

STAT 443: Lab 8

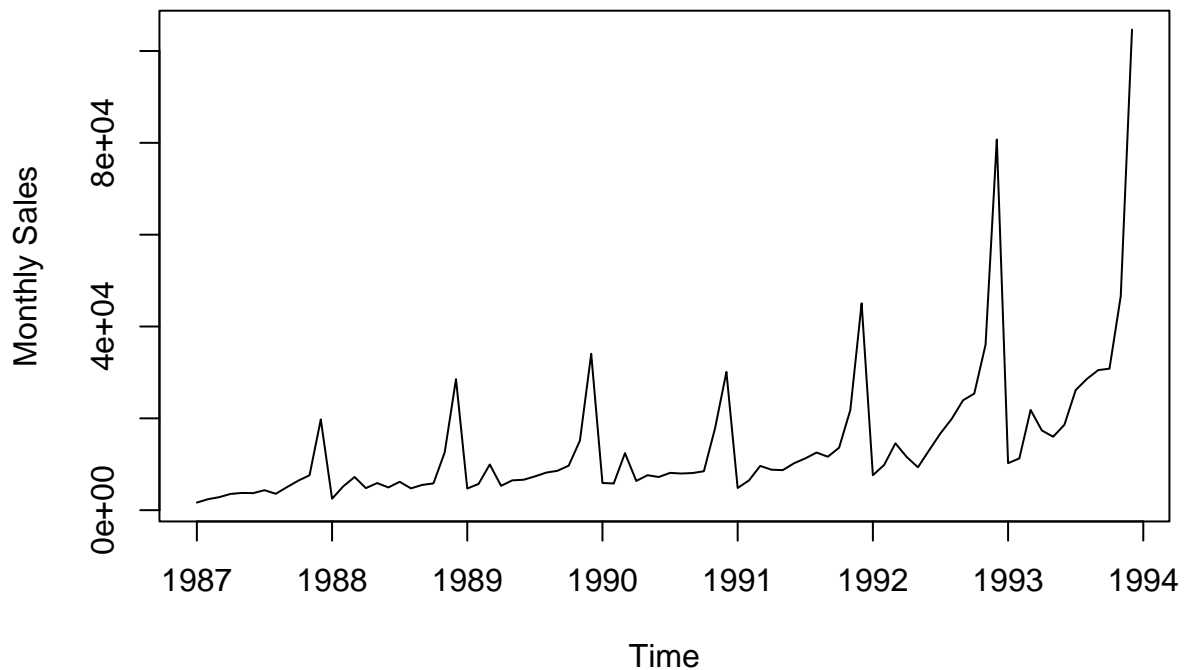
Wenxuan Zan (61336194)

