



# *R For Time Series*

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# Outline

- *Time series forecasting in R*
  - *Moving average*
  - *Holt-Winter methods*
    - *Exponential Smoothing*
    - *Double exponential Smoothing*
    - *Holt-Winter*



# Read data

```
#### Prep: Load R package; Set working directory; Load the data to R
# Remove all variables from the R environment to create a fresh start
rm(list=ls())

# We next load some packages that are generally useful for data analytics.
# In each case, check first to see if a required package is installed. If not, then install it
# and invoke it as a library.
if(!require(stats)){
  install.packages("stats")
  library(stats)
}

# Similarly, we need to change the working directory to the directory where we want to read and save data
# Define a variable, wd, with a string describing the path to the directory where we want to read and save data
# Change this to meet your needs!!!!!!!!!!
wd <- "C:\\Users\\xu_ying\\Google Drive\\Teaching\\DBA\\2022\\Lectures\\6\\Activity"
# Set the working directory to this path
setwd(wd)
# Test by displaying the current working directory
getwd()

# read the data from the data file
result <- read.csv(file = "Timeseries.csv")
head(result)
```

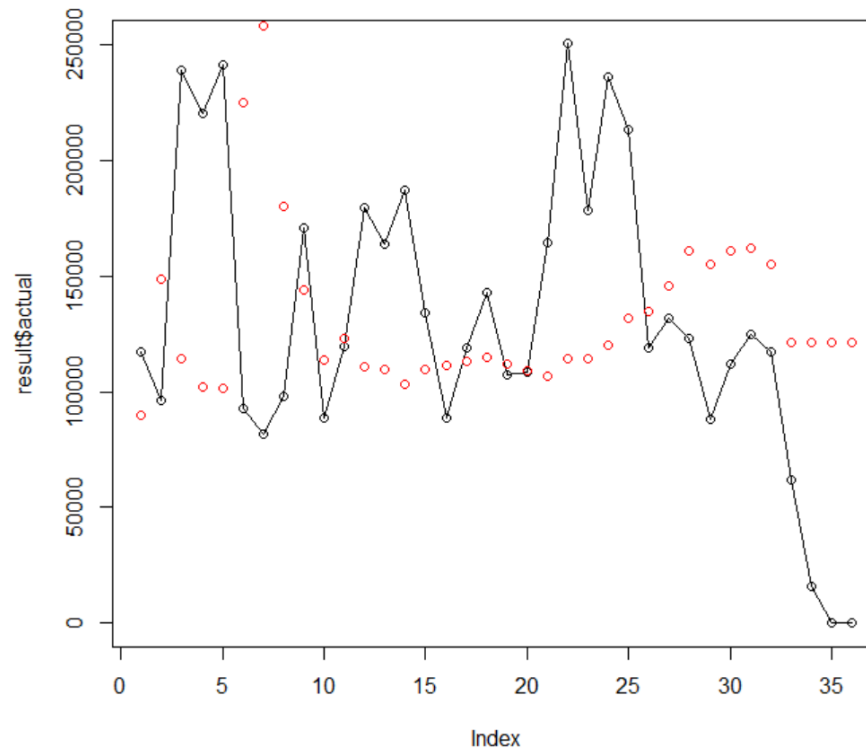


# *Compare the company's forecast with actual*

```
# Note that the database has provided the company's forecast in the column "forecast"
# We first plot the actual demand against the company's forecast for comparison
forecasts <- result$forecast
actuals <- result$actual
plot(actuals)
# Connect the points with lines so the sequence is clear
lines(actuals)
# Now add the corporate forecasts as red circles
points(forecasts,col=c("red"))
# How good are the forecasts? Perfection in the next plot would be a straight line angled at 45 degrees
# You could also plot the actual against forecast by uncomment the command below
# plot(actuals,forecasts)
# So, the forecasts are not good.

# Let's develop a quantitative measure of forecast accuracy.
errors <- forecasts-actuals
# Take the absolute difference of forecasts versus actuals.
abserrors <- abs(errors)
# Compute the total of the absolute errors
totalerror <- sum(abserrors)
# Compute the total actual demand
totalactual <- sum(actuals)
# The ratio is the relative absolute error of forecast
if (totalactual>0) {
  relativeabsoluteerror <- totalerror/totalactual
} else {
  relativeabsoluteerror <- 0
}
# Practitioners multiply the relative absolute error this by 100 to get what they call the WAPE (Weighted Average Percent Error)
WAPE <- relativeabsoluteerror*100
WAPE
# So, the Weighted Average Percent Error is about 49%. That is pretty high.
# And this is the largest selling product in the largest segment in the largest region!
# The forecast errors for smaller selling products will likely be much worse.
```

