STAT 443: Lab 8

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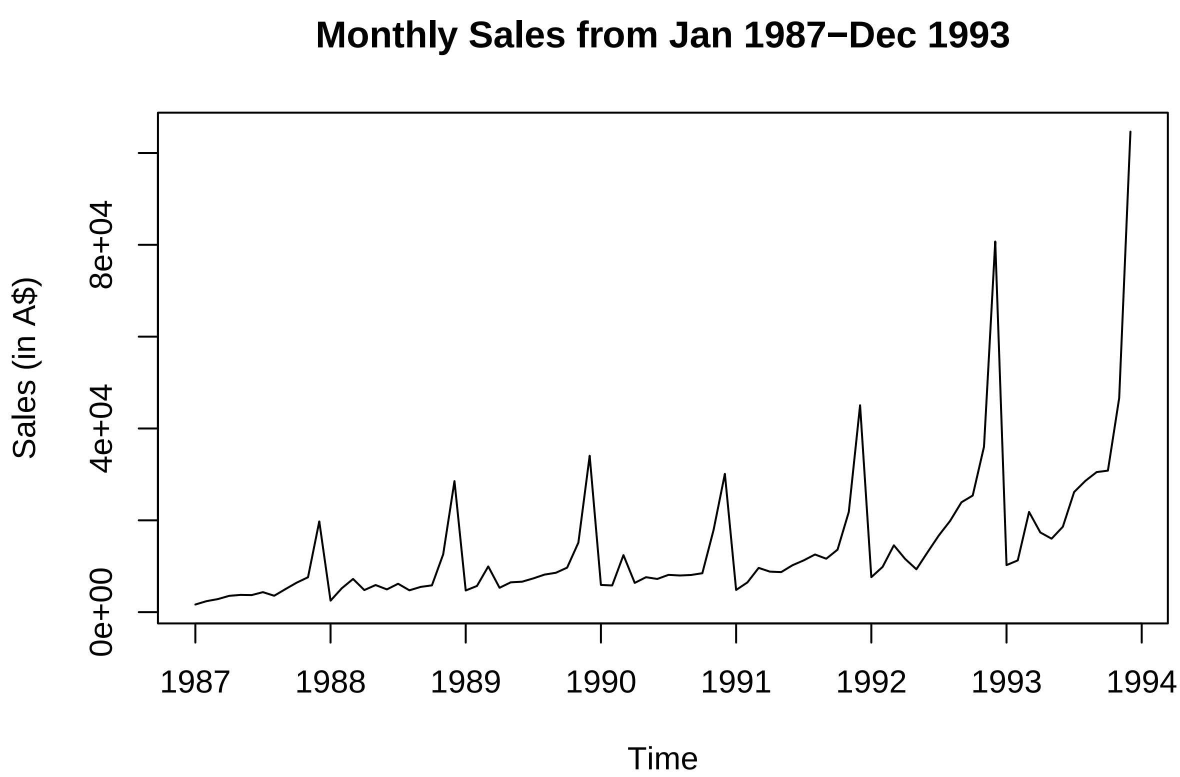
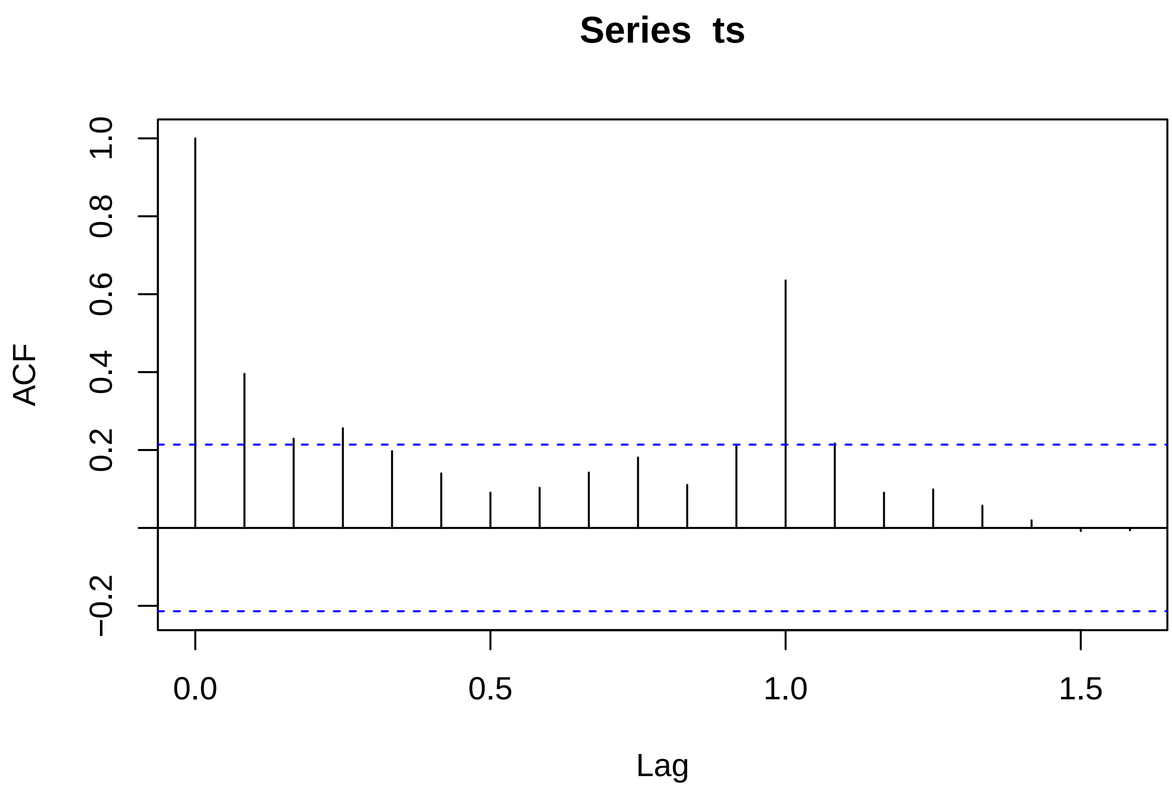
Problem 1

```
data <- read.delim("souvenir.txt", header = F)
ts <- ts(data$V1, start = c(1987,1), frequency = 12)
plot(ts, xlab = "Time", ylab = "Sales (in A$)",
     main = "Monthly Sales from Jan 1987-Dec 1993")
```




```
acf(ts)
```



