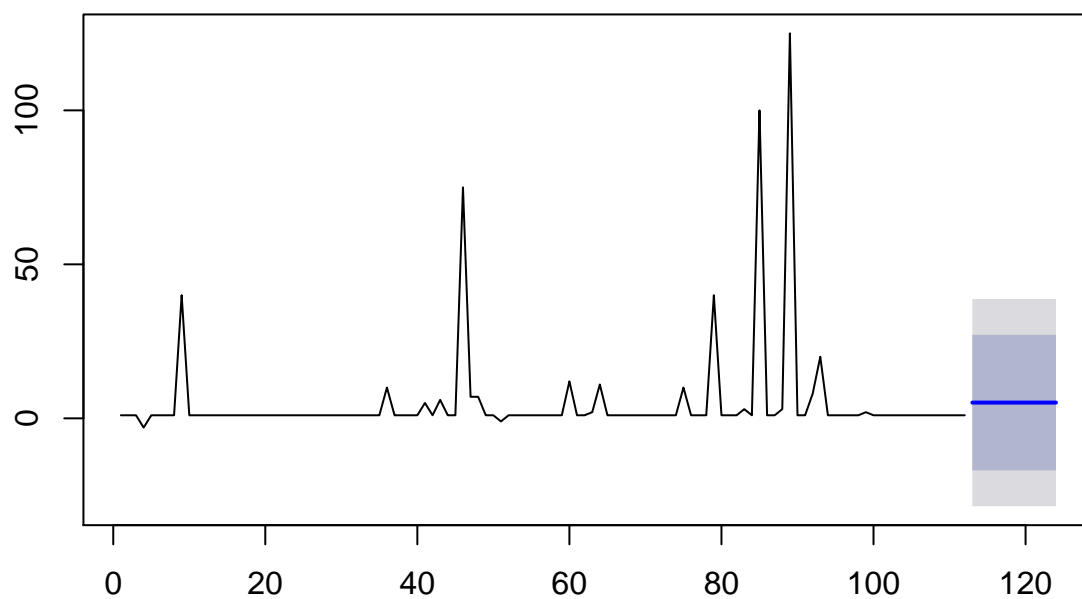
Book ID: 10

Forecasts from ARIMA(1,0,1) with non-zero mean



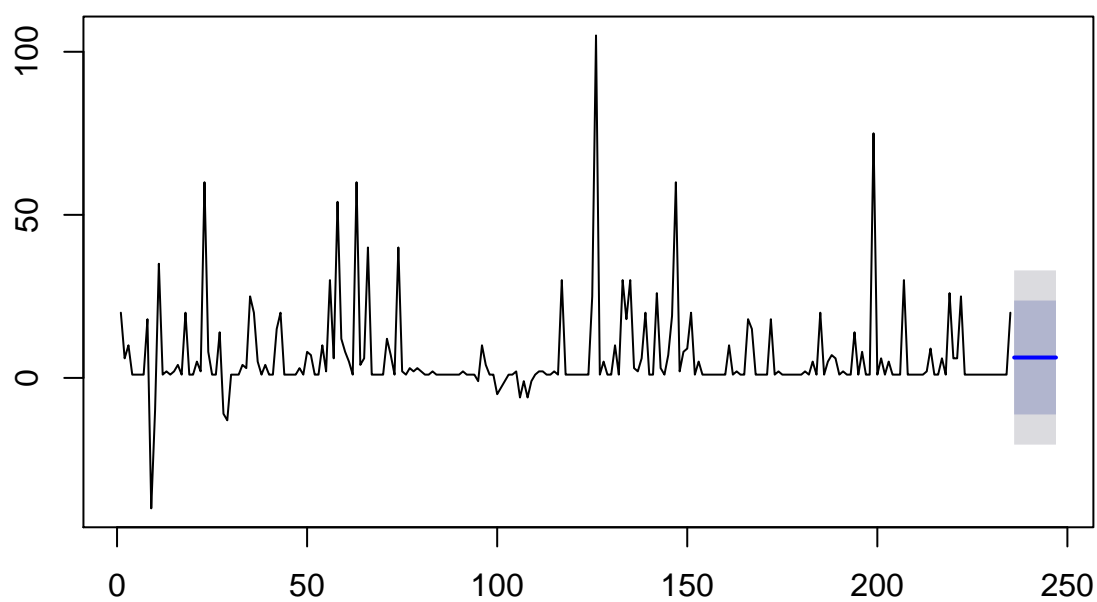
Book ID: 11

Forecasts from ARIMA(0,0,0) with non-zero mean



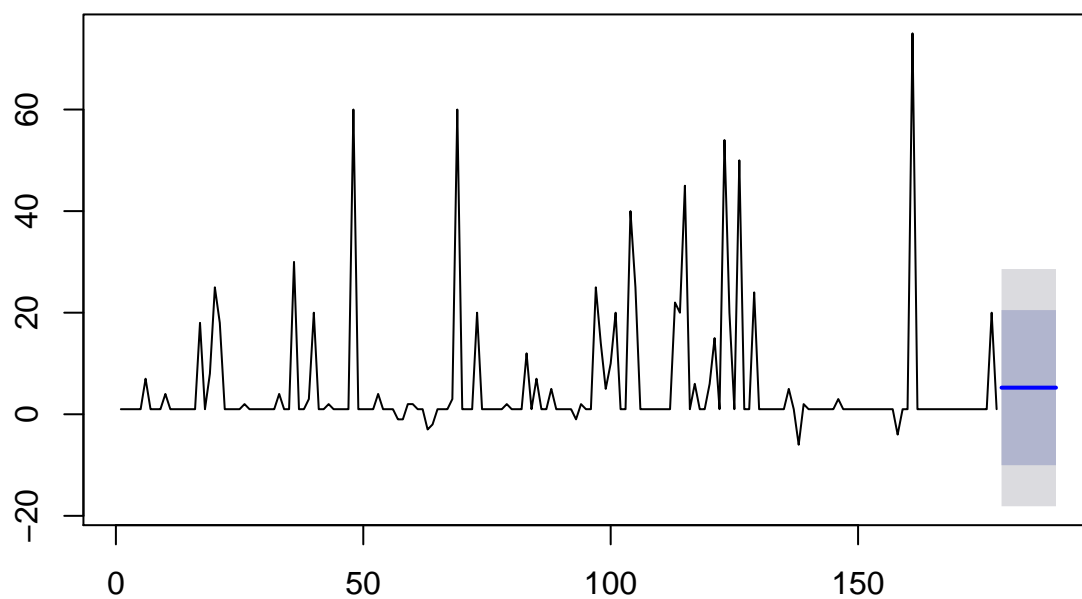
Book ID: 14

Forecasts from ARIMA(0,0,0) with non-zero mean



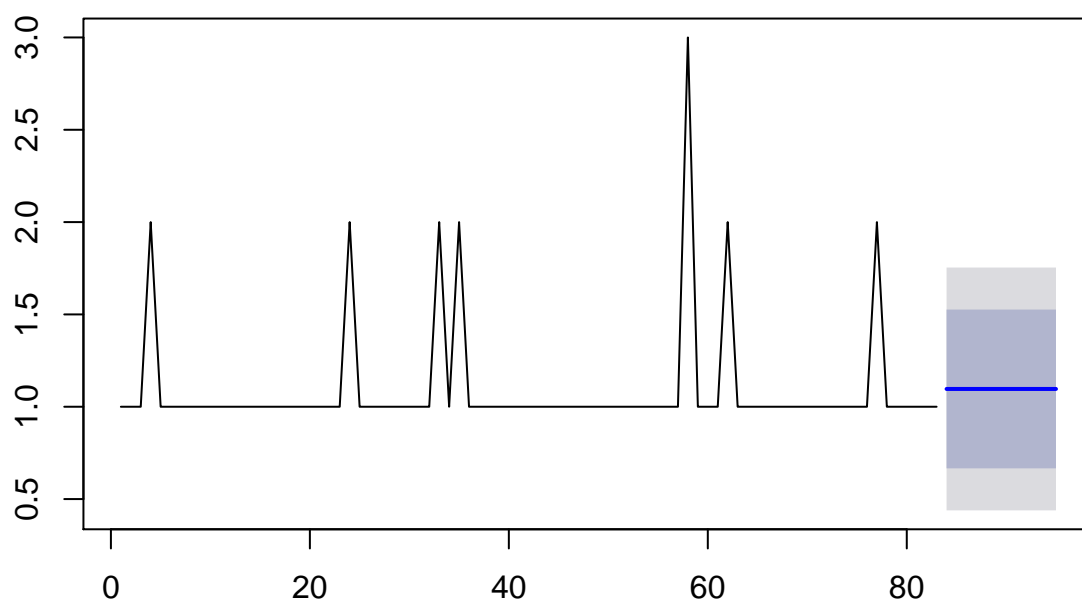
Book ID: 15

Forecasts from ARIMA(0,0,0) with non-zero mean



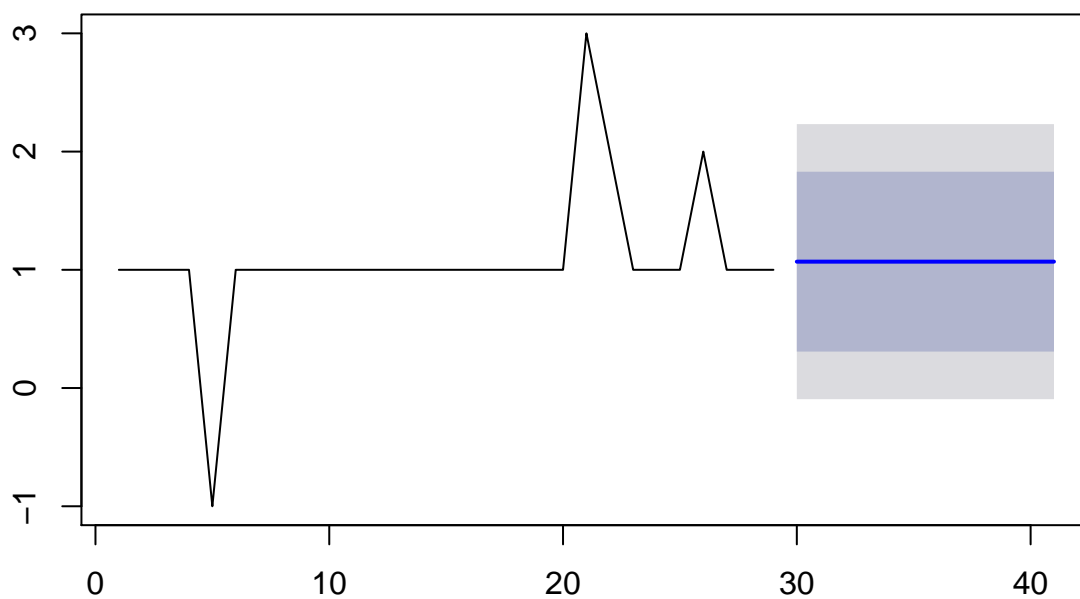
Book ID: 16

Forecasts from ARIMA(0,0,0) with non-zero mean



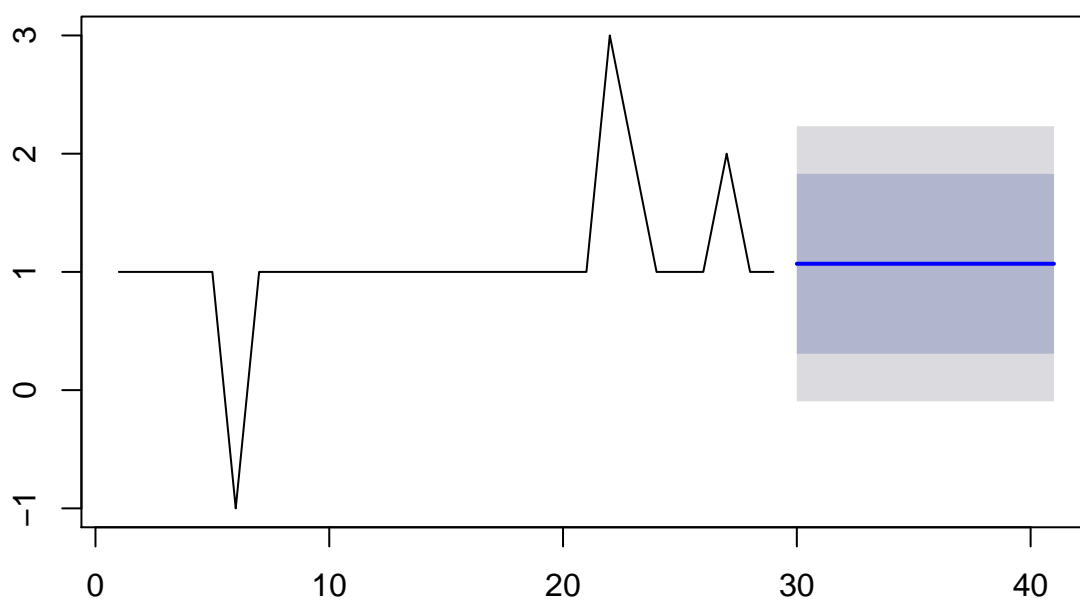
Book ID: 17

Forecasts from ARIMA(0,0,0) with non-zero mean



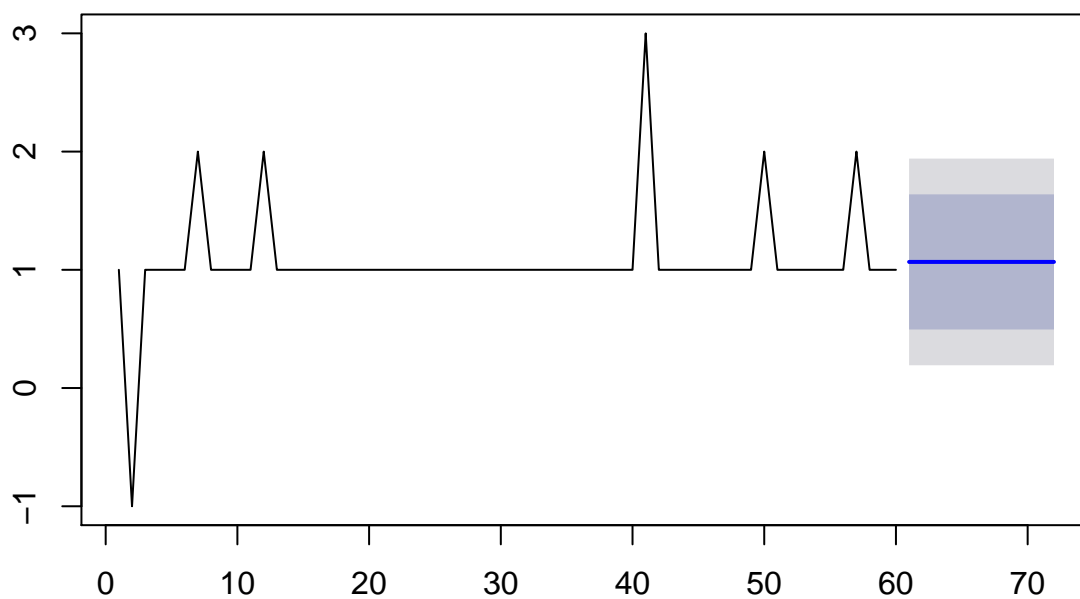
Book ID: 18

Forecasts from ARIMA(0,0,0) with non-zero mean



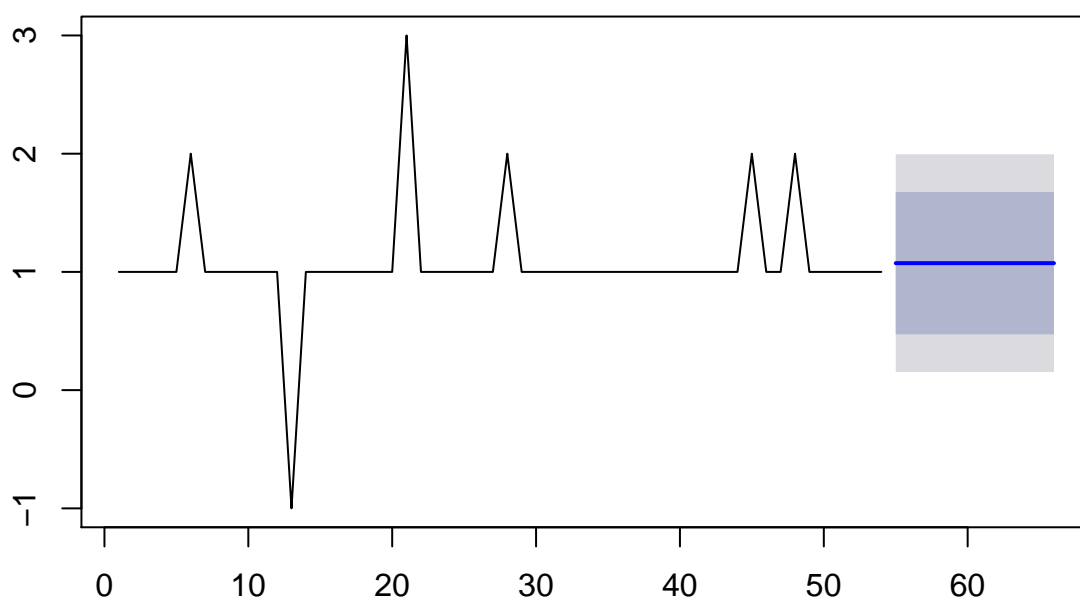
Book ID: 19

Forecasts from ARIMA(0,0,0) with non-zero mean



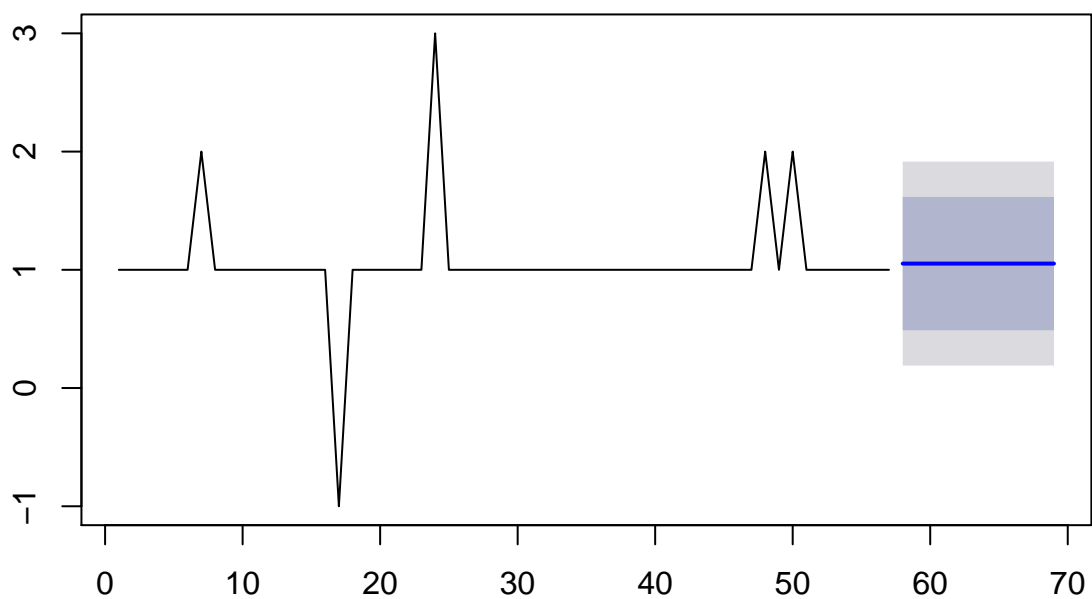
Book ID: 20

Forecasts from ARIMA(0,0,0) with non-zero mean



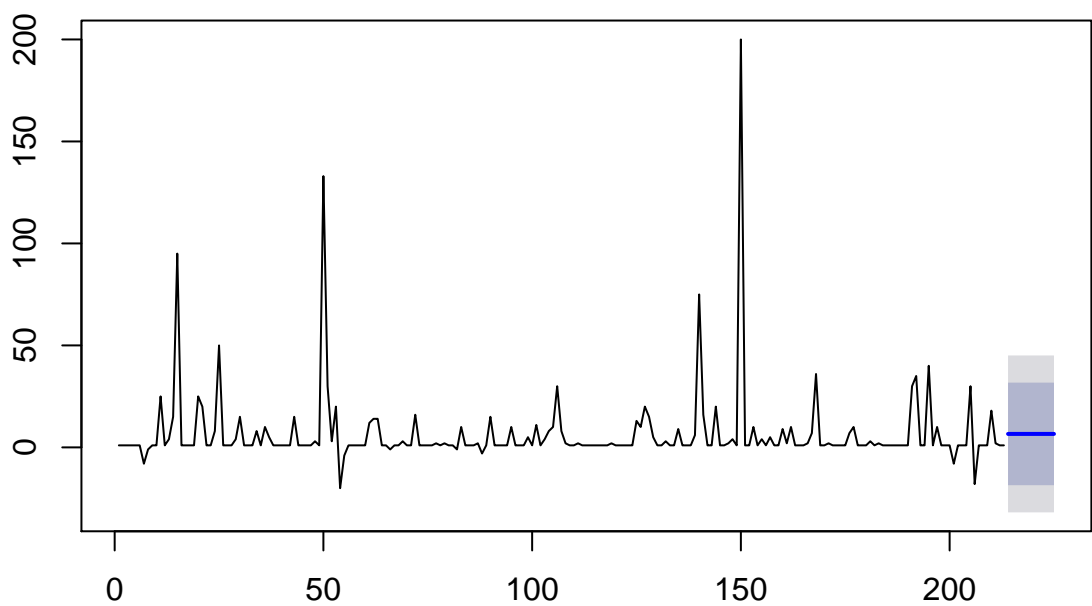
Book ID: 21

Forecasts from ARIMA(0,0,0) with non-zero mean