# Output



```
> WAPE <- relativeabsoluteerror*100  
> WAPE  
[1] 49.05694
```

# Moving Average 3

```
# Next we try different forecasting methods in R
##### Moving Average Forecasting Starts #####
# The moving average technique takes a vector of weights over a certain number of periods. Let's do a moving average over
weights <- rep(1/3,3)
weights
# There are many ways to implement moving average in R. The filter method is easy.
# The argument "sides=1" says to just use data to the left of point to be forecast.
maforecasts <- round(filter(actuals,weights,method="convolution",sides=1,circular=FALSE))
# The first few fitted values are NA because there is insufficient history to calculate the moving average.
# Omit NA entries.
maforecasts <- na.omit(maforecasts)
# The resulting structure is a time series. We just want the fitted values
class(maforecasts)
forecasts <- as.numeric(maforecasts)
str(forecasts)
```

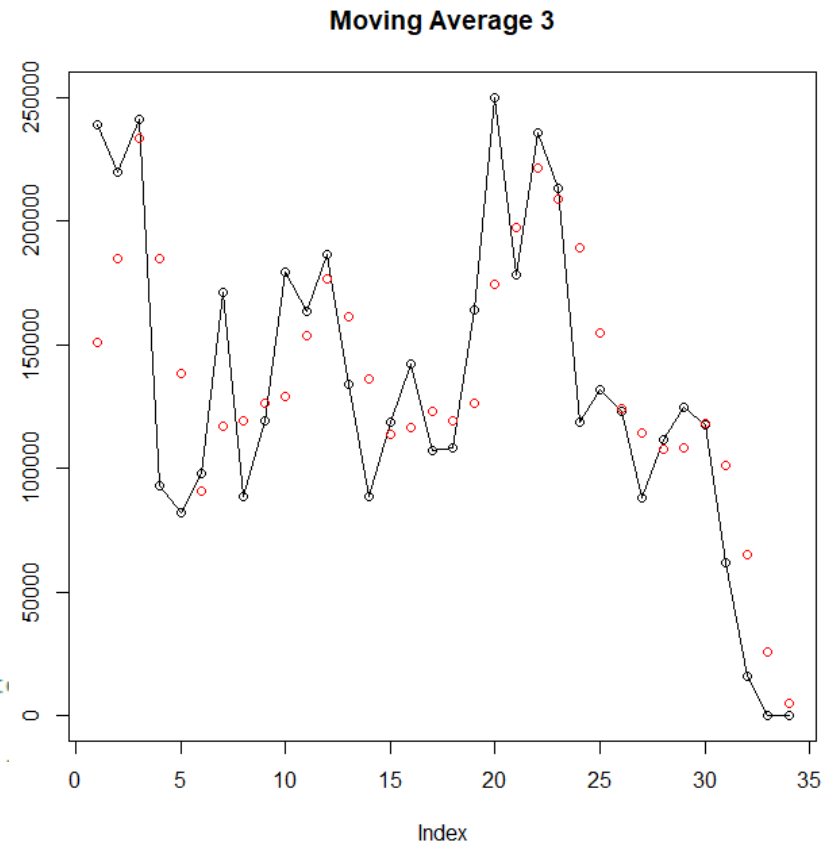


# Moving Average 3: Output

```
# Plot the data
# Omit the first few entries in actuals which has not predictions
actualsnew <- tail(actuals, length(forecasts))
plot(actualsnew)
# Connect the points with lines so the sequence is clear
lines(actualsnew)
# Now add the corporate forecasts as red circles
points(forecasts,col=c("red"))
title("Moving Average 3")

# Calculate the quantitative measure of forecast accuracy.
errors <- forecasts-actualsnew
# Take the absolute difference of forecasts versus actuals.
absererrors <- abs(errors)
# Compute the total of the absolute errors
totalerror <- sum(absererrors)
# Compute the total actual demand
totalactual <- sum(actualsnew)
# The ratio is the relative absolute error of forecast
if (totalactual>0) {
  relativeabsoluteerror <- totalerror/totalactual
} else {
  relativeabsoluteerror <- 0
}
# Practitioners multiply the relative absolute error this by 100 to
WAPE <- relativeabsoluteerror*100
WAPE
```

```
> WAPE <- relativeabsoluteerror*100
> WAPE
[1] 22.01729
```





# *Exponential Smoothing*

```
# We try another powerful technique Holt-winters method.
##### Holt-winters method Starts #####

##### Get read for Holt_winters #####
# Holt-winters requires a time series structure. So we convert the actuals vector into a time series by specifying the frequency.
tsactuals <- ts(actuals,frequency=12)
str(tsactuals)
plot(tsactuals)

# Here we try three Holt-winters methods
# We first try Holt-winters with just exponential smoothing (beta=False,gamma=False)
##### Holt-winters with just exponential smoothing (beta=False,gamma=False) #####
hw <- Holtwinters(tsactuals, beta=FALSE,gamma=FALSE)
# The Holt Winters data structure is complicated. We want to extract the first column of the fitted values.
hwfitted <- fitted(hw)[,1]
# The fitted values are a time series so we convert it to numeric (and round them to whole numbers for simplicity).
forecasts <- round(as.numeric(fitted(hw)[,1]))
```



