

ISyE 4031 Regression and Forecasting

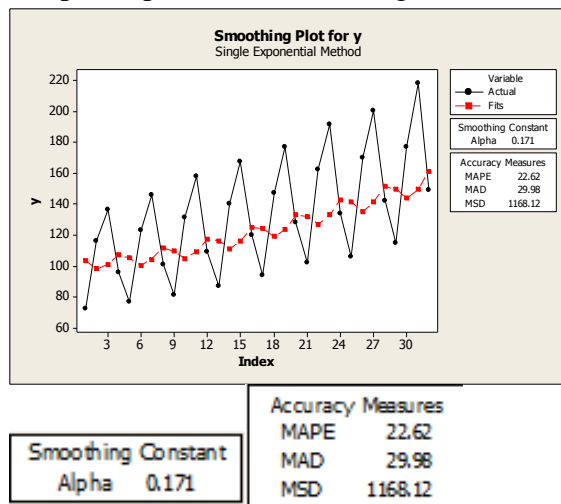
Homework 10 Solutions

Spring 2016

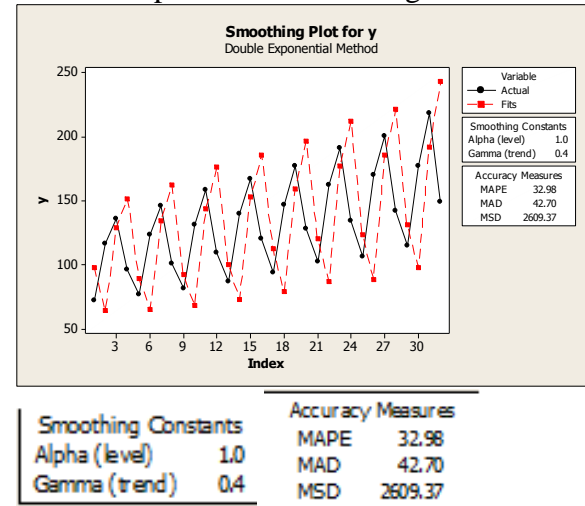
1. Tiger Sports Drink data.

– Minitab solutions

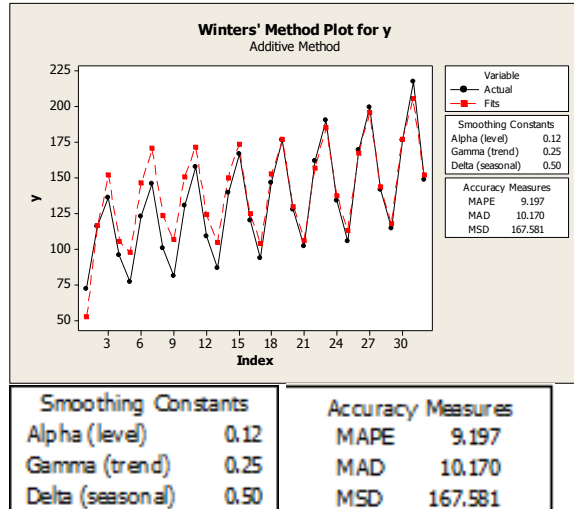
Simple Exponential Smoothing



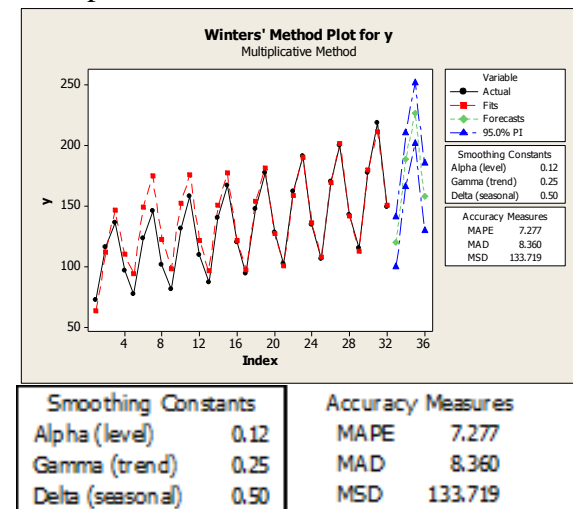
Double Exponential Smoothing



Additive Holt-Winters'



Multiplicative Holt-Winters'



– R solutions:

Simple Exponential Smoothing (Optimum α)

```
> y.ts = ts(Mydata, frequency =4)
```

```
> plot(y.ts)
```

```
# By using R's optimal alpha:
```

```
> ses.exp = hw(y.ts, initial="simple", beta=FALSE, gamma=FALSE)
```

```
# Alternatively use function hw(y.ts, alpha = 0.171, beta=FALSE, gamma=FALSE)
```

```
# You can also use HoltWinters( ) function as below.
```

```
> ses = ses.exp$fitted
```

```
> lines(ses, type="o", pch=22, lty=2, col="red")
```

```
> mad.ses = sum(abs(y-ses)/length(y))
```

```
> mape.ses = 100*sum(abs((y-ses)/y)/length(y))
```

```
> msd.ses = sum((y-ses)^2/length(y))
```

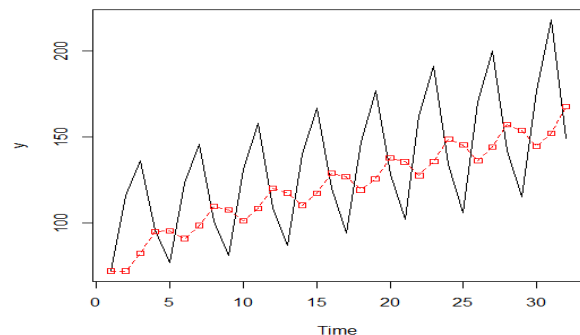
```
HoltWinters(x = y.ts, beta = FALSE, gamma = FALSE)
```

Smoothing parameters:

alpha: 0.2363389

beta : FALSE

gamma: FALSE



Simple Exponential Smoothing

MAPE = 22.98

MAD = 31.29

MSD = 1265.68

Double Exponential Smoothing (Optimum α , γ)

```
> des.exp <- hw(y.ts, initial = 'simple', gamma=FALSE)
```

```
> des = des.exp$fitted
```

```
# Alternatively use function hw(y.ts, alpha = 1, beta=0.4, gamma=FALSE)
```

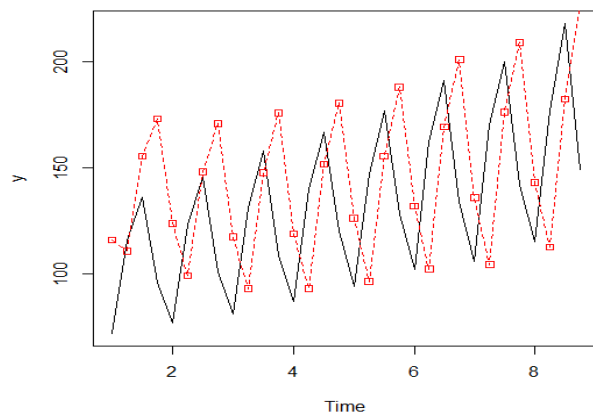
```
HoltWinters(y.ts, gamma=FALSE)
```

Smoothing parameters:

alpha: 1

beta : 1

gamma: FALSE



Double Exponential Smoothing
 MAPE = 34.17
 MAD = 41.56
 MSD = 2190.66

Additive Holt-Winters' Exponential Smoothing (Optimum α , γ , δ)

```
> hwa.exp <- hw(y.ts, seasonal="additive", initial="simple")
```

```
> hwa <- hwa.exp
```

#Alternatively, use

```
#hw(y.ts, seasonal="additive", initial="simple", alpha=0.12, beta=0.25, gamma=0.5)
```

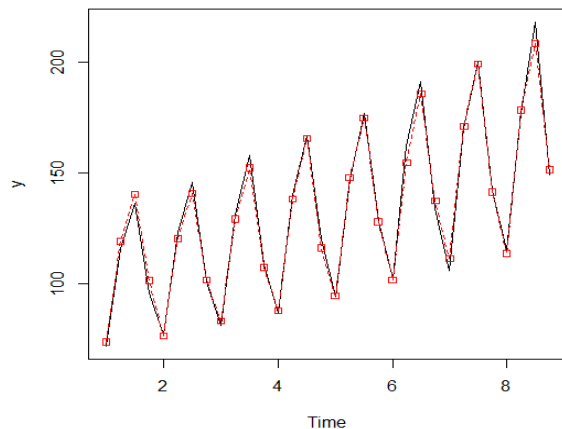
```
HoltWinters(x = y.ts)
```

Smoothing parameters:

alpha: 0.0168574

beta : 1

gamma: 1

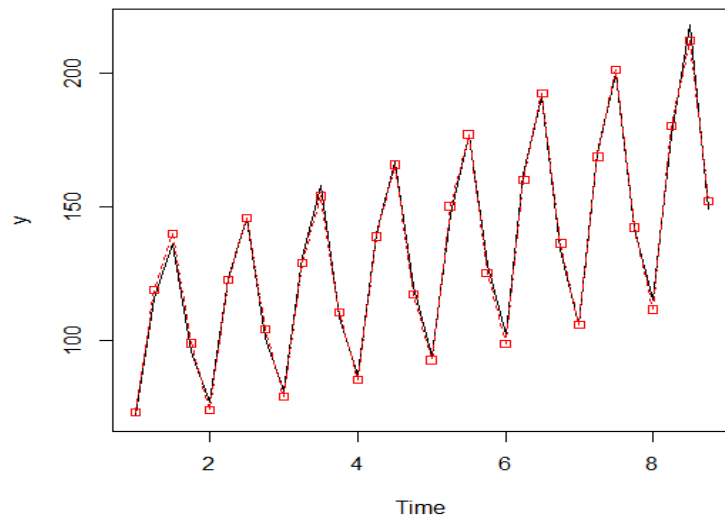


Additive Holt-Winters
 MAPE = 2.001
 MAD = 2.69
 MSD = 12.36

Multiplicative Holt-Winters' Exponential Smoothing (Optimum α , γ , δ)

```
> hwm.exp <- hw(y.ts, seasonal="multiplicative", initial="simple")
```

```
> hwm <- hwm.exp$fitted
```



Multiplicative Holt-Winters
MAPE = 1.74
MAD = 2.17
MSD = 6.47

Among all methods multiplicative Holt-Winter's performs the best. All accuracy measures: MAPE, MAD, and MSD are the smallest.

When we look at the time-series, we see a trend and increasing seasonality (multiplicative seasonality). Multiplicative Holt-Winter's method is the most appropriate for this type of time-series.

2. Exercise 8.14.

$$\begin{aligned} \text{a. } \hat{y}_{20}(16) &= \ell_{16} + 4b_{16} + sn_{20-4} \\ &= \ell_{16} + 4b_{16} + sn_{16} = 36.3426 + 4(.9809) + (-10.9088) = 29.3574 \end{aligned}$$

A 95% prediction interval for bike sales in period 20.

$$\begin{aligned} c_{\tau} &= c_4 = 1 + \alpha^2(1 + \gamma)^2 + \alpha^2(1 + 2\gamma)^2 + \alpha^2(1 + 3\gamma)^2 \\ &= 1 + (.561)^2(1 + 0)^2 + (.561)^2(1 + 2(0))^2 + (.561)^2(1 + 3(0))^2 = 1 + 3(.561)^2 = 1.9442 \end{aligned}$$

$$\begin{aligned} [\hat{y}_{20}(16) \pm z_{[.025]}s\sqrt{c_4}] \\ = [29.3574 \pm 1.96(1.2025)\sqrt{1.9442}] = [29.3574 \pm 3.2863] = [26.0711, 32.6437] \end{aligned}$$

$$\begin{aligned} \text{b. } \hat{y}_{21}(16) &= \ell_{16} + 5b_{16} + sn_{21-4} = \ell_{16} + 5b_{16} + sn_{17} \\ &= \ell_{16} + 5b_{16} + sn_{13} \quad (sn_{13} \text{ is last estimate for seasonal factor in quarter 1}) \\ &= 36.3426 + 5(.9809) - 14.2162 = 27.0309 \end{aligned}$$

A 95% prediction interval for bike sales in period 21

$$\begin{aligned} c_{\tau} &= c_5 = 1 + \alpha^2(1 + \gamma)^2 + \alpha^2(1 + 2\gamma)^2 + \alpha^2(1 + 3\gamma)^2 + [\alpha(1 + 4\gamma) + (1 - \alpha)\delta]^2 \\ &= c_4 + [\alpha(1 + 4\gamma) + (1 - \alpha)\delta]^2 = 1.9442 + [.561(1 + 4(0) + .439(0))]^2 = 2.2589 \end{aligned}$$

$$\begin{aligned} [\hat{y}_{21}(16) \pm z_{[.025]}s\sqrt{c_5}] \\ = [27.0309 \pm 1.96(1.2025)\sqrt{2.2589}] = [27.0309 \pm 3.5423] = [23.4886, 30.5732]. \end{aligned}$$

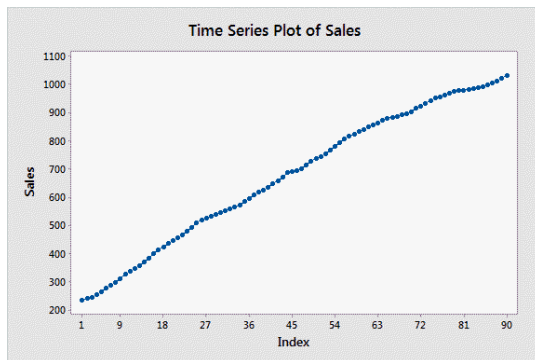
3. Exercise 9.3.