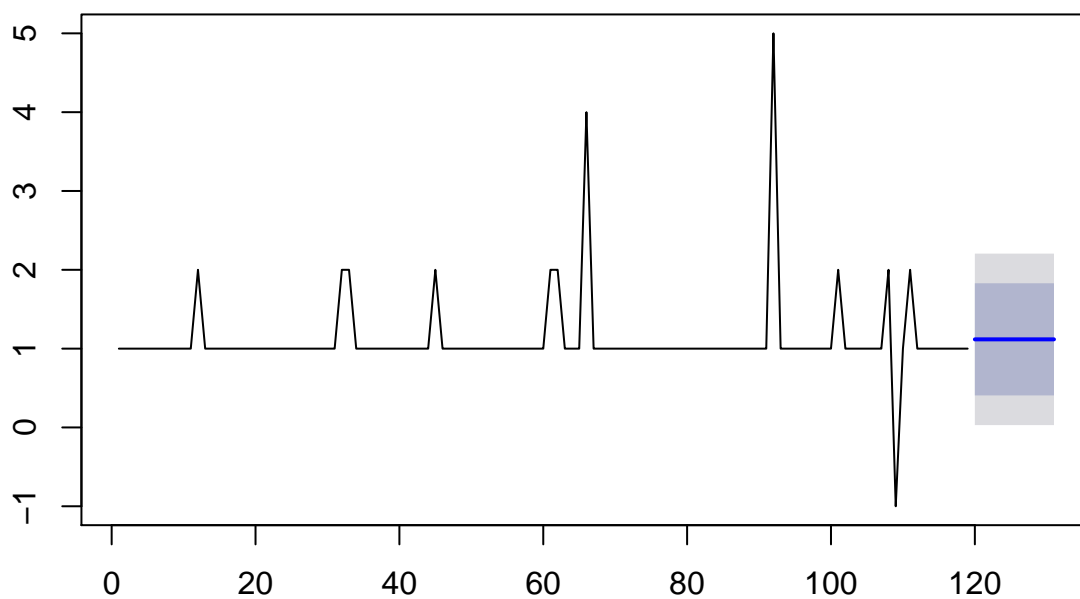
Book ID: 22

Forecasts from ARIMA(0,0,0) with non-zero mean



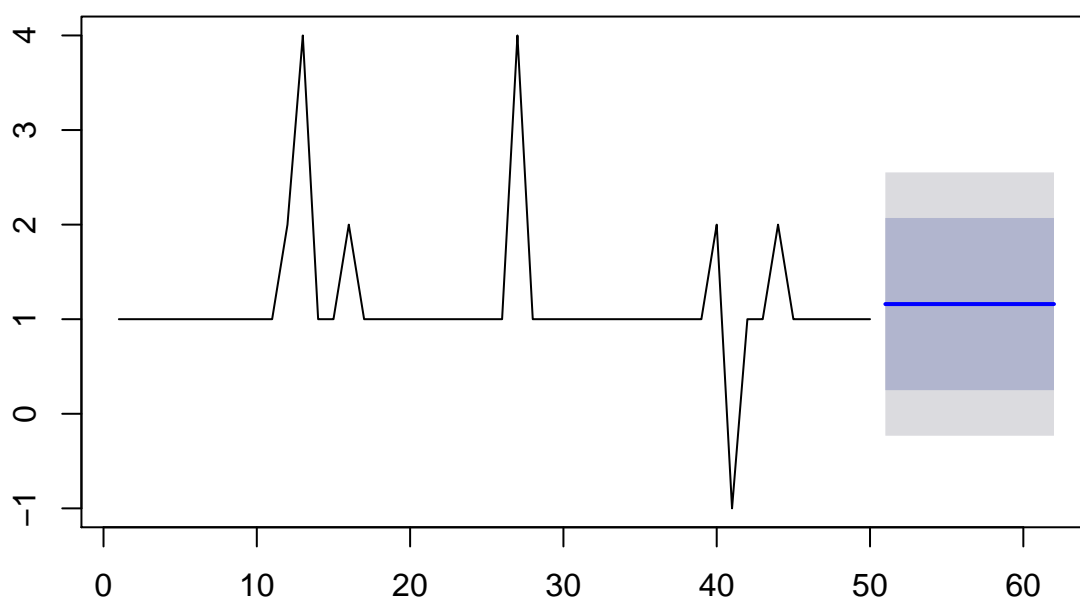
Book ID: 23

Forecasts from ARIMA(0,0,0) with non-zero mean



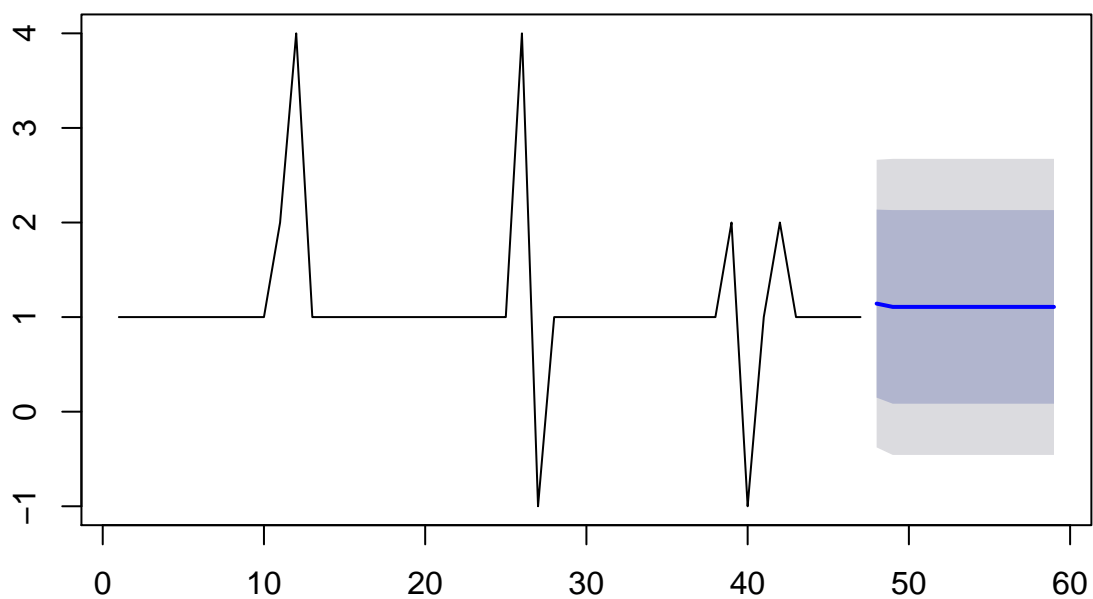
Book ID: 24

Forecasts from ARIMA(0,0,0) with non-zero mean



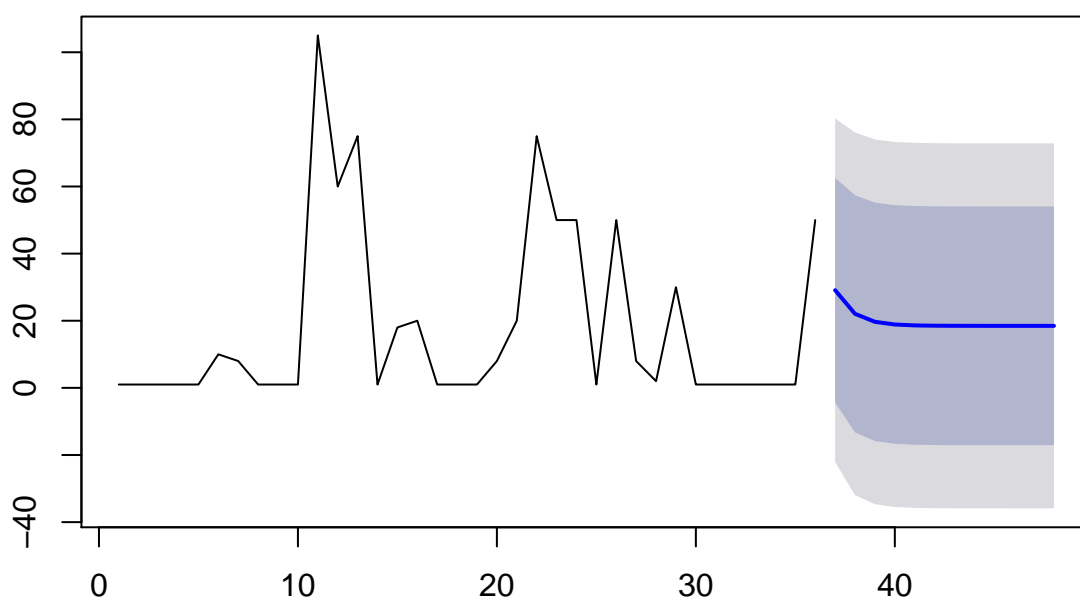
Book ID: 25

Forecasts from ARIMA(0,0,1) with non-zero mean



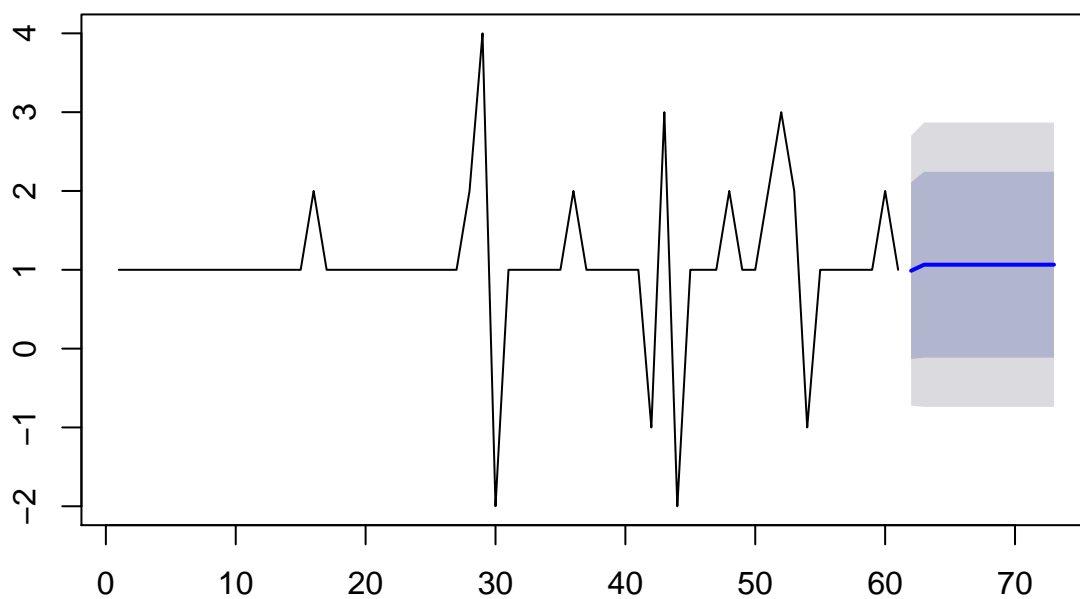
Book ID: 26

Forecasts from ARIMA(1,0,0) with non-zero mean



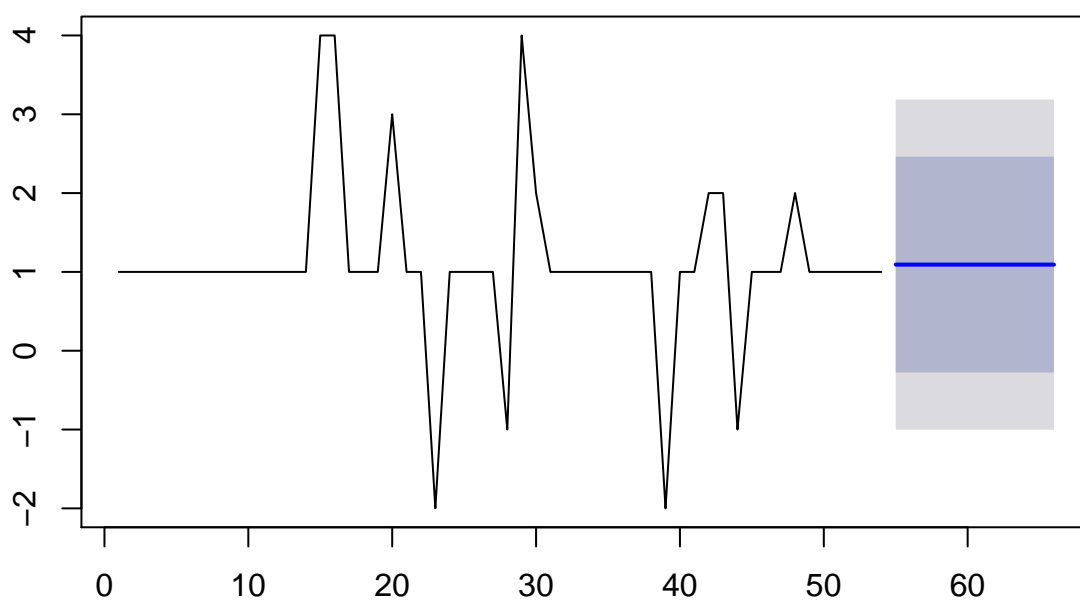
Book ID: 27

Forecasts from ARIMA(0,0,1) with non-zero mean



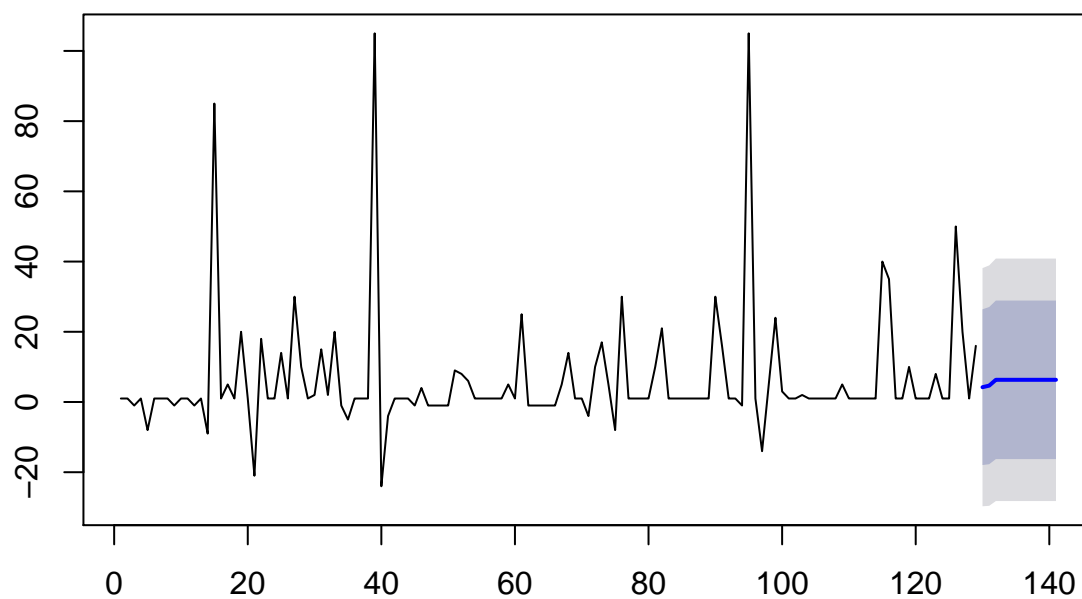
Book ID: 28

Forecasts from ARIMA(0,0,0) with non-zero mean



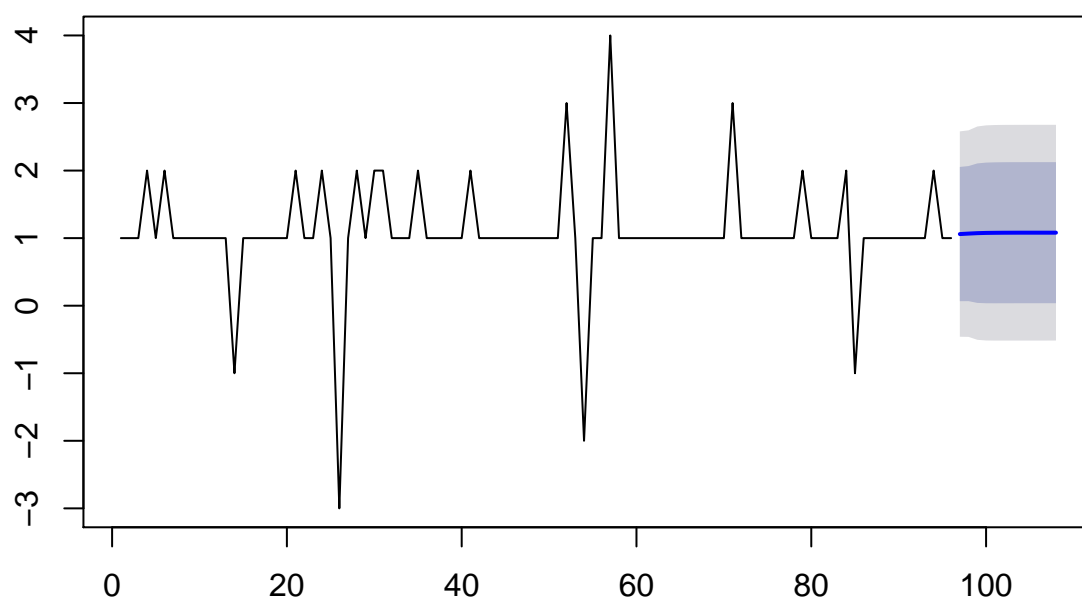
Book ID: 29

Forecasts from ARIMA(0,0,2) with non-zero mean



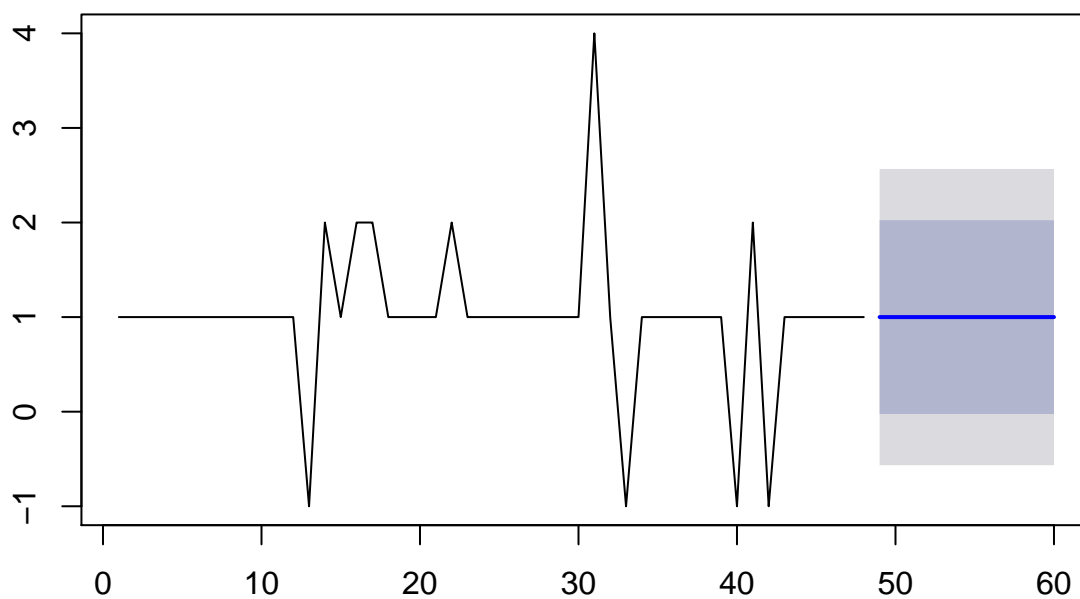
Book ID: 30

Forecasts from ARIMA(1,0,2) with non-zero mean



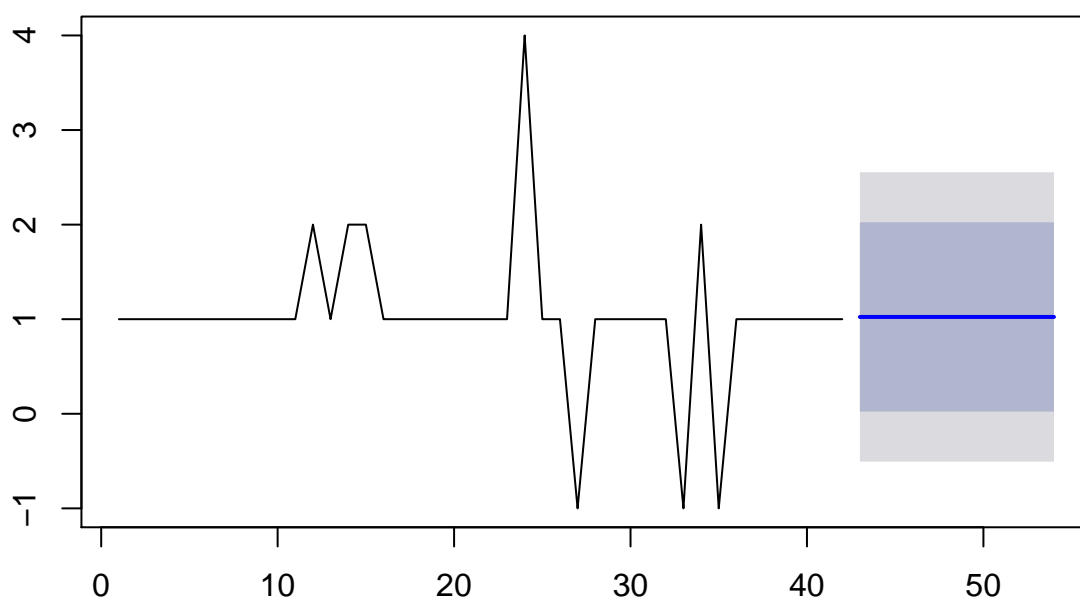
Book ID: 31

Forecasts from ARIMA(0,0,0) with non-zero mean