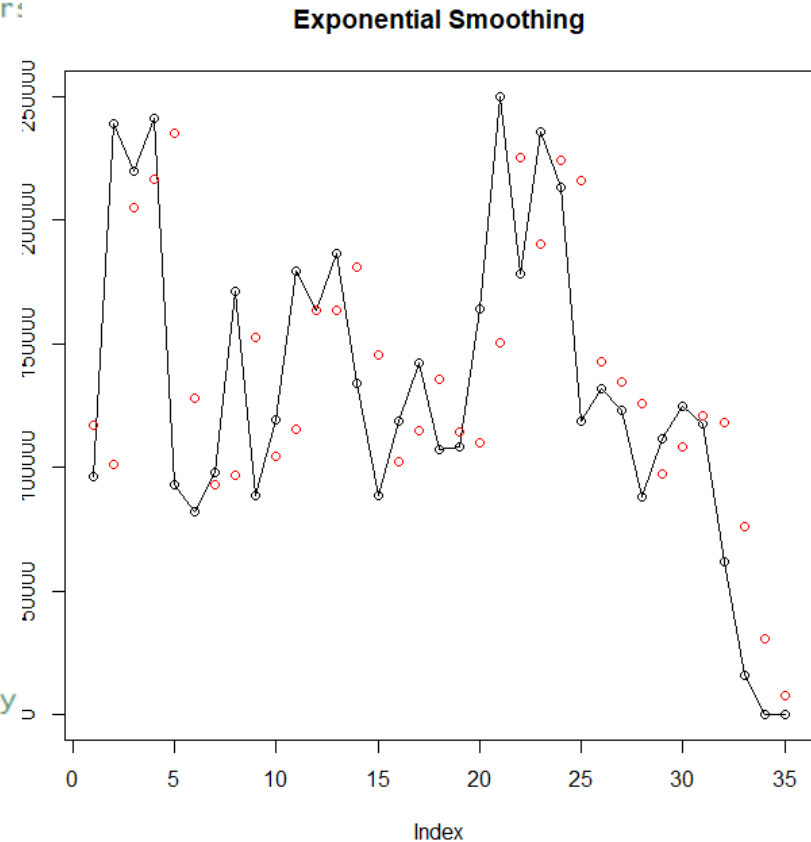
# Exponential Smoothing: Output



```
# Plot the Holt-Winters forecasts
# The fitted values are missing the first entry, so we the fir:
actualsnew <- tail(actuals, length(forecasts))
plot(actualsnew)
# Connect the points with lines so the sequence is clear
lines(actualsnew)
# Now add the corporate forecasts as red circles
points(forecasts,col=c("red"))
title("Exponential Smoothing")

# Calculate the quantitative measure of forecast accuracy.
errors <- forecasts-actualsnew
# Take the absolute difference of forecasts versus actuals.
abserrors <- abs(errors)
# Compute the total of the absolute errors
totalerror <- sum(abserrors)
# Compute the total actual demand
totalactual <- sum(actualsnew)
# The ratio is the relative absolute error of forecast
if (totalactual>0) {
  relativeabsoluteerror <- totalerror/totalactual
} else {
  relativeabsoluteerror <- 0
}
# Practitioners multiply the relative absolute error this by
WAPE <- relativeabsoluteerror*100
WAPE

> WAPE <- relativeabsoluteerror*100
> WAPE
[1] 30.74229
```





# *Double Exponential Smoothing*

```
# We secondly try Holt-winters without seasonality (double exponential smoothing (gamma=FALSE))
##### Holt-winters without seasonality (gamma=FALSE) #####
# Now call the Holt-winters function without seasonality (gamma=FALSE). This is equivalent to double exponential smoothing.
hw <- Holtwinters(tsactuals, gamma=FALSE)
# The Holt winters data structure is complicated. We want to extract the first column of the fitted values.
hwfitted <- fitted(hw)[,1]
# The fitted values are a time series so we convert it to numeric (and round them to whole numbers for simplicity).
forecasts <- round(as.numeric(fitted(hw)[,1]))
```

**Input your code for plotting and calculating WAPE  
(see answer below)**

```
> WAPE <- relativeabsoluteerror*100
> WAPE
[1] 32.7282
```

# *Holt-Winters*

Input your code for the forecasting, plotting and calculating WAPE  
(see answer below)

```
> WAPE <- relativeabsoluteerror*100
> WAPE
[1] 31.79599
```

# *Which methods works the best?*

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