12 March, 2023

Question 1

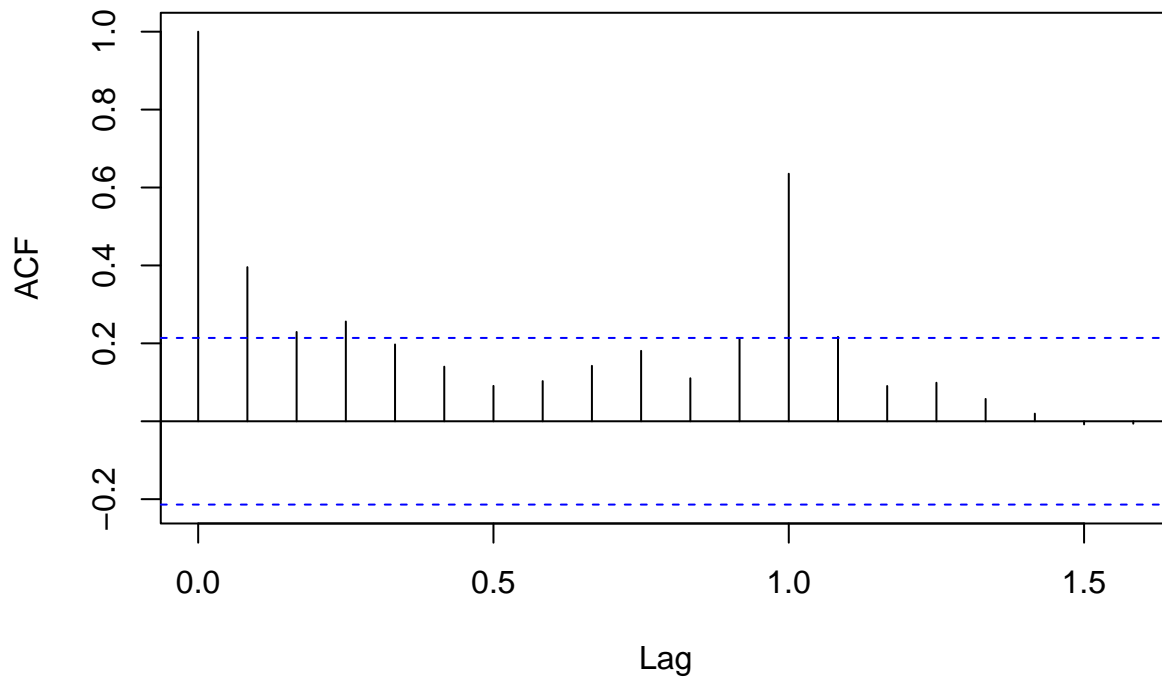
```
data <- read.csv("souvenir.txt", header = FALSE)
colnames(data) <- c("Monthly Sales")
sales_ts <- ts(data, start = c(1987,1), frequency = 12)
training_data <- window(sales_ts, start = c(1987,1), end = c(1993,1))
testing_data <- window(sales_ts, start = c(1993,2), end = c(1993,12))
plot(sales_ts,
     ylab = "Monthly Sales",
     main = "Time Series Plot for Monthly Sales Data")
```

Time Series Plot for Monthly Sales Data



```
acf(sales_ts,
     main = "Sample acf Values for Monthly Sales Data")
```