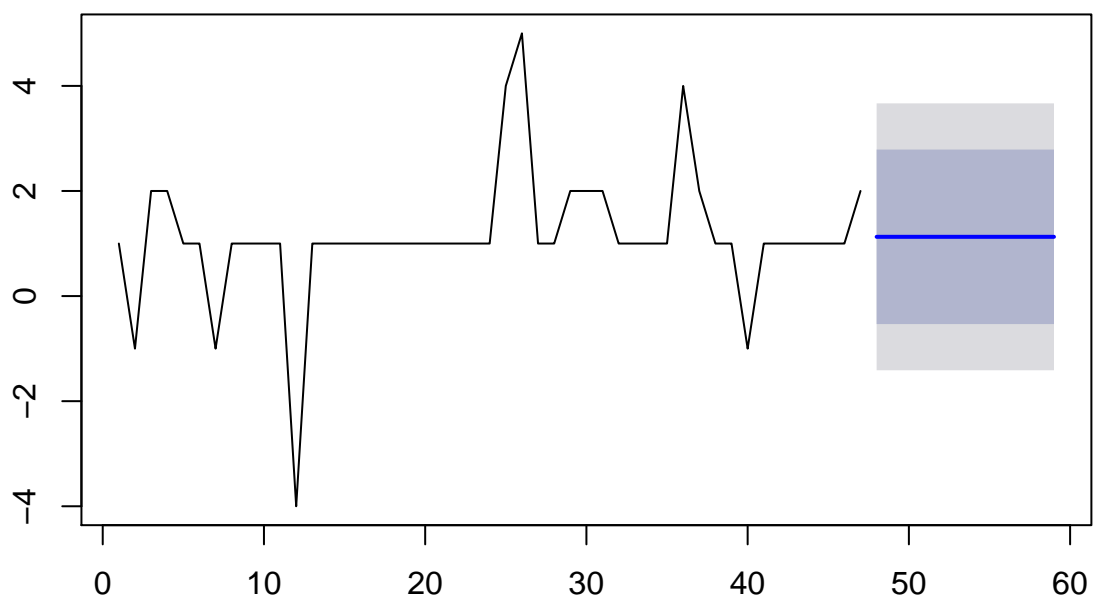
Book ID: 32

Forecasts from ARIMA(0,0,0) with non-zero mean



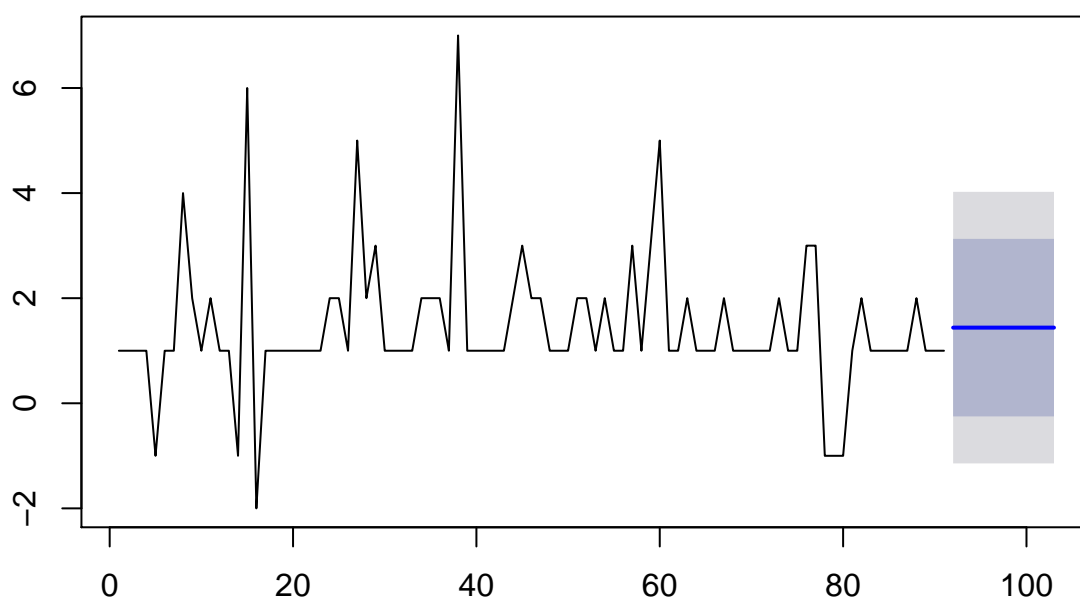
Book ID: 33

Forecasts from ARIMA(0,0,0) with non-zero mean



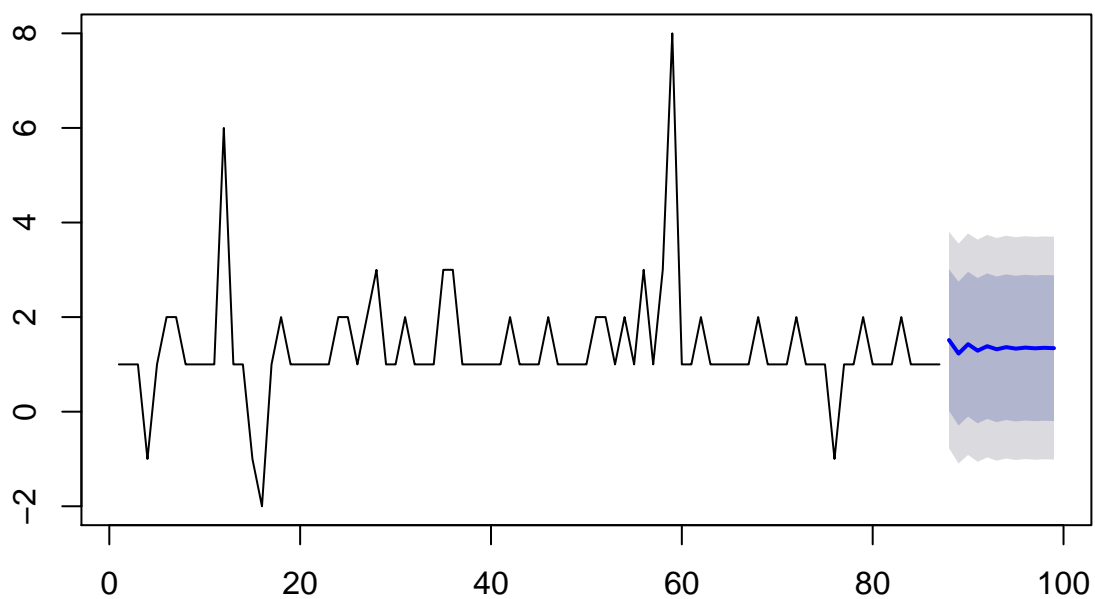
Book ID: 34

Forecasts from ARIMA(0,0,0) with non-zero mean



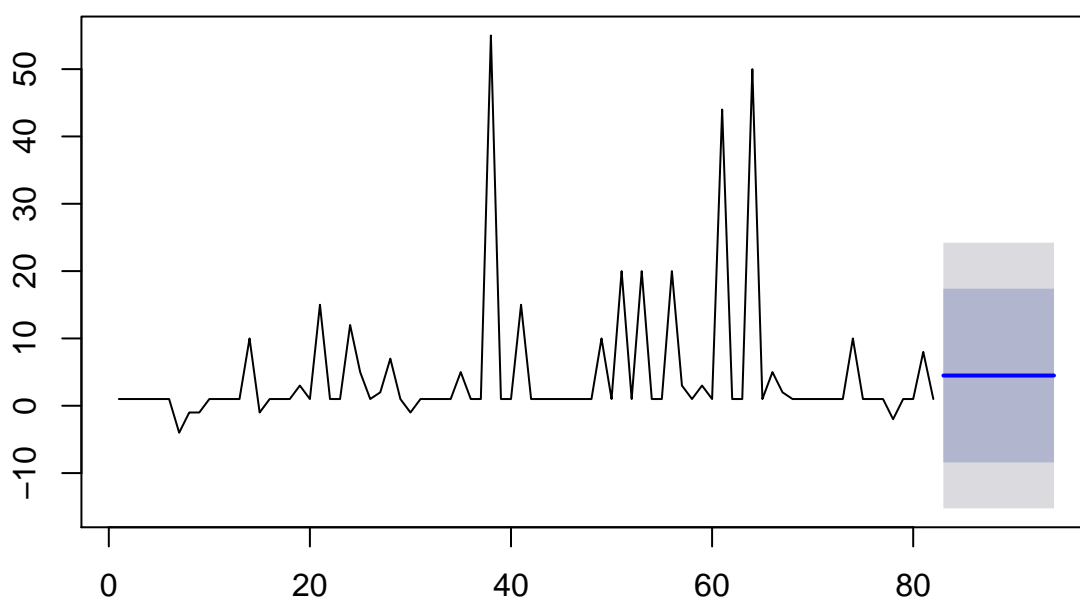
Book ID: 35

Forecasts from ARIMA(1,0,1) with non-zero mean



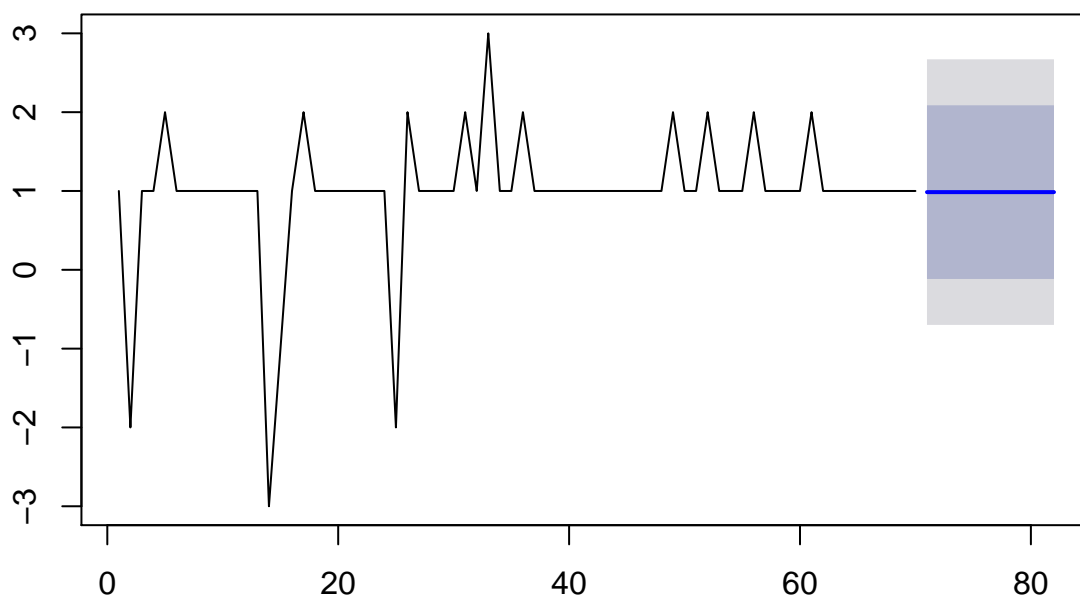
Book ID: 36

Forecasts from ARIMA(0,0,0) with non-zero mean



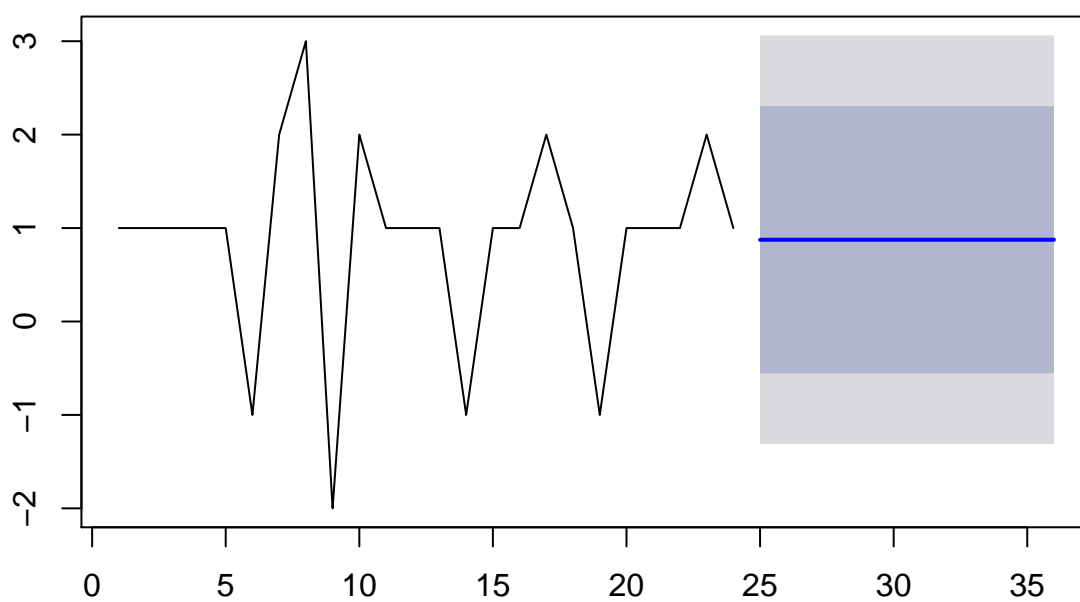
Book ID: 37

Forecasts from ARIMA(0,0,0) with non-zero mean



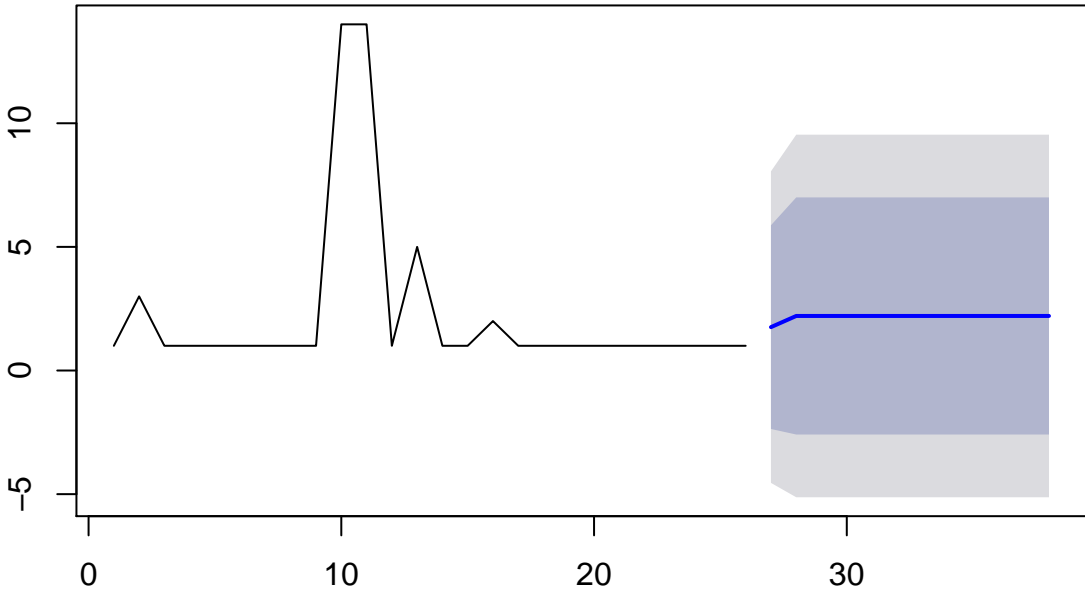
Book ID: 38

Forecasts from ARIMA(0,0,0) with non-zero mean



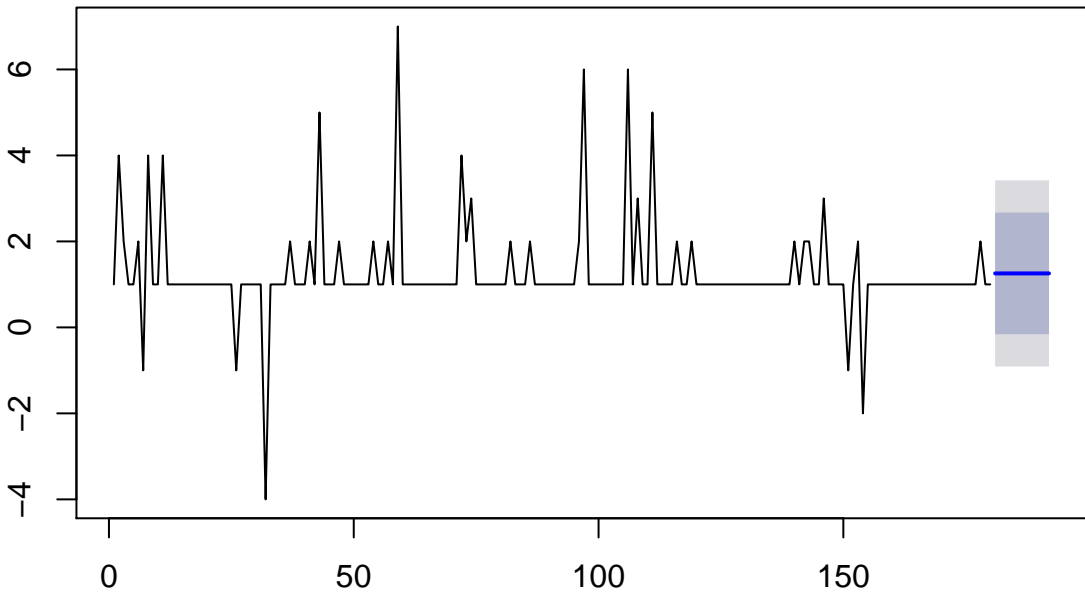
Book ID: 39

Forecasts from ARIMA(0,0,1) with non-zero mean



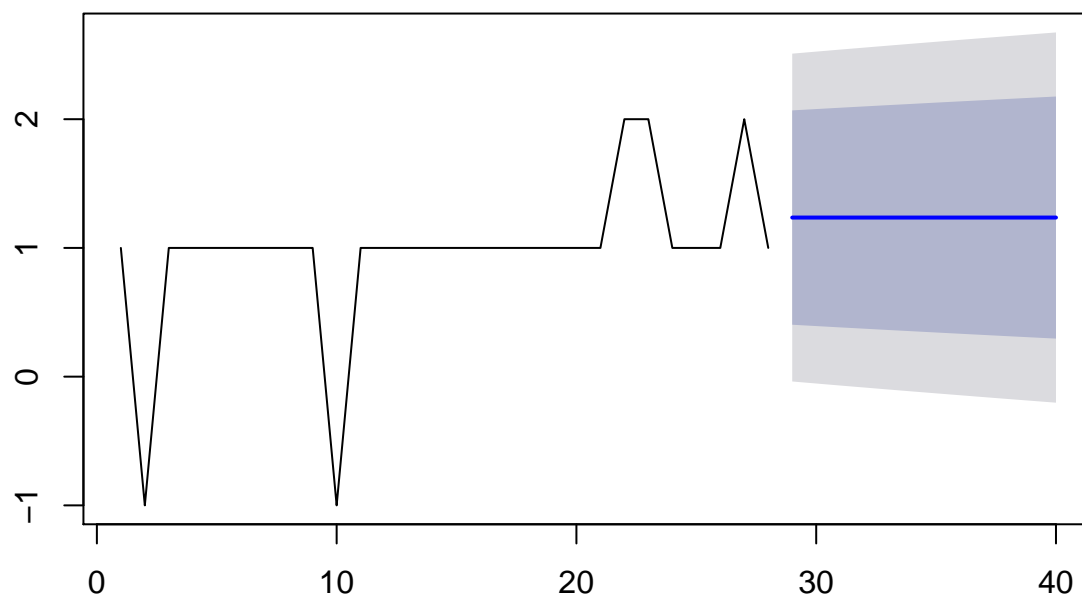
Book ID: 40

Forecasts from ARIMA(0,0,0) with non-zero mean



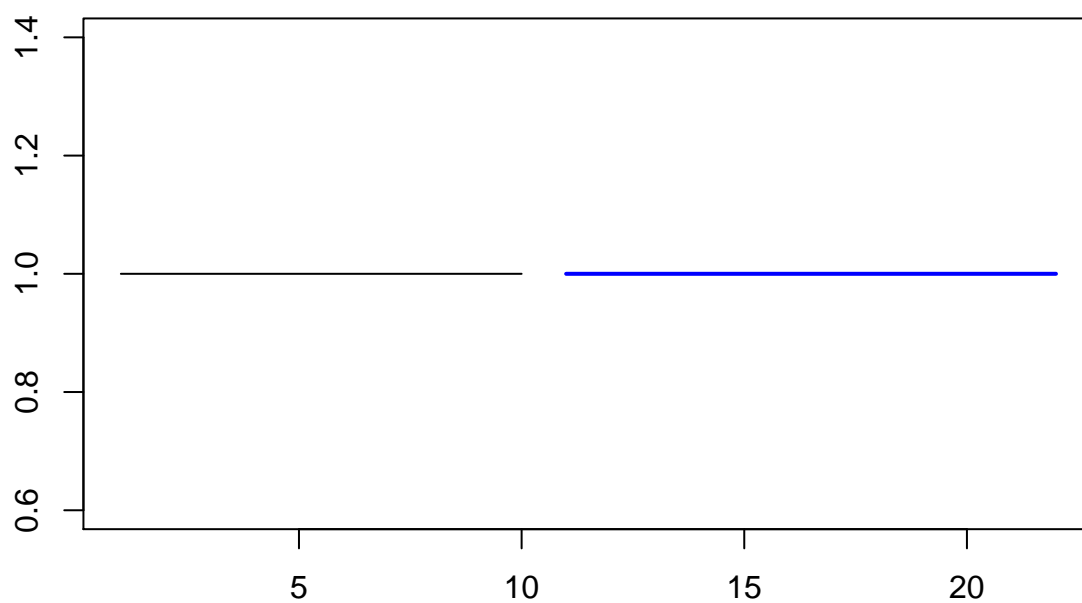
Book ID: 41

Forecasts from ARIMA(0,1,1)