- a. The SAC dies down very slowly. Therefore, the original values are nonstationary.
- d. The SAC in Figure 9.16 dies down quickly. Therefore, the first differences are stationary.
- e. The SAC in Figure 9.16(a) dies down quickly. The SPAC in Figure 9.16(b) has a spike at lag 1 and cuts off after lag 1.

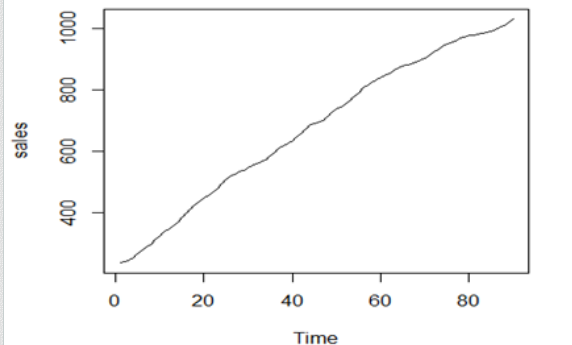
4. Toothpaste sales data.

- a. Time-series plot.

– Minitab solution

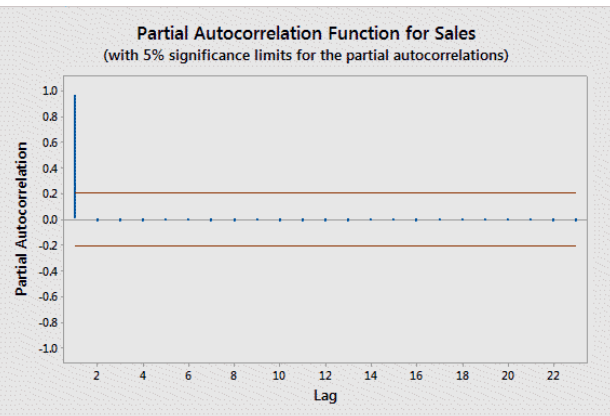
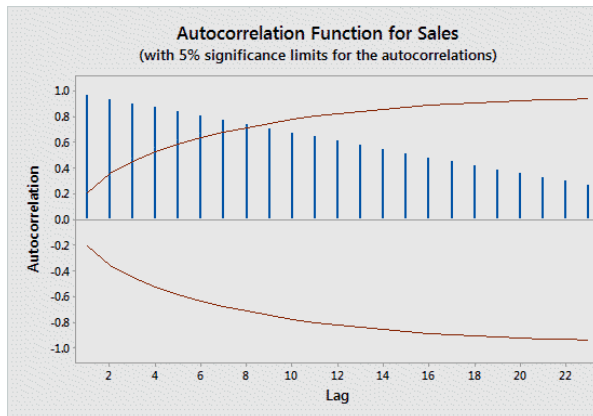


– R solution

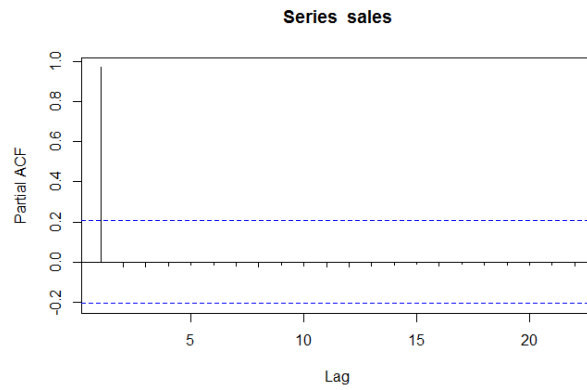
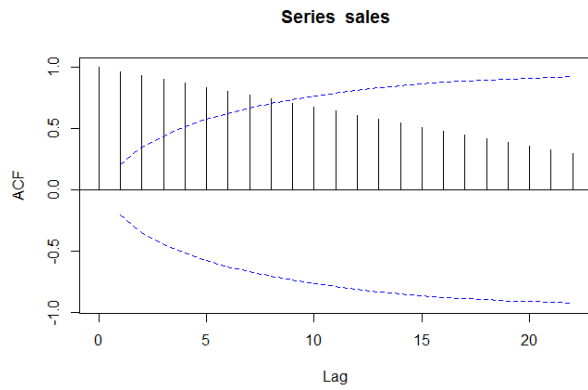


- b. SAC and SPAC for the original data.