Sample acf Values for Monthly Sales Data

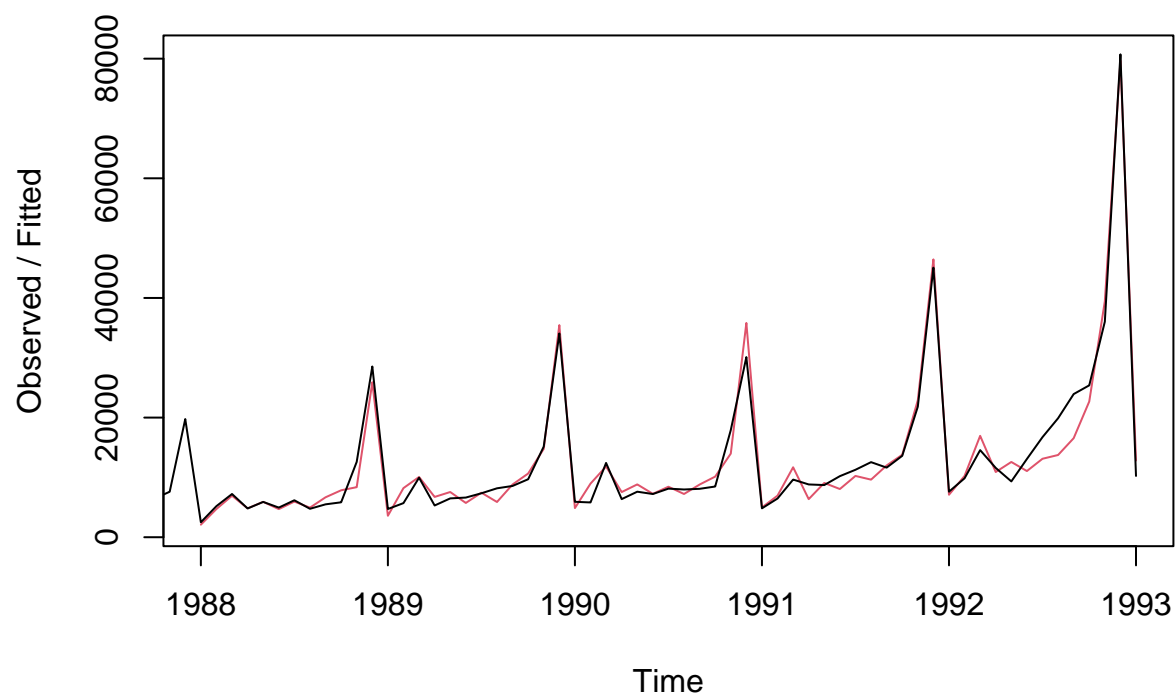


Looking at the time series plot, there is clear seasonal variation and an upward trend , and the variation seems to be increasing with time. So I would suggest a multiplicative model.

Question 2

```
HWmodel <- HoltWinters(training_data,seasonal = "multiplicative")
plot(HWmodel)
```

Holt-Winters filtering



HWmodel

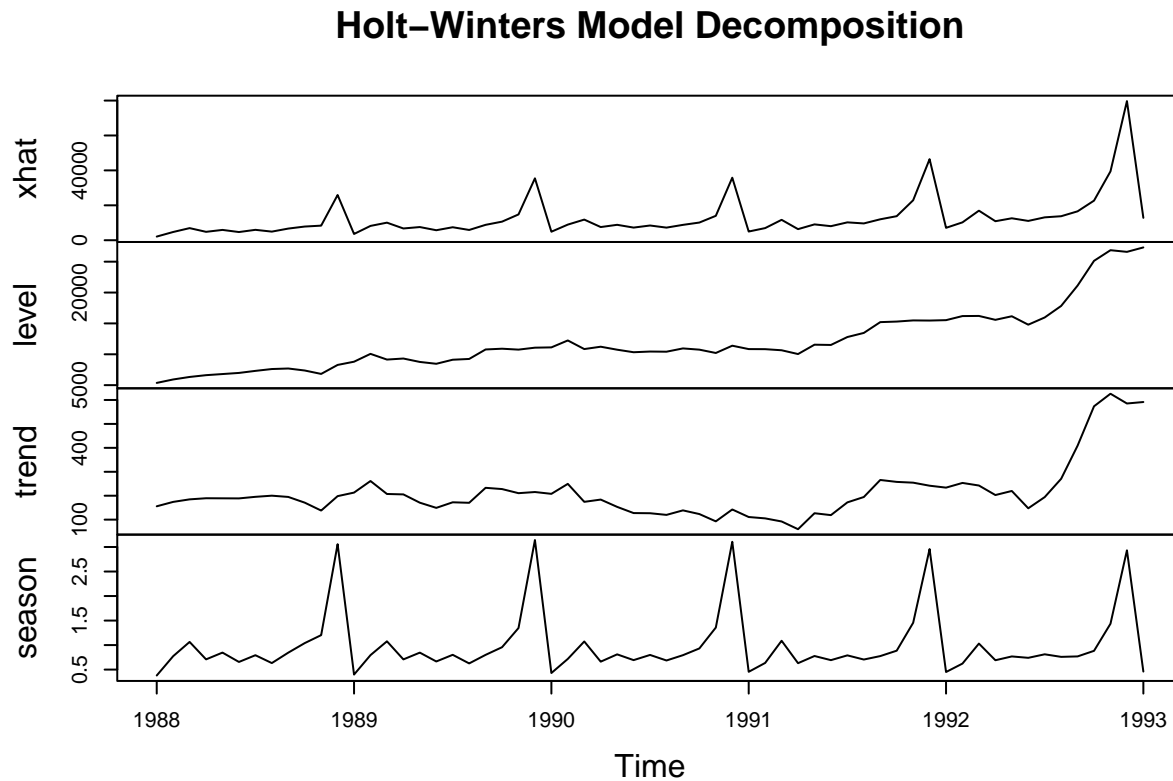
```
## Holt-Winters exponential smoothing with trend and multiplicative seasonal component.
##
## Call:
## HoltWinters(x = training_data, seasonal = "multiplicative")
##
## Smoothing parameters:
##  alpha: 0.3746875
##  beta : 0.04573451
##  gamma: 0.4522636
##
## Coefficients:
##           [,1]
## a  2.579865e+04
## b  4.953699e+02
## s1  6.159633e-01
## s2  9.869614e-01
## s3  7.026077e-01
## s4  7.061663e-01
## s5  7.761045e-01
## s6  8.690603e-01
## s7  8.417587e-01
## s8  8.517196e-01
## s9  9.110375e-01
## s10 1.398782e+00
## s11 2.943041e+00
## s12 4.312388e-01
```