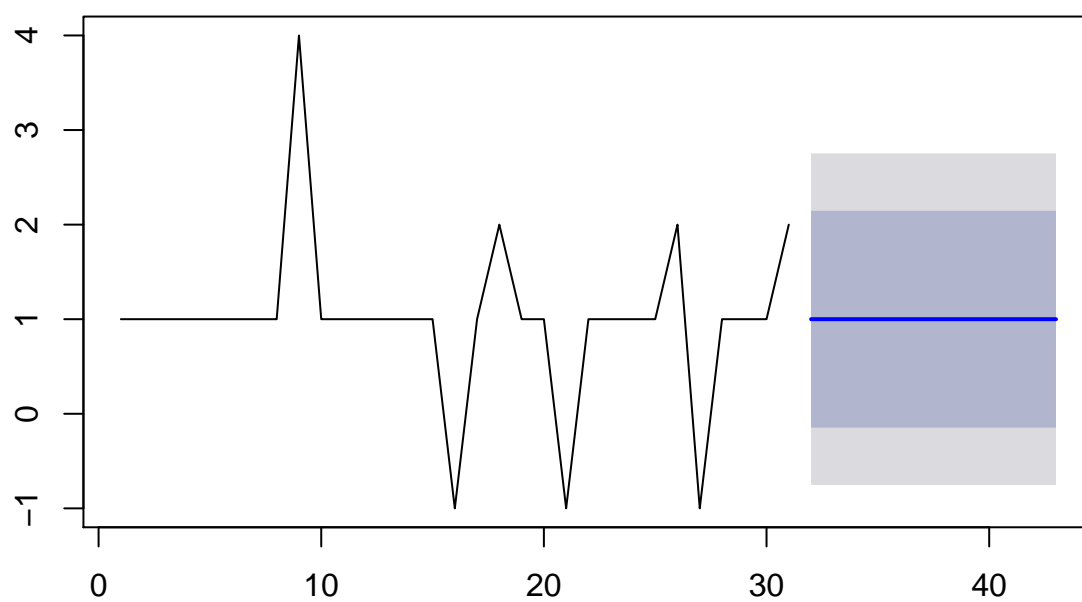
25

Forecasts from ARIMA(0,0,0) with non-zero mean



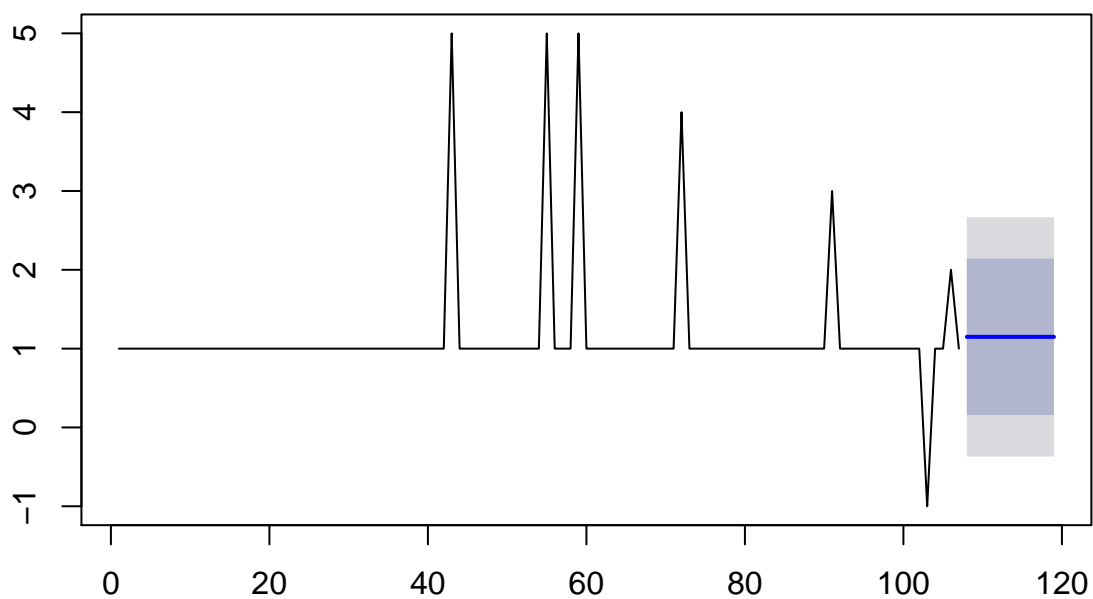
Book ID: 49

Forecasts from ARIMA(0,0,0) with non-zero mean



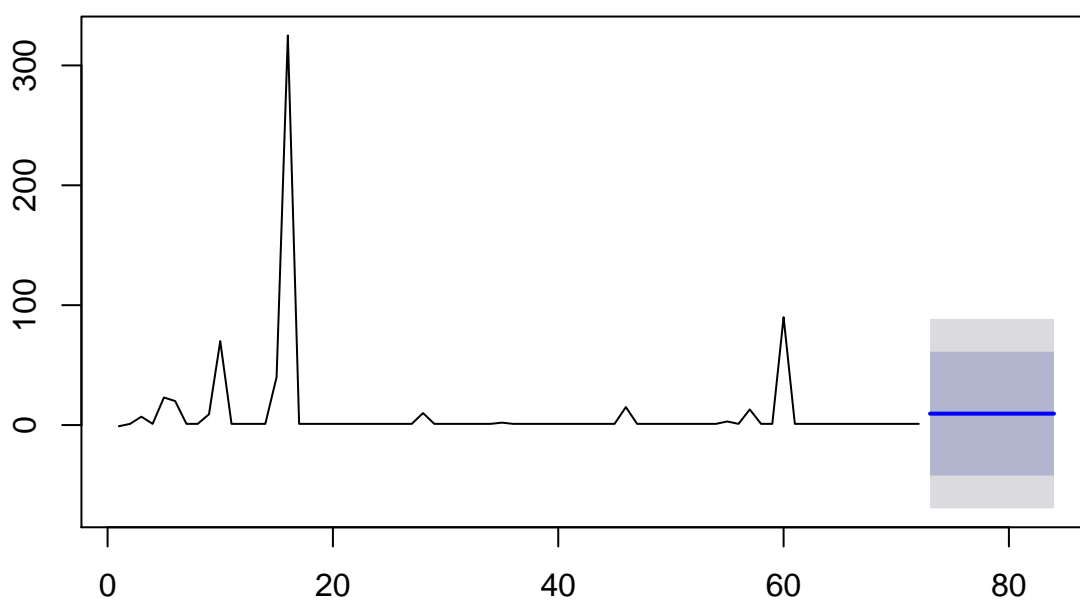
Book ID: 54

Forecasts from ARIMA(0,0,0) with non-zero mean



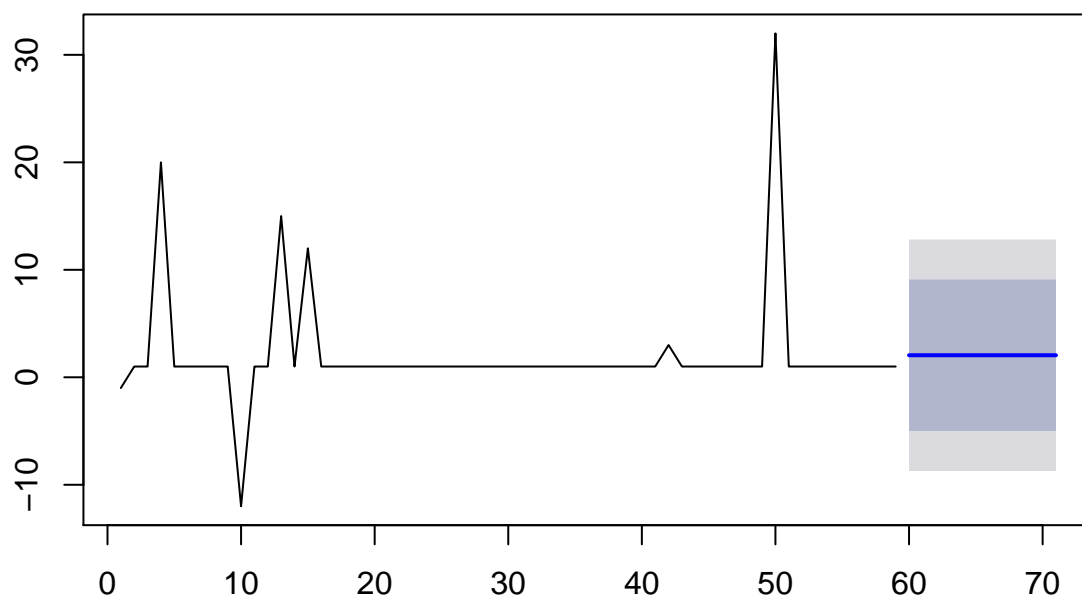
Book ID: 56

Forecasts from ARIMA(0,0,0) with non-zero mean



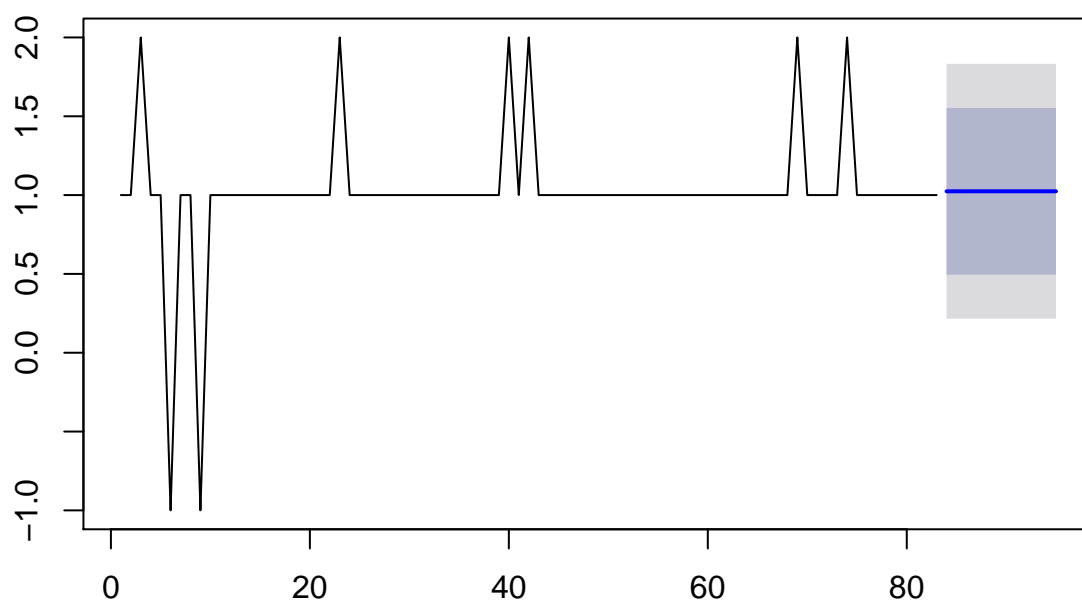
Book ID: 57

Forecasts from ARIMA(0,0,0) with non-zero mean



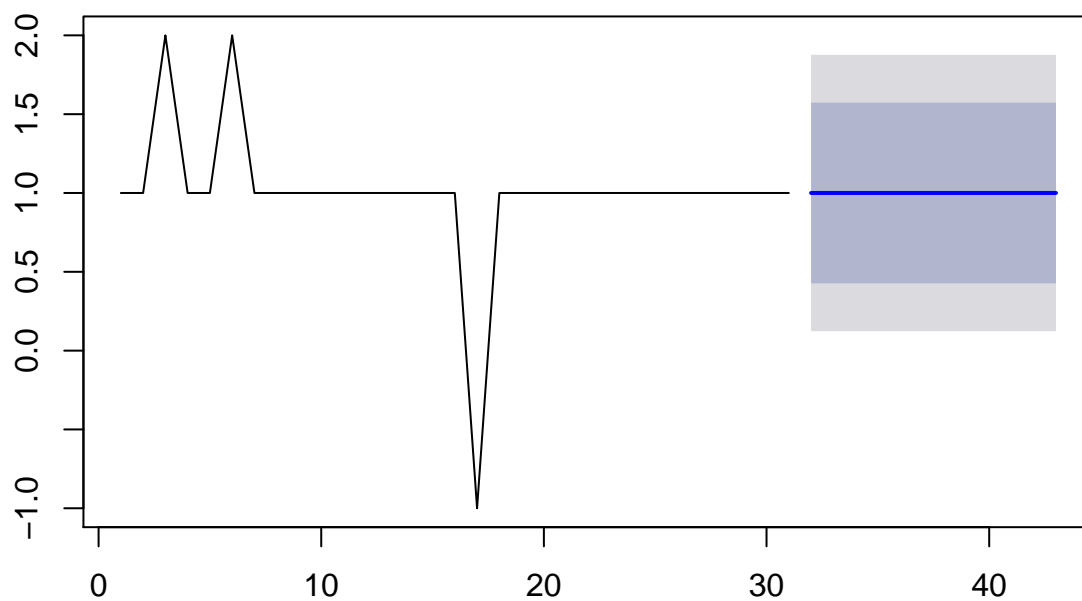
Book ID: 58

Forecasts from ARIMA(0,0,0) with non-zero mean



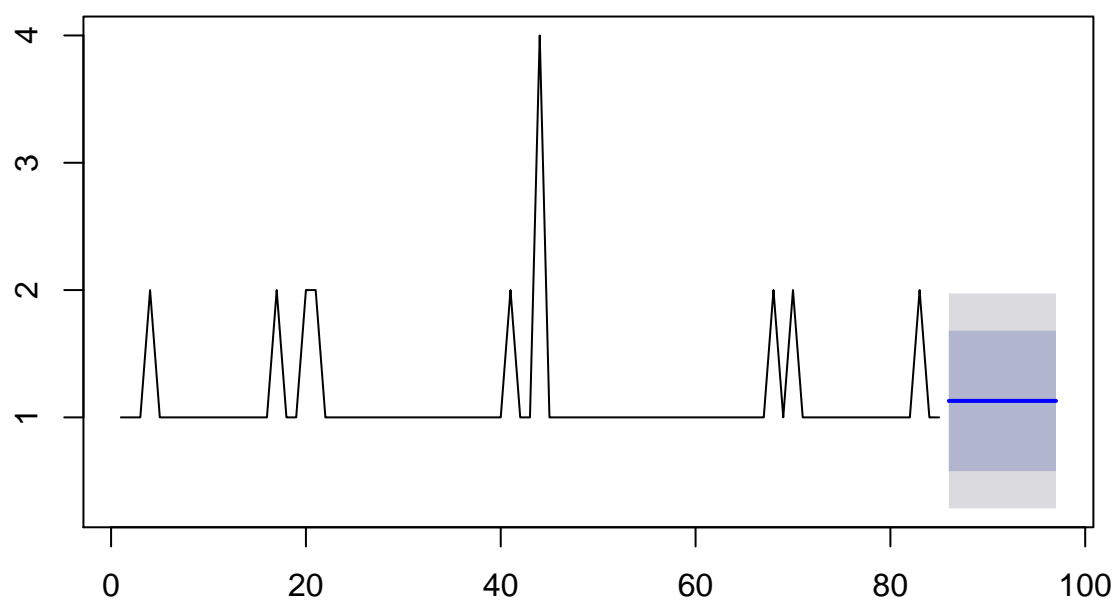
Book ID: 59

Forecasts from ARIMA(0,0,0) with non-zero mean



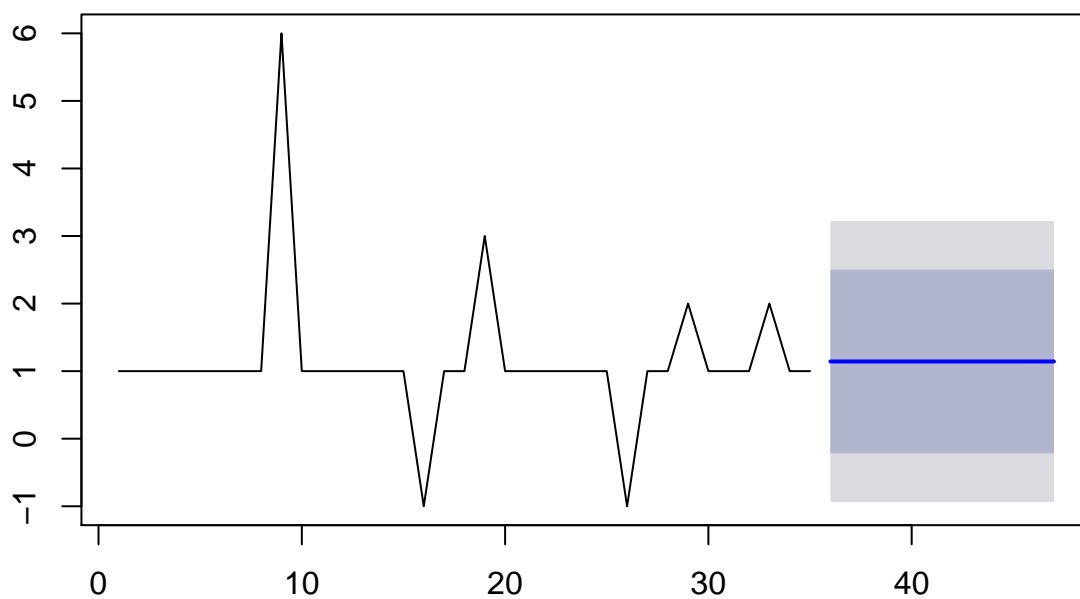
Book ID: 60

Forecasts from ARIMA(0,0,0) with non-zero mean



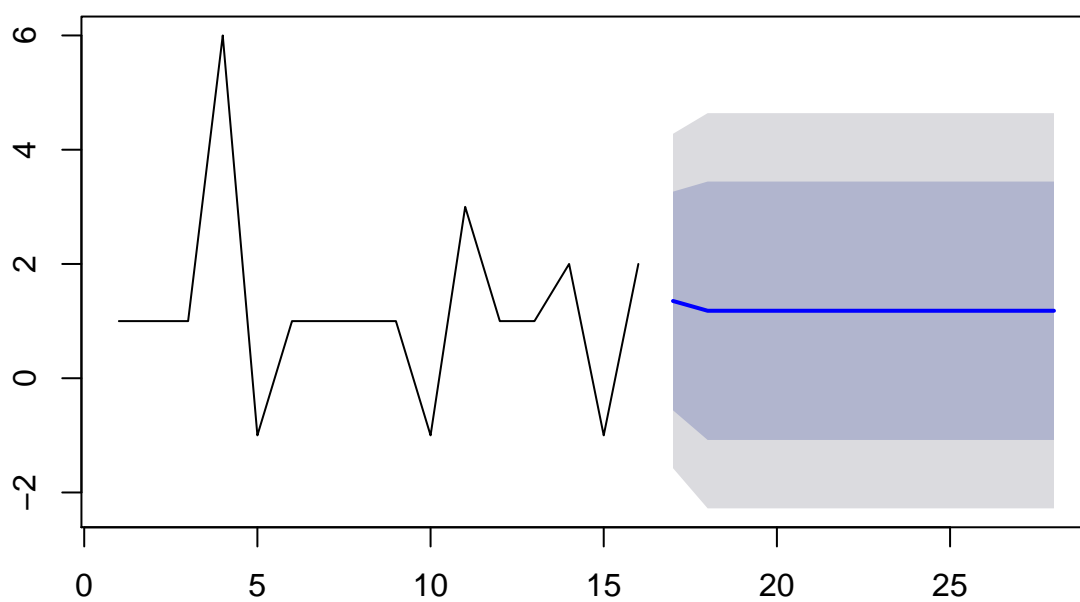
Book ID: 61

Forecasts from ARIMA(0,0,0) with non-zero mean



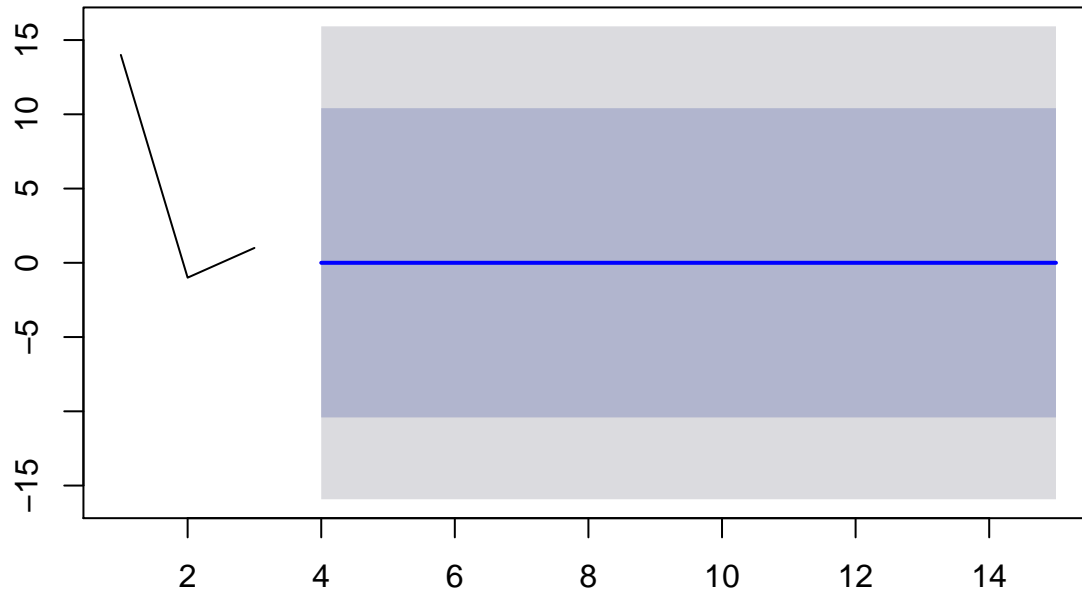
Book ID: 62

Forecasts from ARIMA(0,0,1) with non-zero mean



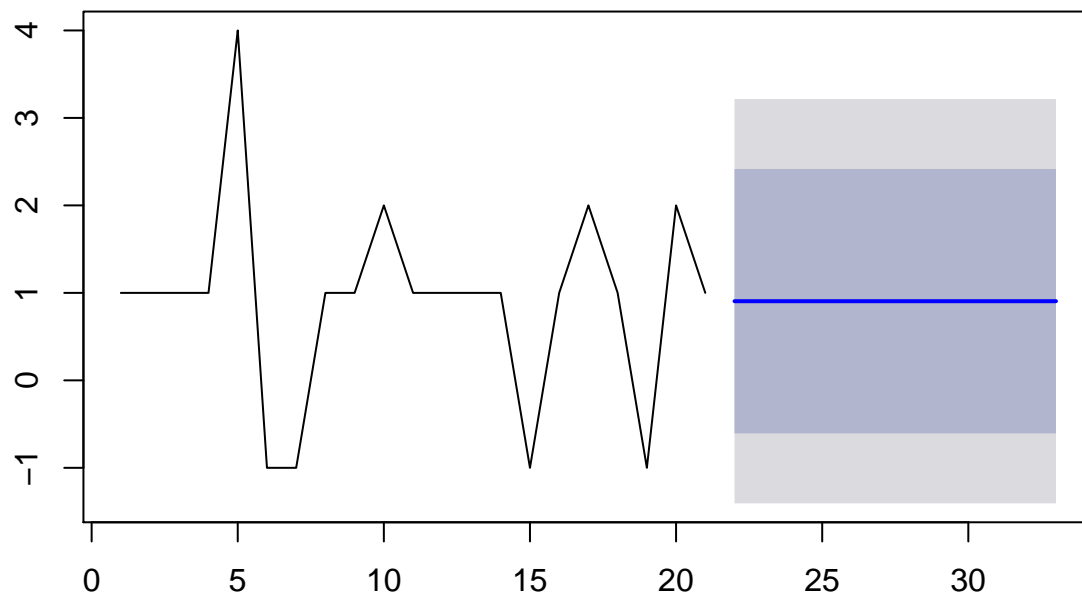
Book ID: 63

Forecasts from ARIMA(0,0,0) with zero mean



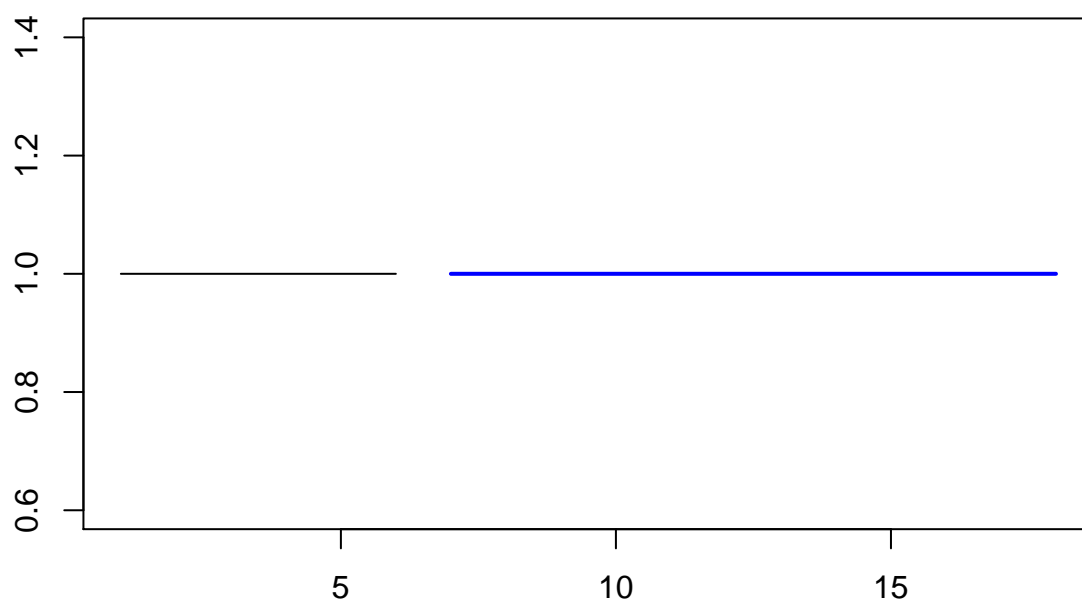
Book ID: 86

Forecasts from ARIMA(0,0,0) with non-zero mean



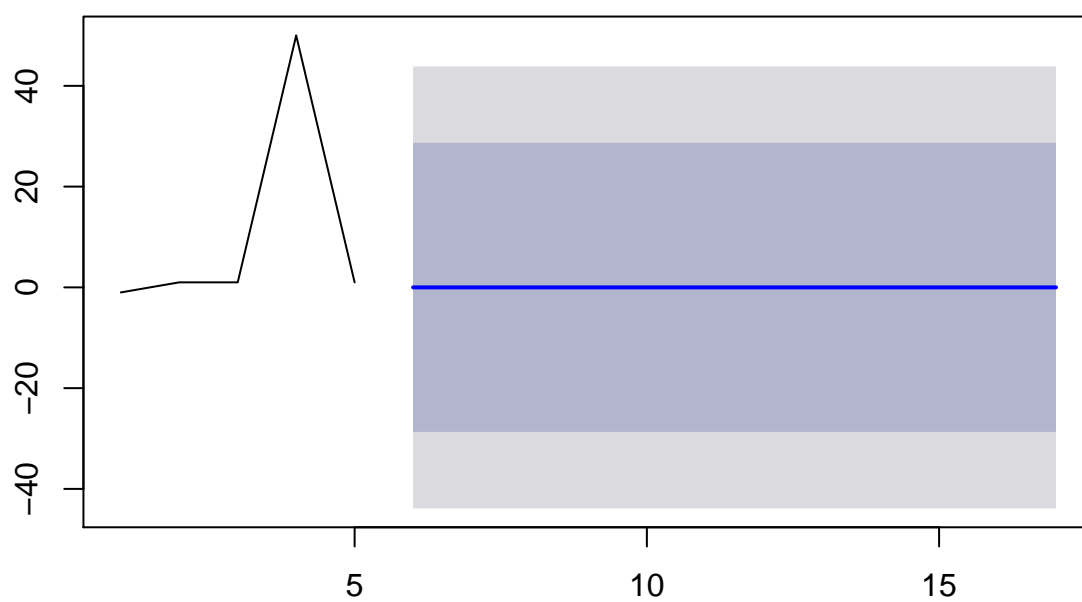
Book ID: 90

Forecasts from ARIMA(0,0,0) with non-zero mean



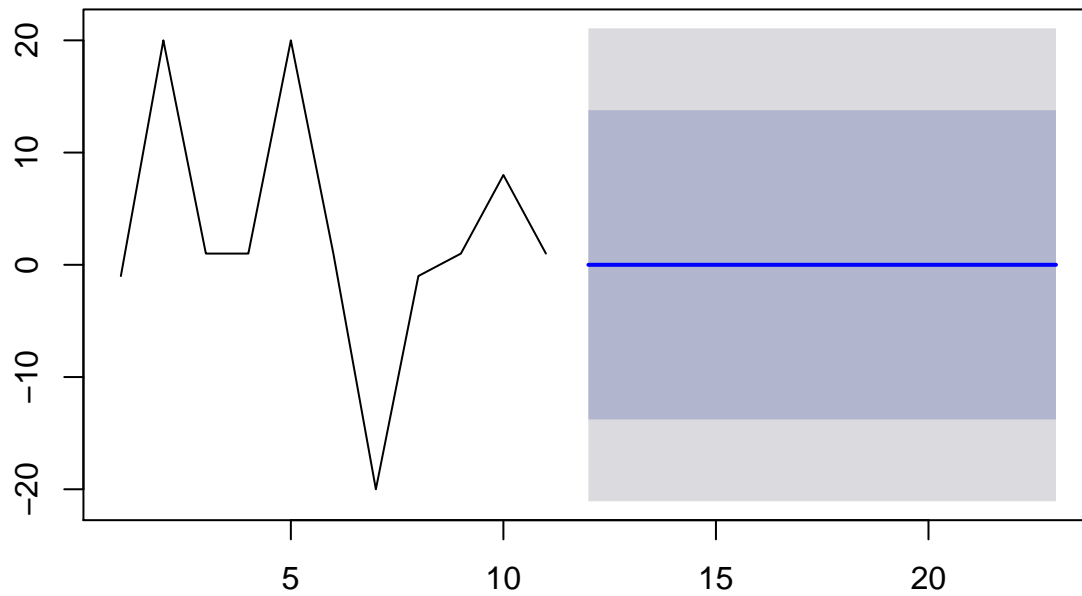
Book ID: 91

Forecasts from ARIMA(0,0,0) with zero mean



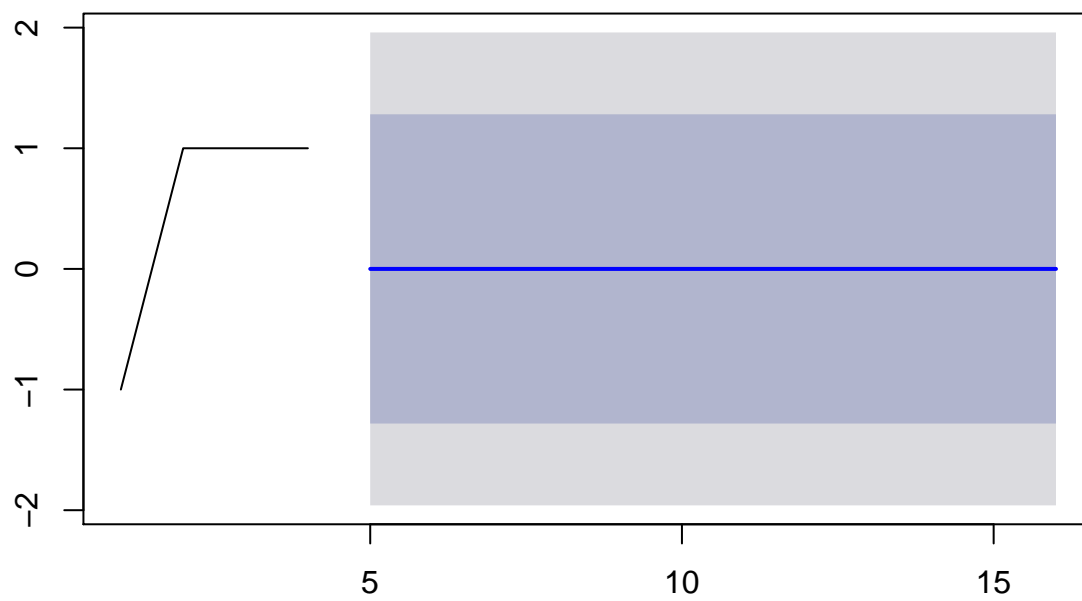
Book ID: 92

Forecasts from ARIMA(0,0,0) with zero mean