The series seems to have higher and higher peaks, which points to the existence of a multiplicative seasonal effect. The ACF clearly points out a period of 12 months or 1 year.

Problem 2

```
#Extracting
prediction_ts <- window(ts, start = c(1987,1), end = c(1992, 12))
#Fitting prediction model using HoltWinters()
model_smooth <- HoltWinters(prediction_ts, seasonal = c("multiplicative"))
#Providing parameter values
model_smooth$alpha
```

```
##     alpha
## 0.3469842
```

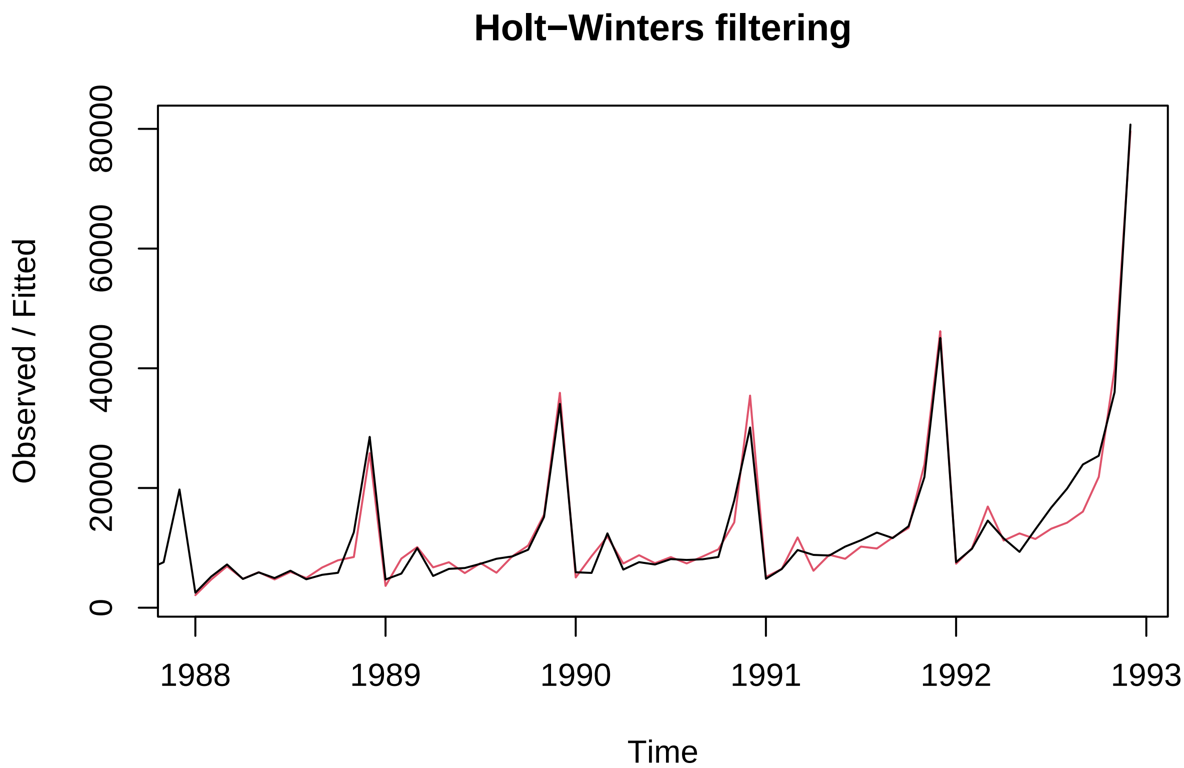
```
model_smooth$beta
```

```
##       beta
## 0.07501578
```

```
model_smooth$gamma
```

```
##     gamma
## 0.5711478
```