The estimated parameter values from the model are:

$$\alpha = 0.375, \beta = 0.046, \gamma = 0.452$$

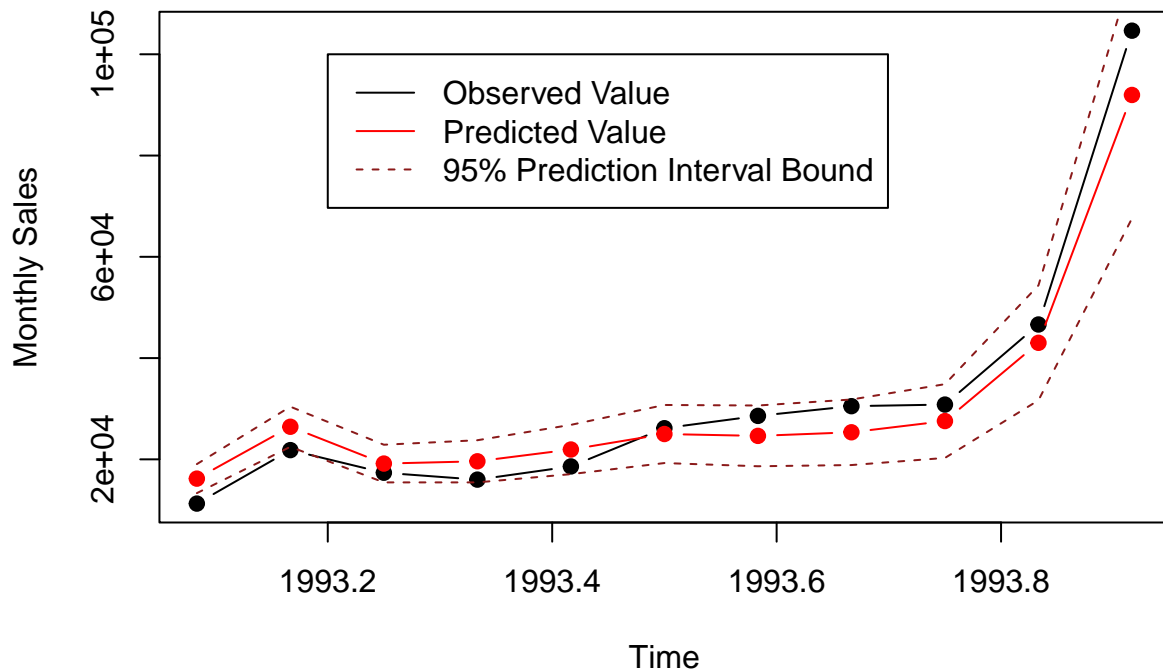
Question 3

```
plot(fitted(HWmodel),  
     main = "Holt-Winters Model Decomposition")
```