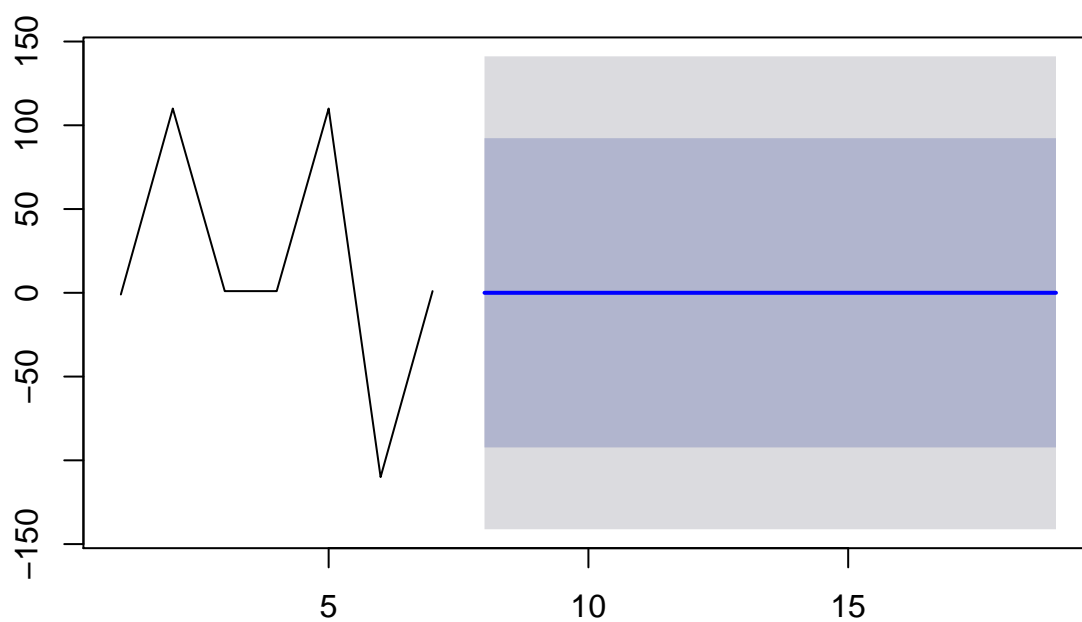
Book ID: 93

Forecasts from ARIMA(0,0,0) with zero mean



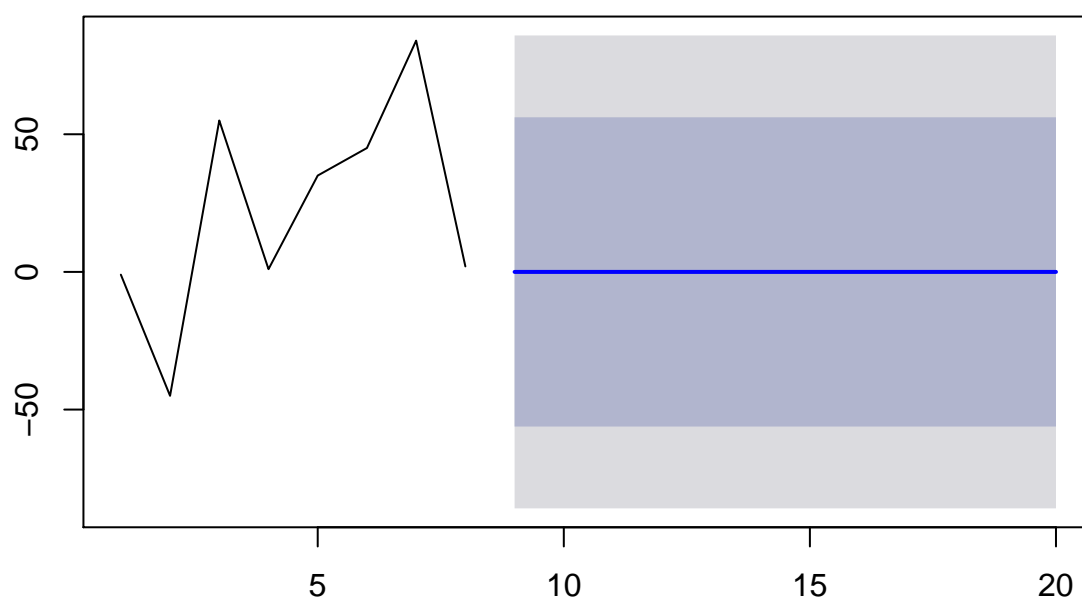
Book ID: 94

Forecasts from ARIMA(0,0,0) with zero mean



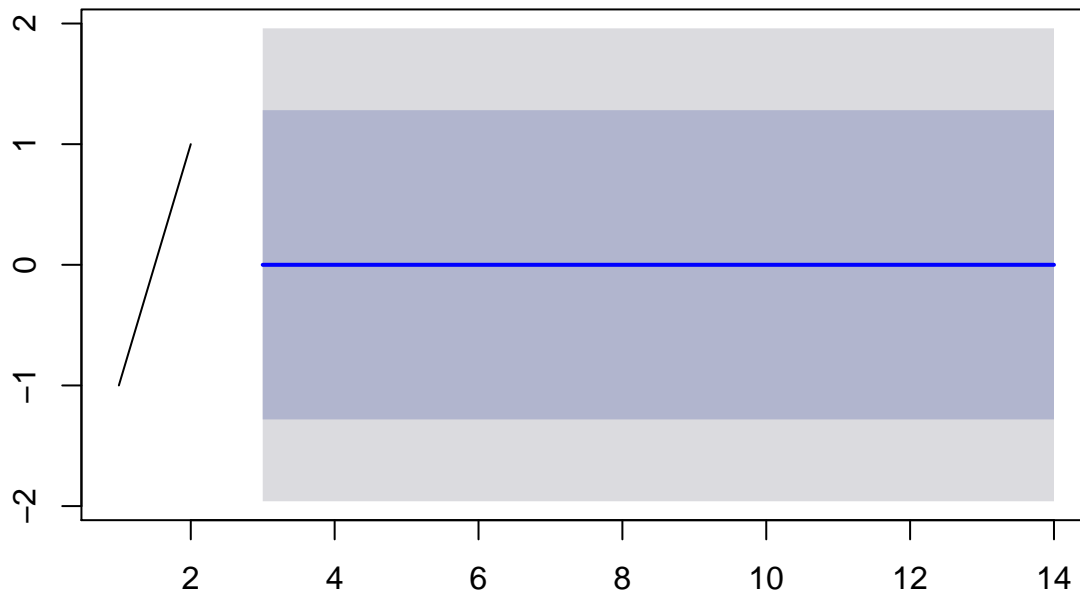
Book ID: 95

Forecasts from ARIMA(0,0,0) with zero mean



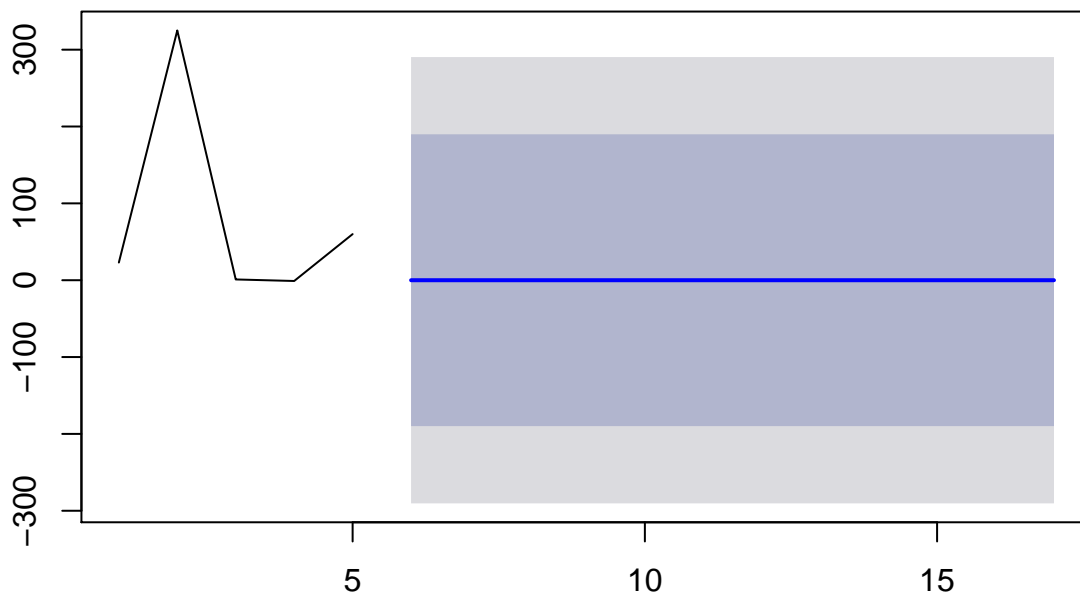
Book ID: 96

Forecasts from ARIMA(0,0,0) with zero mean



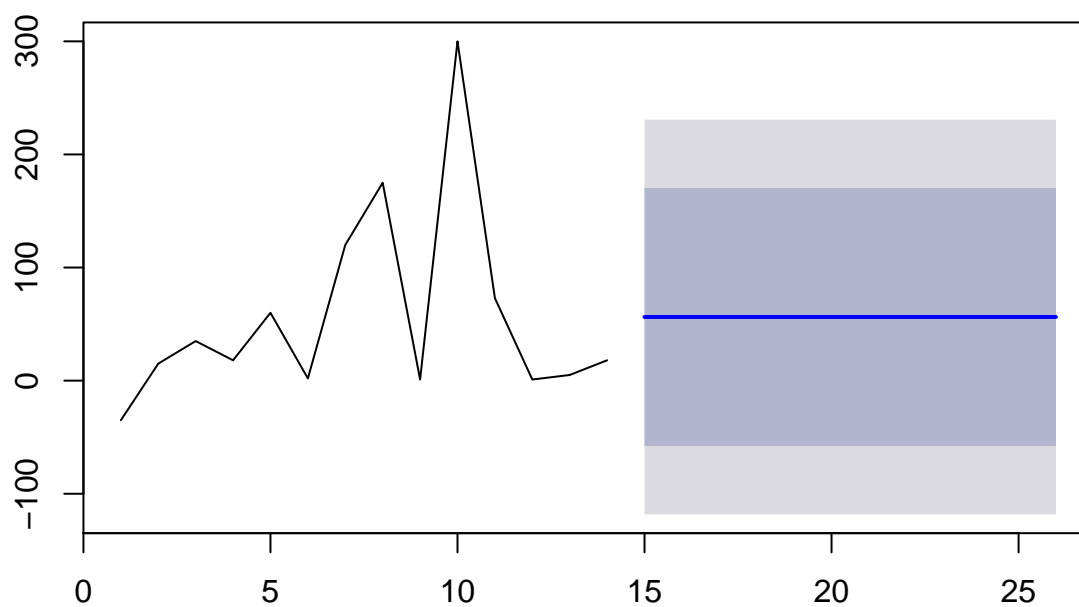
Book ID: 97

Forecasts from ARIMA(0,0,0) with zero mean



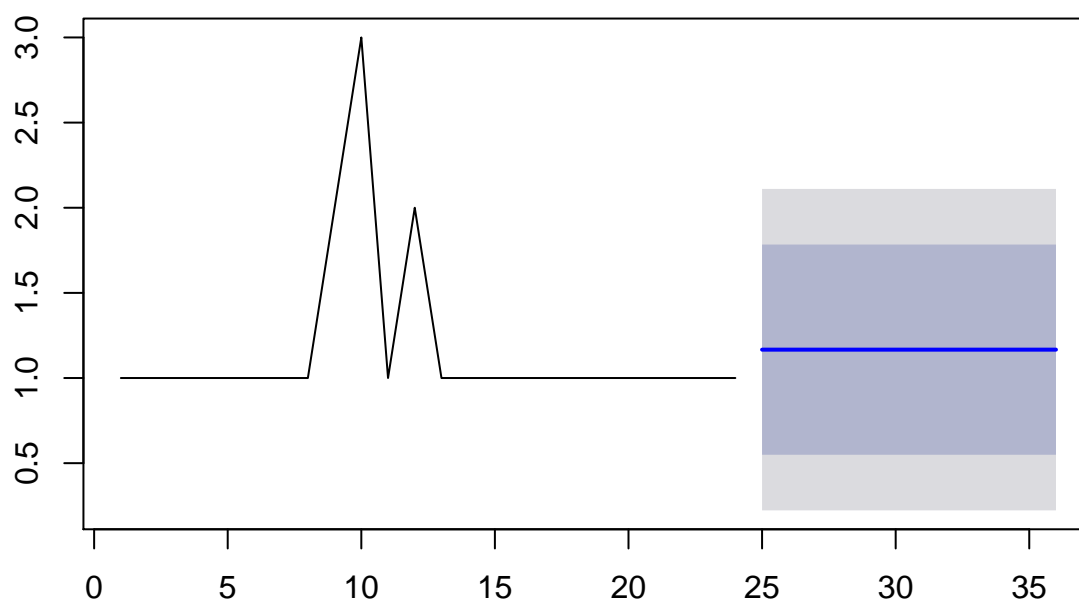
Book ID: 103

Forecasts from ARIMA(0,0,0) with non-zero mean



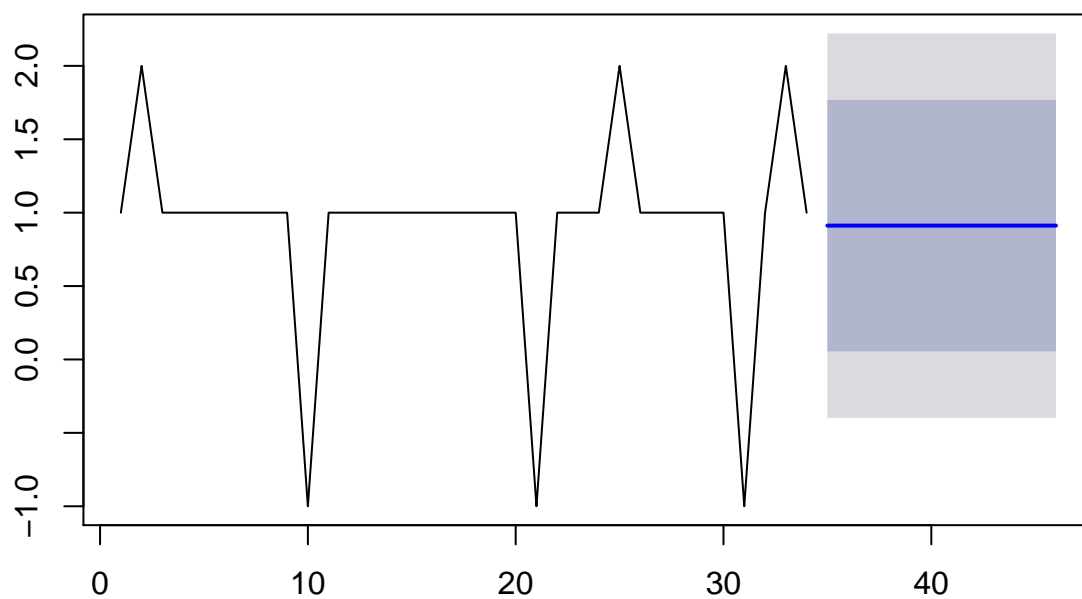
Book ID: 109

Forecasts from ARIMA(0,0,0) with non-zero mean



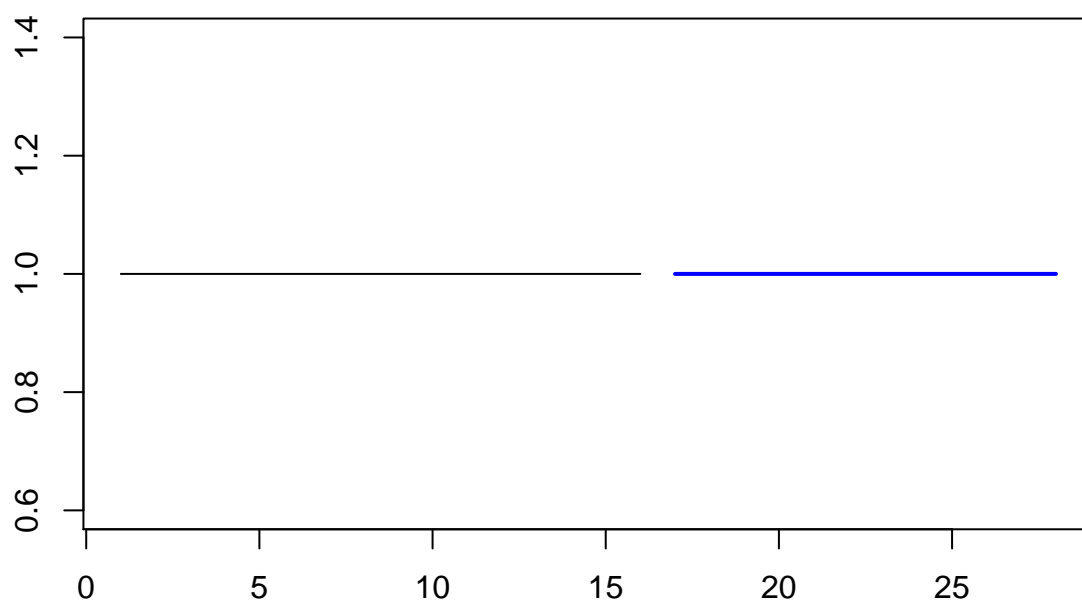
Book ID: 110

Forecasts from ARIMA(0,0,0) with non-zero mean



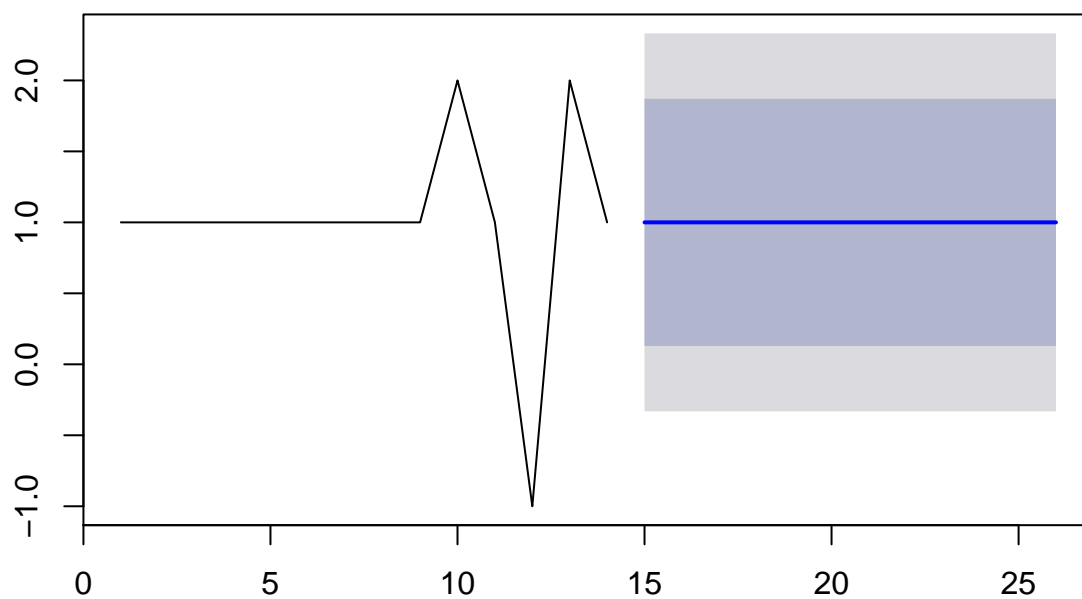
Book ID: 128

Forecasts from ARIMA(0,0,0) with non-zero mean



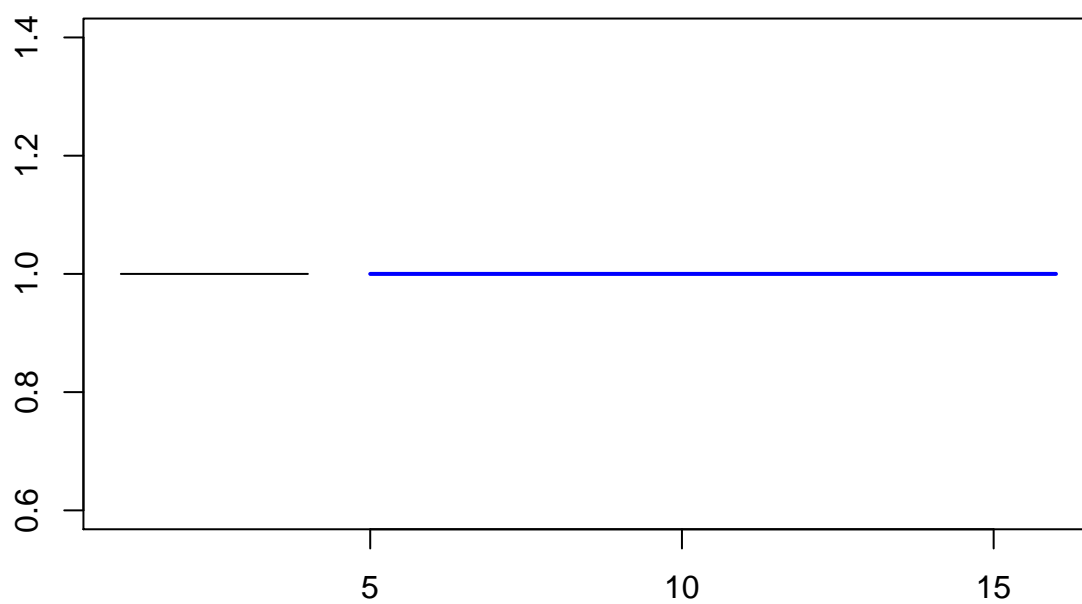
Book ID: 129

Forecasts from ARIMA(0,0,0) with non-zero mean



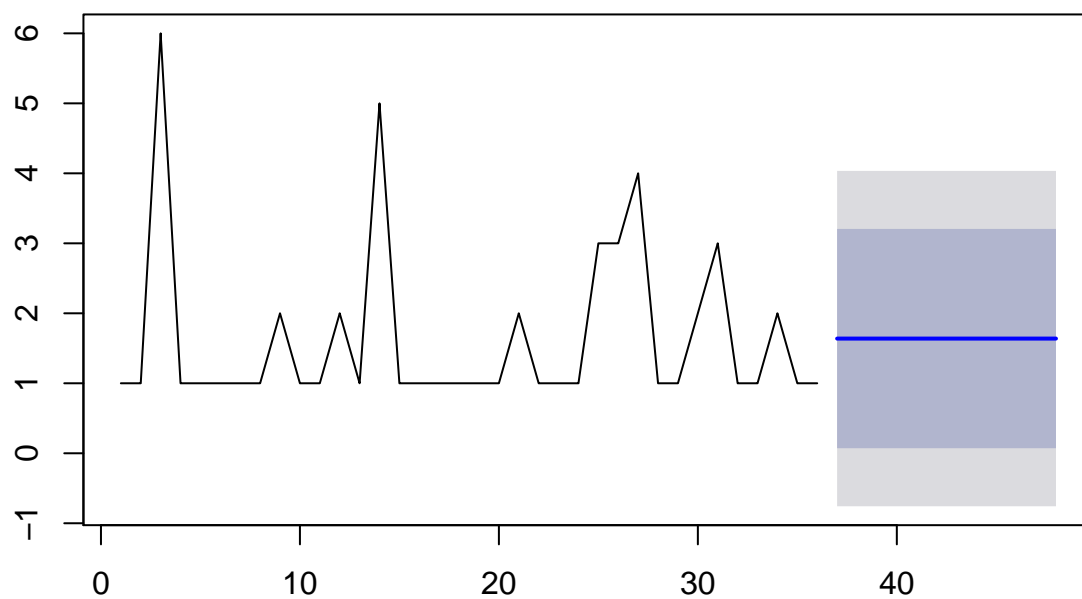
Book ID: 132

Forecasts from ARIMA(0,0,0) with non-zero mean



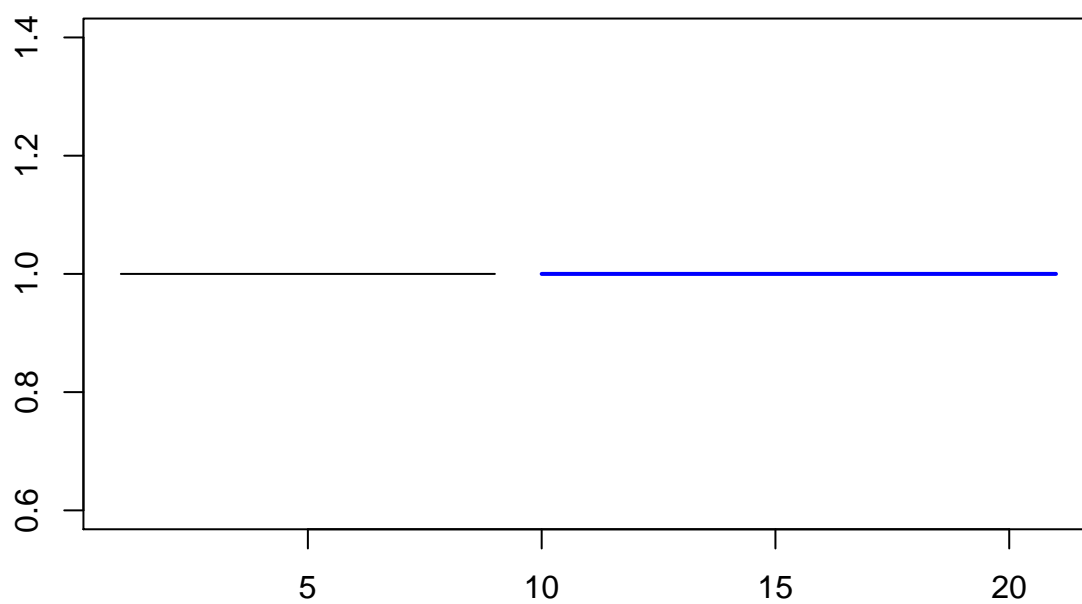
Book ID: 165

Forecasts from ARIMA(0,0,0) with non-zero mean



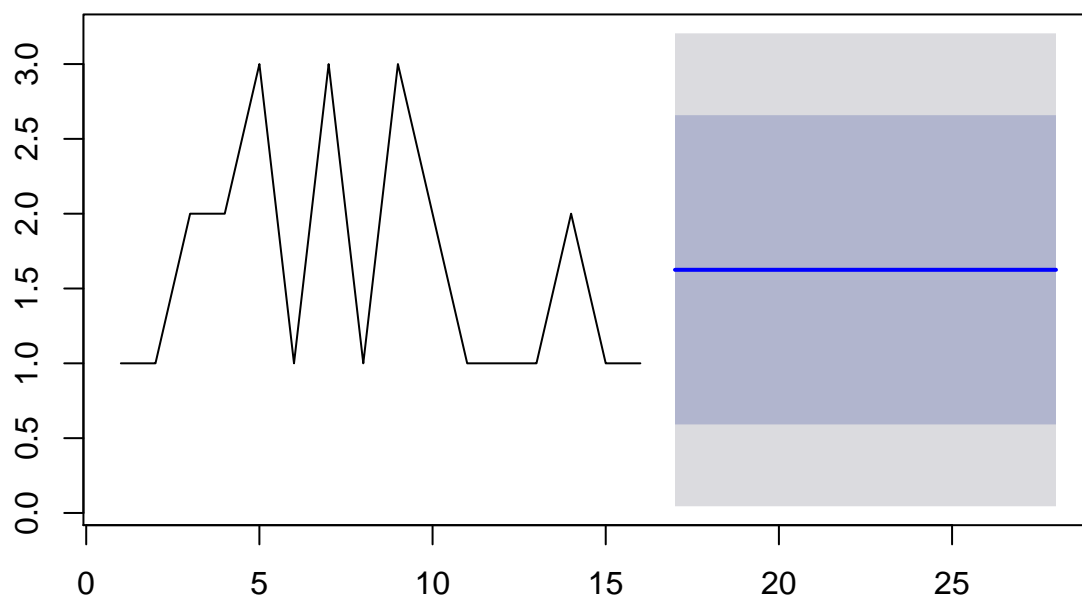
Book ID: 166

Forecasts from ARIMA(0,0,0) with non-zero mean



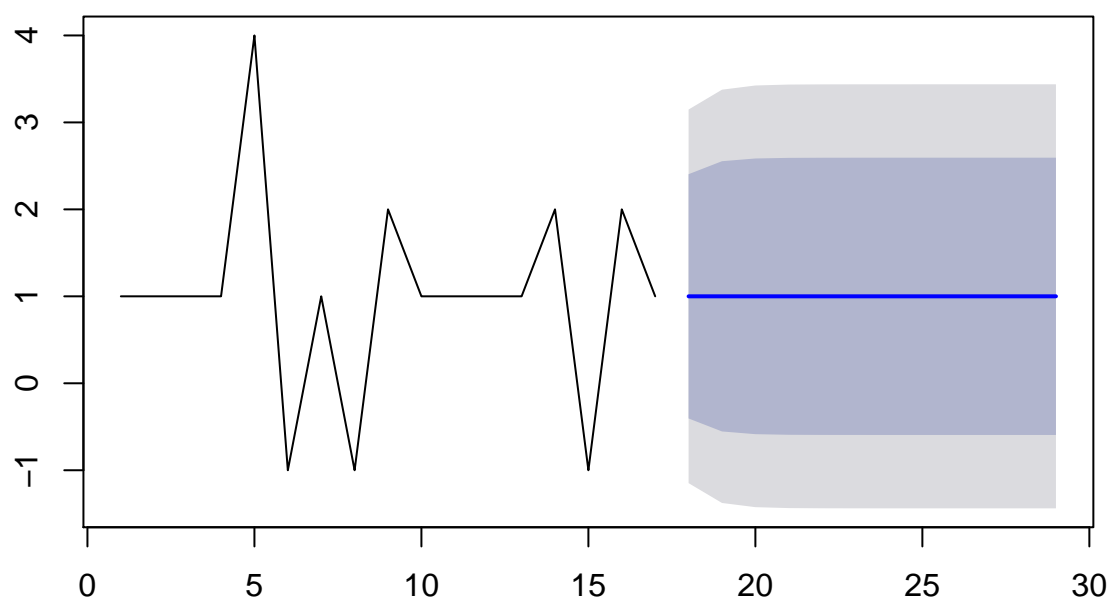
Book ID: 172

Forecasts from ARIMA(0,0,0) with non-zero mean



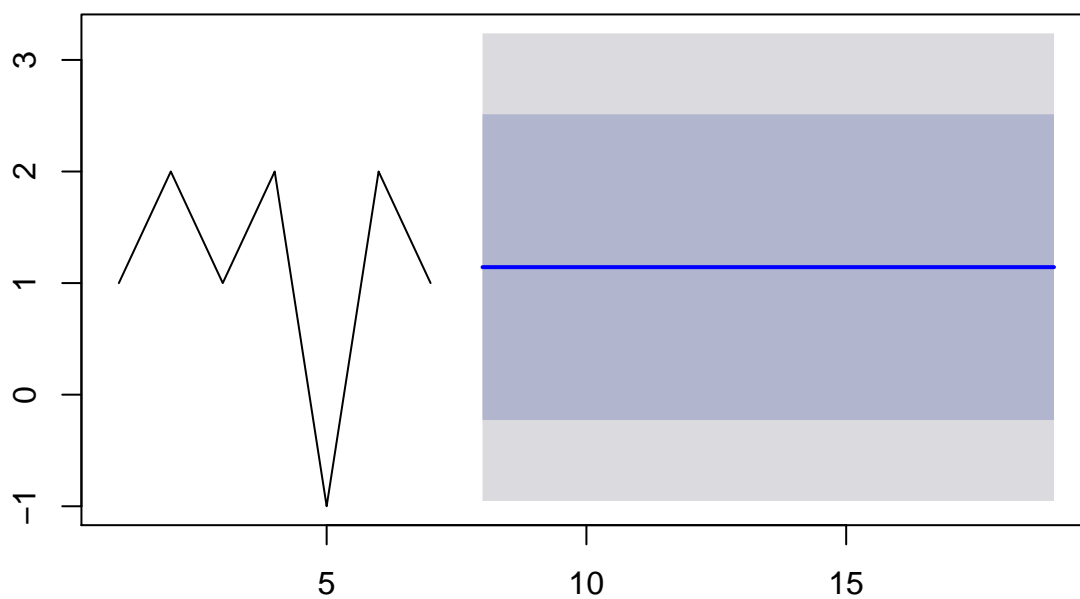
Book ID: 195