– Minitab solutions



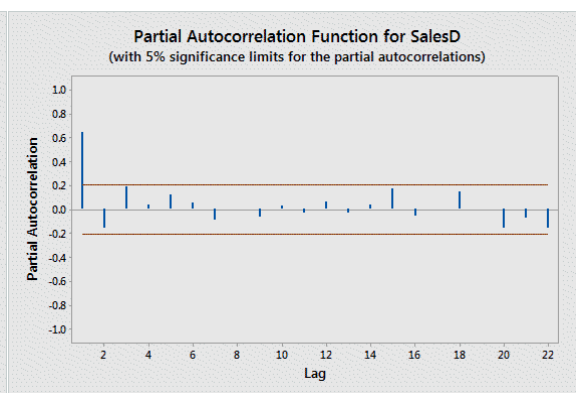
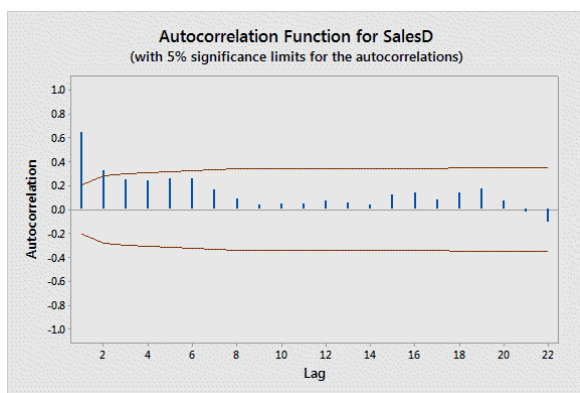
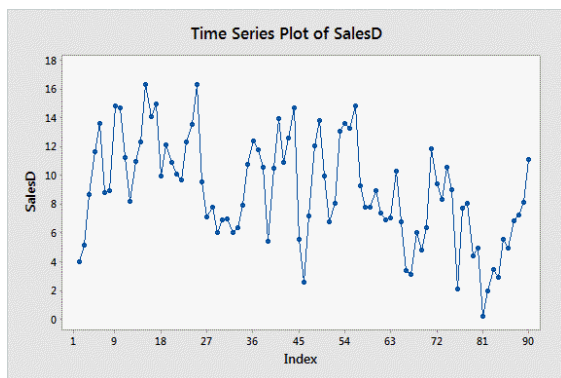
– R solutions



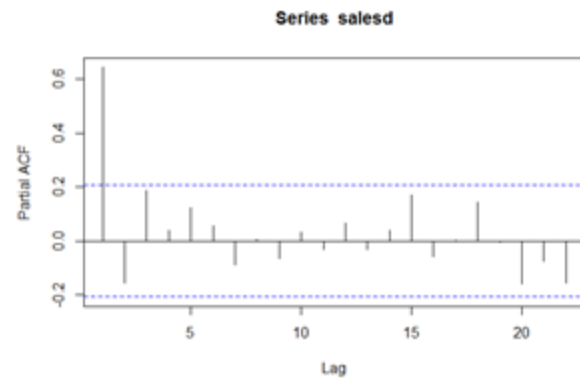
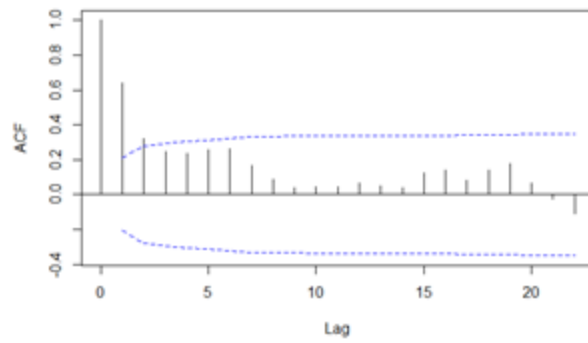
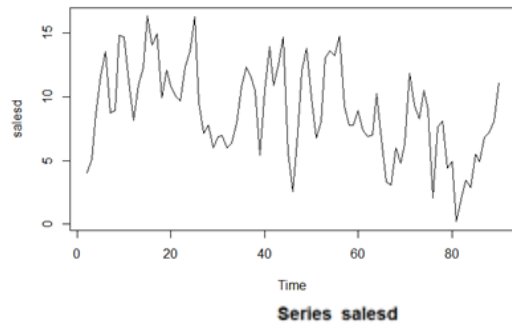
The SAC dies down very slowly. Therefore, the original values are nonstationary. Taking the differences is required.

c. SAC and SPAC for the first differences.

– Minitab solutions



– R solutions



The SAC dies down quickly and the SPAC has a spike at lag 1 and cuts off after lag 1.
Therefore, the first differences are stationary.