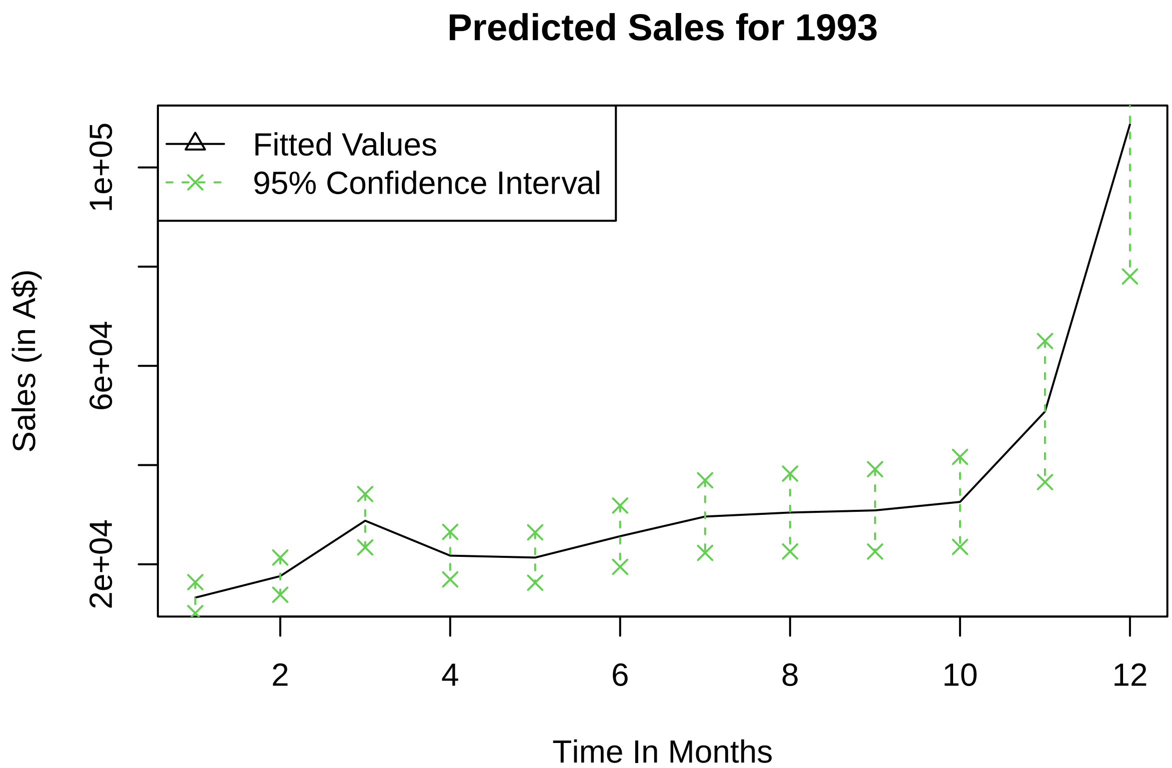
```r
#Plotting
plot(model_smooth)
```



The Holt-Winter Smoothing parameters are $\alpha = 0.3469842$, $\beta = 0.0750158$ and $\gamma = 0.5711478$.