Forecasts from ARIMA(1,0,0) with non-zero mean



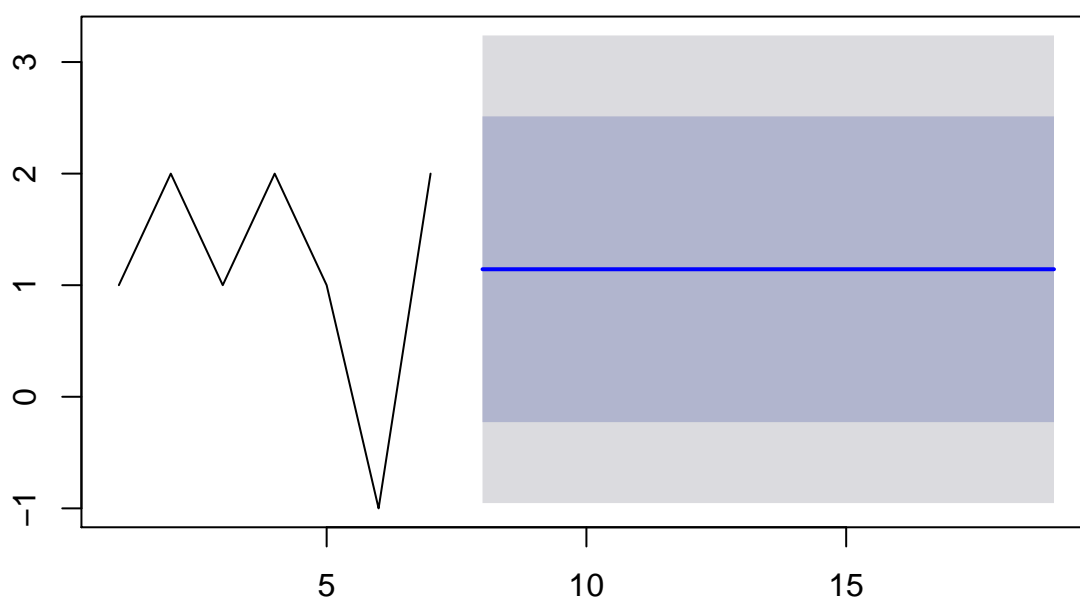
Book ID: 196

Forecasts from ARIMA(0,0,0) with non-zero mean



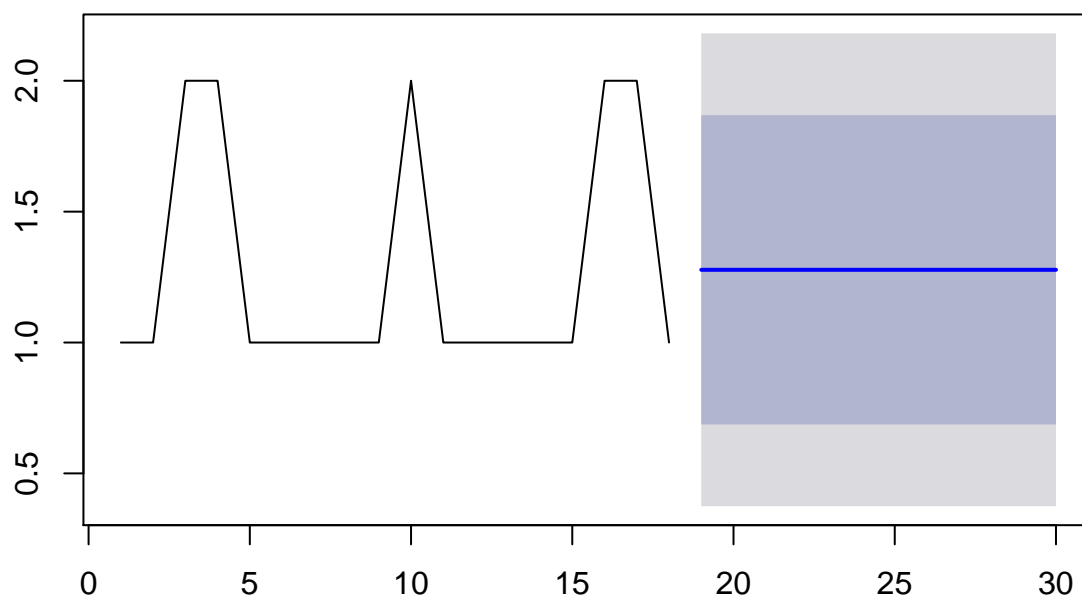
Book ID: 197

Forecasts from ARIMA(0,0,0) with non-zero mean



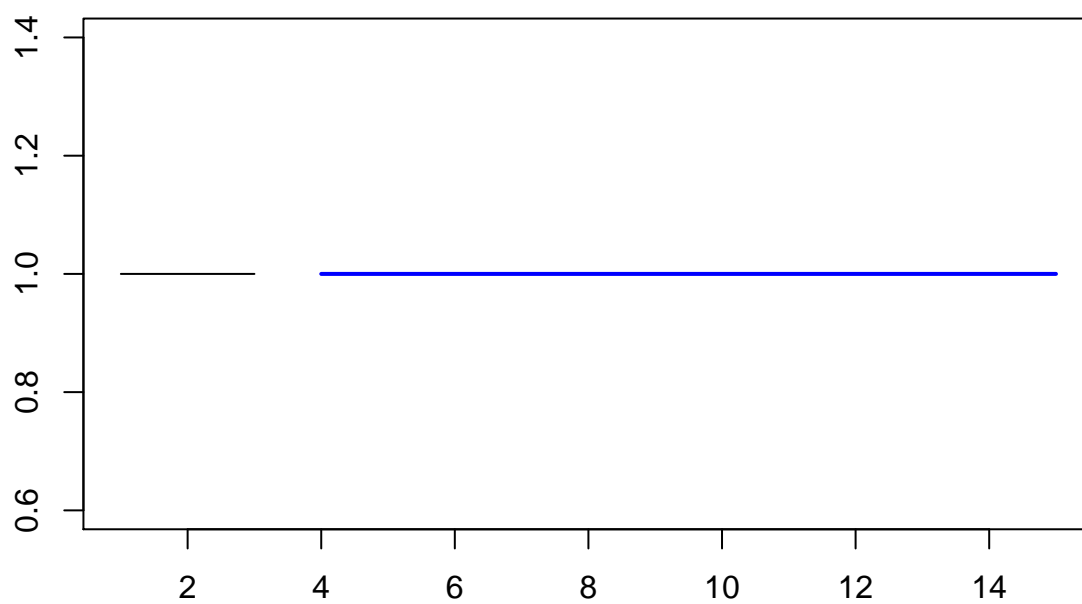
Book ID: 239

Forecasts from ARIMA(0,0,0) with non-zero mean



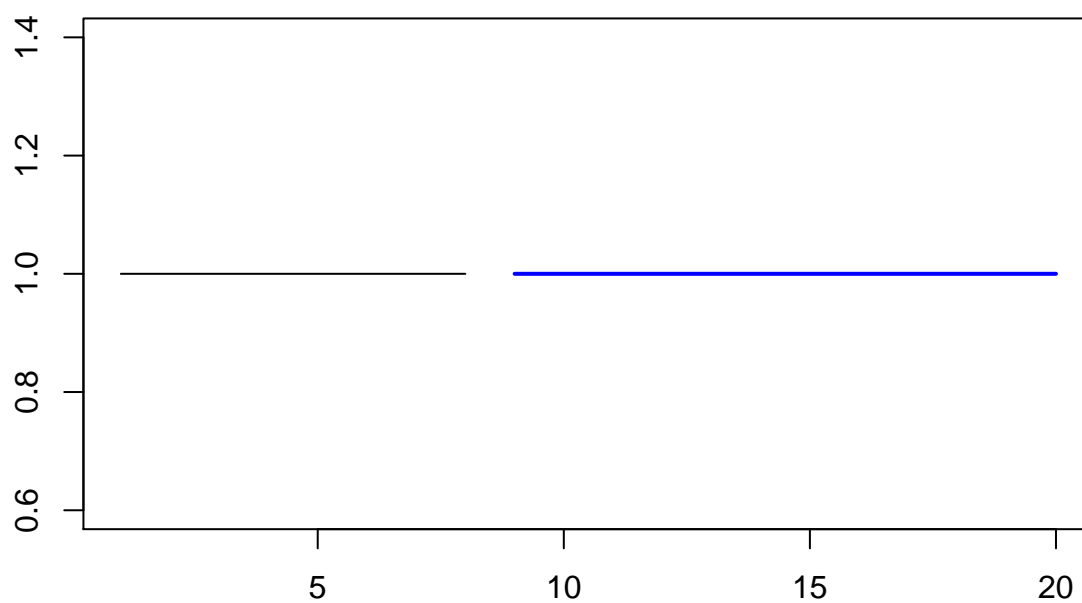
Book ID: 243

Forecasts from ARIMA(0,0,0) with non-zero mean



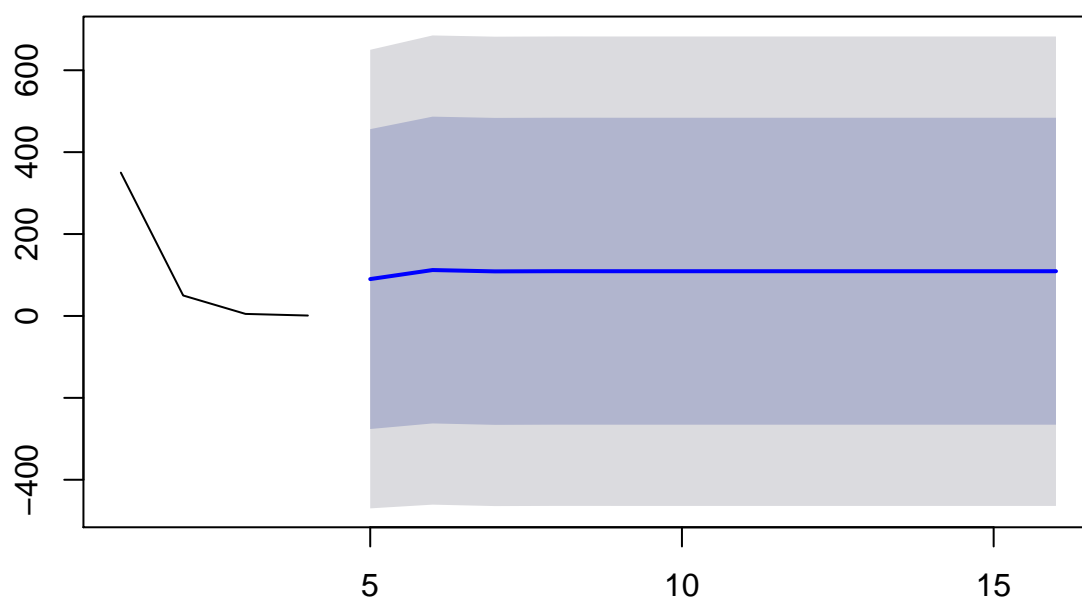
Book ID: 244

Forecasts from ARIMA(0,0,0) with non-zero mean



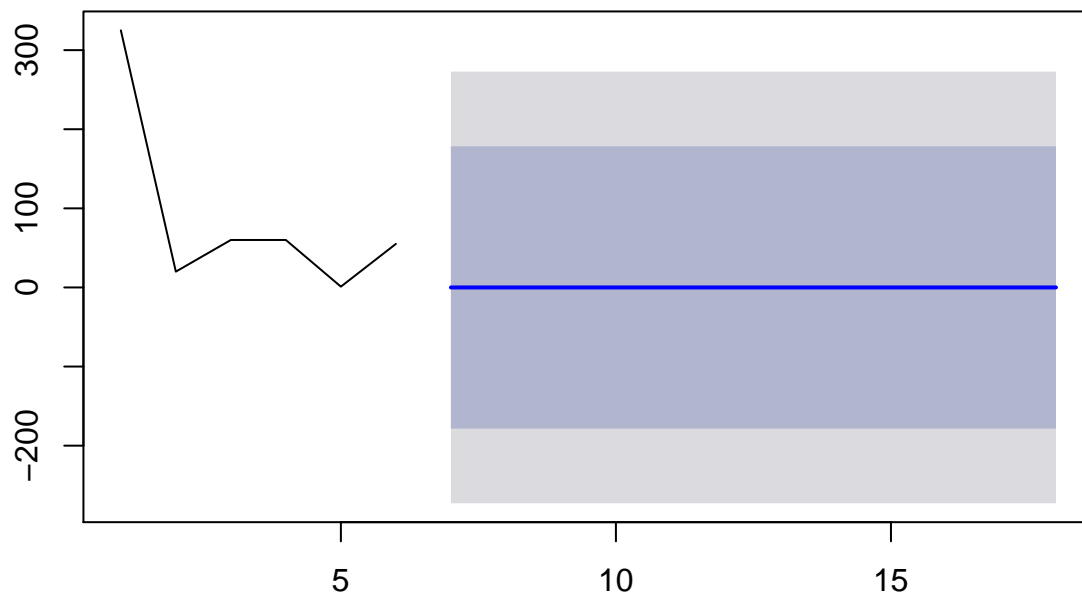
Book ID: 324

Forecasts from ARIMA(1,0,1) with non-zero mean



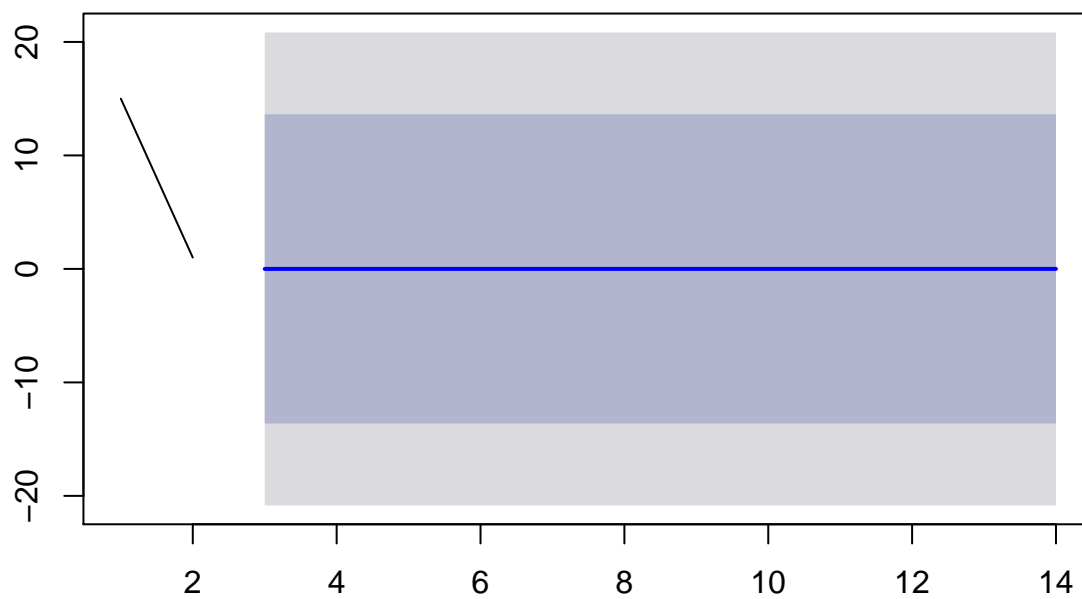
Book ID: 325

Forecasts from ARIMA(0,0,0) with zero mean



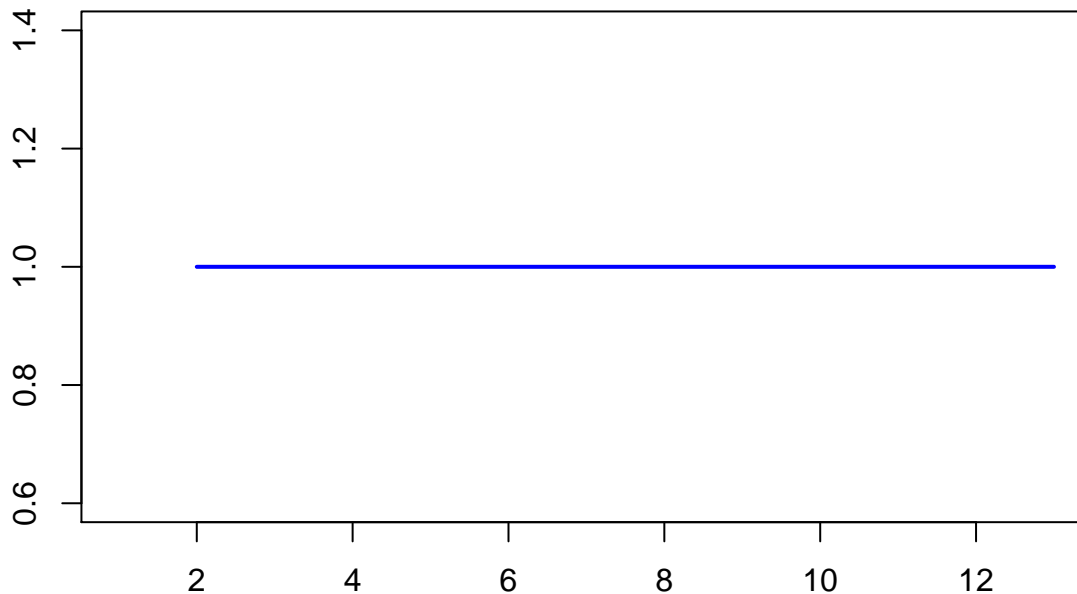
Book ID: 364

Forecasts from ARIMA(0,0,0) with zero mean



Book ID: 542

Forecasts from ARIMA(0,0,0) with non-zero mean



```
# Print SMAPE Score for all the book titles
for (i in isbn_list){
  ISBN <- final_dataset[final_dataset$ISBN == i,]
  cat(i)
  train_data_all <- ISBN[ISBN$Date.Ordered.Year < "2018",]
  test_data_all <- ISBN[ISBN$Date.Ordered.Year >= "2018",]
  #Arima model
  arima_all <- auto.arima(ISBN$Quantity.Ordered)
  forecast_all <- forecast(arima_all, h = 12)
  pred <- mean(as.vector(forecast_all$mean))
  test <- mean(test_data_all$Quantity.Ordered)
  smape <- (sum(abs(test-pred))/(abs(test)+abs(pred)))/length(test)
  smape
}
```

```
## 12345678910111415161718192021222324252627282930313233343536373839404142434954565758596061626386909192
```