Question 4

```
predicted_sales <- predict(HWmodel,  
                           n.ahead = 11,  
                           prediction.interval = TRUE,  
                           level = 0.95)  
plot(testing_data, type = "b", pch = 19)  
lines(predicted_sales[, "fit"], col = "red", type = "b", pch = 19)  
lines(predicted_sales[, "upr"], col = "firebrick4", lty = "dashed")  
lines(predicted_sales[, "lwr"], col = "firebrick4", lty = "dashed")  
legend(1993.2,  
       100000,  
       legend = c("Observed Value",  
                  "Predicted Value",  
                  "95% Prediction Interval Bound"),  
       lty = c("solid", "solid", "dashed"),  
       col = c("black", "red", "firebrick4"))
```



All predictions are fairly close to the observed values, and all predicted values fall within the 95% prediction interval. In this regard, the forecast is reasonably accurate.

Question 5

```
predicted_sales[1:3,"fit"]
```

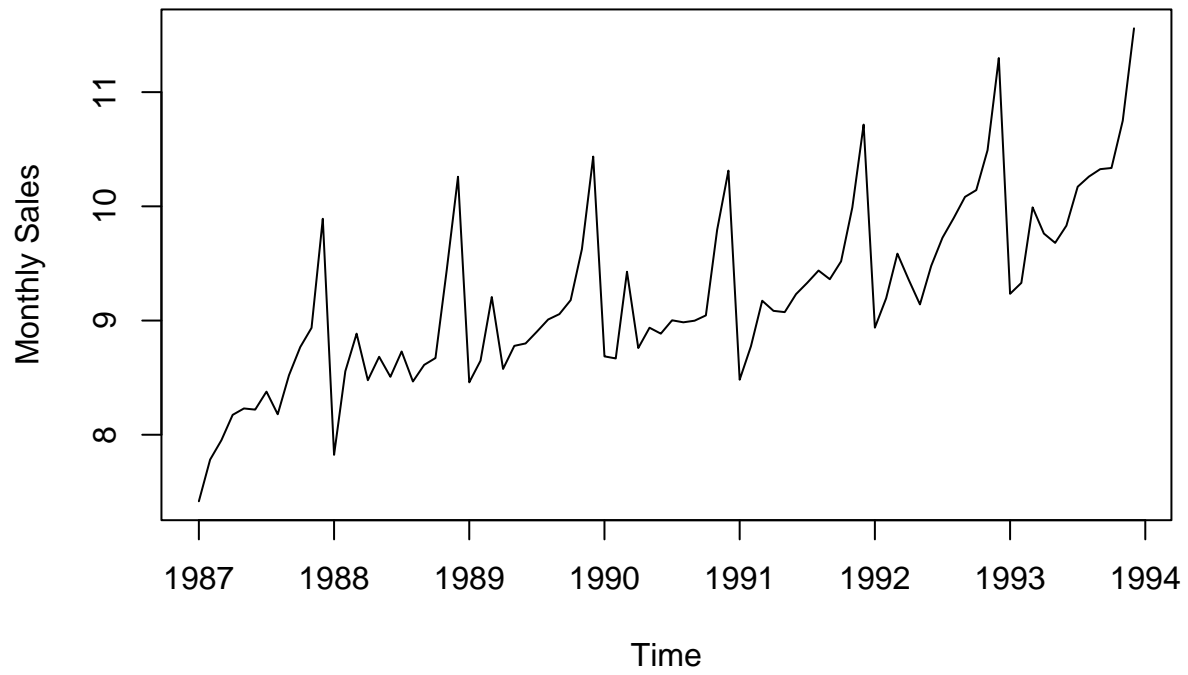
```
## [1] 16196.15 26440.10 19170.49
```

The forecast for February, March and April of 1993 are 16196.15, 26440.10, and 19170.49

Question 6

```
plot(log(sales_ts),
     ylab = "Monthly Sales",
     main = "Log Transformed Time Series")
```

Log Transformed Time Series



It appears that a logarithm transformation could make the transformed time series follows an additive model where the seasonal component does not vary with trend.