Problem 3

```r
# Predicting for 1993
forecast_data <- data.frame(predict(model_smooth, 12,
                                    level = 0.95, n.ahead = 12, prediction.interval = TRUE))
# Plotting
plot(forecast_data$fit, type = "l", xlab = "Time In Months",
     ylab = "Sales (in A$)", main = "Predicted Sales for 1993")
for(i in 1:12){
  segments(x0 = i, y0 = forecast_data[i,2], x1 = i, y1= forecast_data[i,3],lty = 2, col = 3)
}
points(forecast_data$upr, pch = 4, col = 3)
points(forecast_data$lwr, pch = 4, col = 3)
legend("topleft", legend = c("Fitted Values", "95% Confidence Interval"), col = c(1, 3),
       lty = c(1, 2), pch = c(2,4))
```

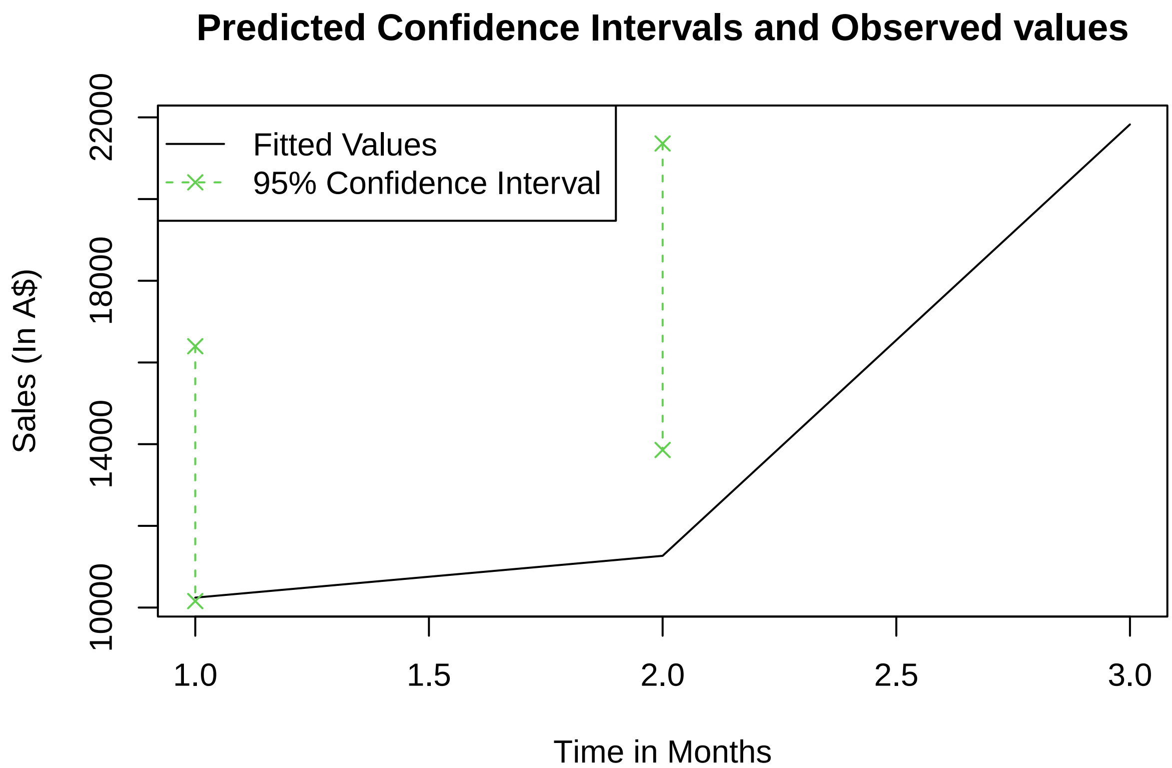



```
# Forecast for first 3 months
forecast_data[1:3,1]
```

```
## [1] 13277.67 17609.17 28784.94
```

Problem 4

```
plot(ts[73:75], type = "l", xlab = "Time in Months" , ylab = "Sales (In A$)",
     main = "Predicted Confidence Intervals and Observed values" )
for(i in 1:3){
  segments(x0 = i, y0 = forecast_data[i,2], x1 = i, y1= forecast_data[i,3],lty = 2, col = 3)
}
points(forecast_data$upr[1:3], pch = 4, col = 3)
points(forecast_data$lwr[1:3], pch = 4, col = 3)
legend("topleft", legend = c("Fitted Values", "95% Confidence Interval"),
       col = c(1, 3), lty = c(1, 2), pch = c(NA,4))
```



The 95% CI interval for the Jan 1993 is 1.0158098×10^4 to 1.6397236×10^4 while the observed value is 1.024324×10^4.