Step 5: Determine Dependent Vs Independent Variables in Regression Modelling for one title

Price as independent variable

```
Quantity.model <- lm(as.formula(Quantity.Ordered~Order.Price), data = train_data_8)
Quantity.model
```

```
##
## Call:
## lm(formula = as.formula(Quantity.Ordered ~ Order.Price), data = train_data_8)
##
## Coefficients:
## (Intercept)  Order.Price
##      3.92857      -0.03571
```

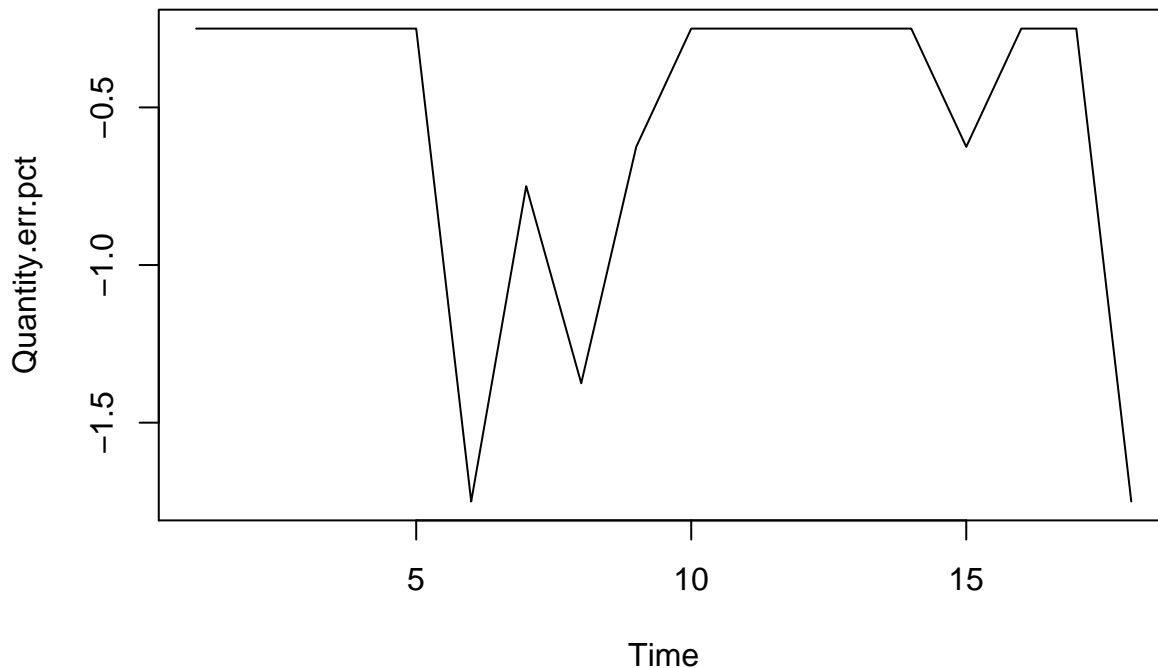
```
options(warn=-1)
Quantity.model.predict <- predict.lm(Quantity.model, newdata = test_data_8)
options(warn=1)
Quantity.model.predict
```

```
## 481 487 492 493 495
## 0.75 0.75 0.75 0.75 0.75
```

```
Quantity.actual <- train_data_8[, 'Quantity.Ordered']
Quantity.err.pct <- (Quantity.model.predict-Quantity.actual)/Quantity.actual
```

```
## Warning in Quantity.model.predict - Quantity.actual: longer object length
## is not a multiple of shorter object length
```

```
plot.ts(Quantity.err.pct)
```



```
# SSE
Quantity.lm.SSE <- sum(sapply((Quantity.model.predict-Quantity.actual), function(z) z^2))
```

```
## Warning in Quantity.model.predict - Quantity.actual: longer object length
## is not a multiple of shorter object length
```

```
Quantity.lm.SSE
```

```
## [1] 22.625
```

```
# SSE as a percentage of mean of actual values
```

```
Quantity.lm.SSE/mean(unlist(Quantity.actual))
```

```
## [1] 27.15
```

Quantity as independent variable

```
Price.model <- lm(as.formula(Order.Price~Quantity.Ordered), data = train_data_8)
Price.model
```

```
##
```

```
## Call:
## lm(formula = as.formula(Order.Price ~ Quantity.Ordered), data = train_data_8)
##
## Coefficients:
##      (Intercept)  Quantity.Ordered
##          86.9259         -0.3111

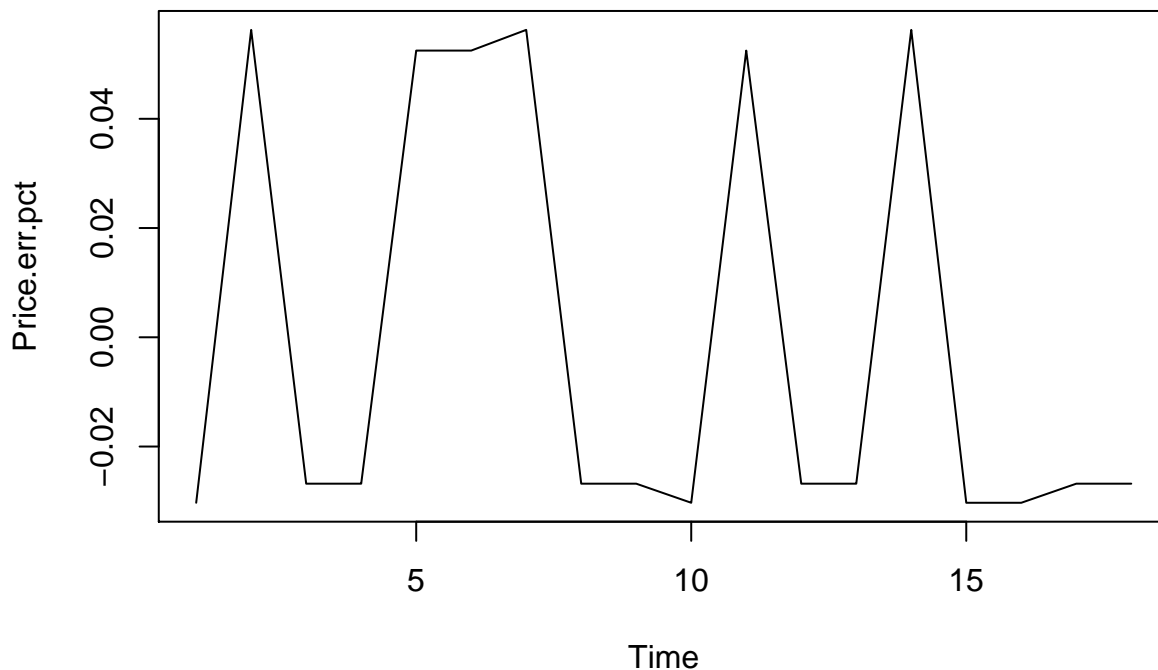
options(warn=-1)
Price.model.predict <- predict.lm(Price.model, newdata = test_data_8)
options(warn=1)
Price.model.predict

##      481      487      492      493      495
## 86.30370 86.61481 86.61481 86.61481 86.30370

Price.actual <- train_data_8[, 'Order.Price']
Price.err.pct <- (Price.model.predict-Price.actual)/Price.actual

## Warning in Price.model.predict - Price.actual: longer object length is not
## a multiple of shorter object length

plot.ts(Price.err.pct)
```



```
# SSE
Price.lm.SSE <- sum(sapply((Price.model.predict-Price.actual), function(z) z^2))

## Warning in Price.model.predict - Price.actual: longer object length is not
## a multiple of shorter object length

Price.lm.SSE

## [1] 194.0481

# SSE as a percentage of mean of actual values
Price.lm.SSE/mean(unlist(Price.actual))

## [1] 2.239016
```

When comparing the 2 models using the sum of squared error as a percentage of the mean of the actual values, the SSE when Price as the dependent variable is less when compared to Quantity being the dependent variable. However, in terms of business interests, we would like to forecast the quantity and hence I believe Quantity should be the dependent variable and Price the independent variable in case of Regression Time Series Problems.