The 95% CI interval for the Feb 1993 is 1.3857408×10^4 to 2.1360936×10^4 while the observed value is 1.126688×10^4.

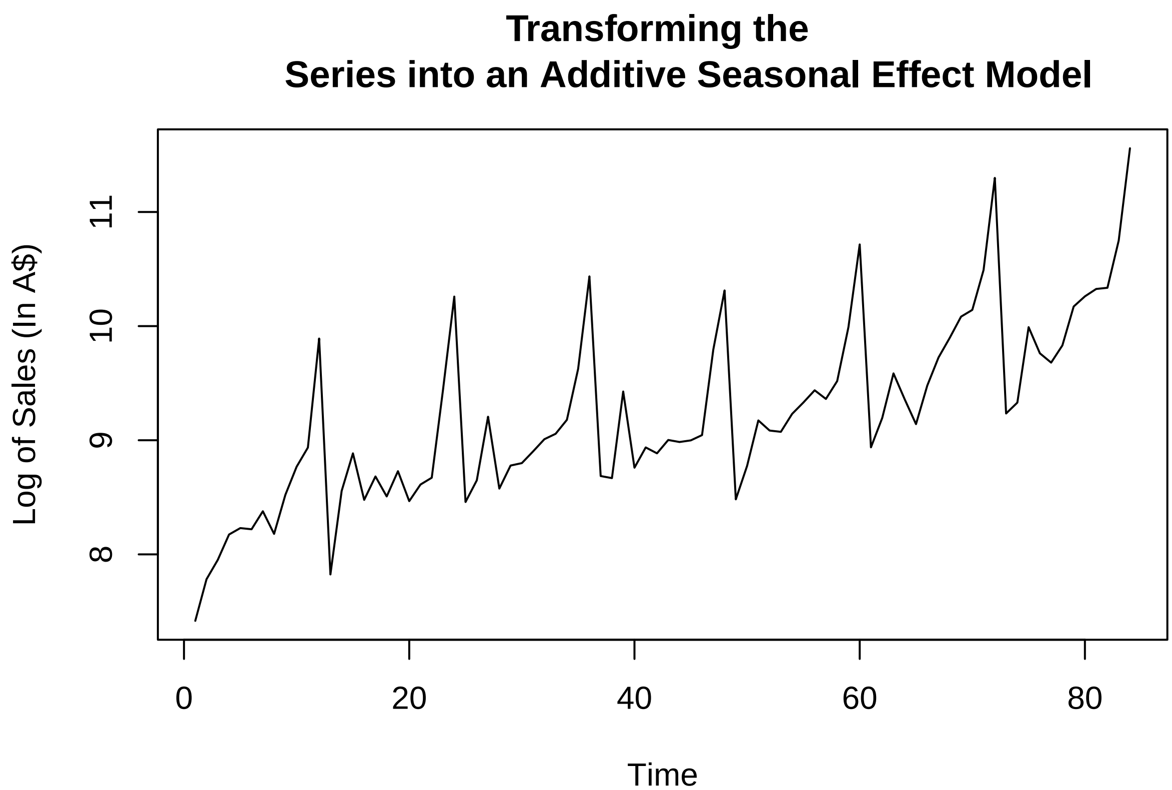
The 95% CI interval for the March 1993 is 2.3407225×10^4 to 3.4162645×10^4 while the observed value is 2.182684×10^4.

This can also be seen in the plot. Only the observed value of the first month lies within the 95% confidence interval.

Problem 5

We could a consider a log transform to convert the model from a multiplicative seasonal effect to an additive seasonal effect. The results would be a time series which looks like this:

```
data2<- log(data)
ts1 <- ts(data2[,1])
plot(ts1, xlab = "Time", ylab = "Log of Sales (In A$)", main = "Transforming the
     Series into an Additive Seasonal Effect Model")
```


Transforming the
Series into an Additive Seasonal Effect Model
Log of Sales (In A$)
8
9
10
11
0
20
40
60
80
Time