STAT 443: Lab 8

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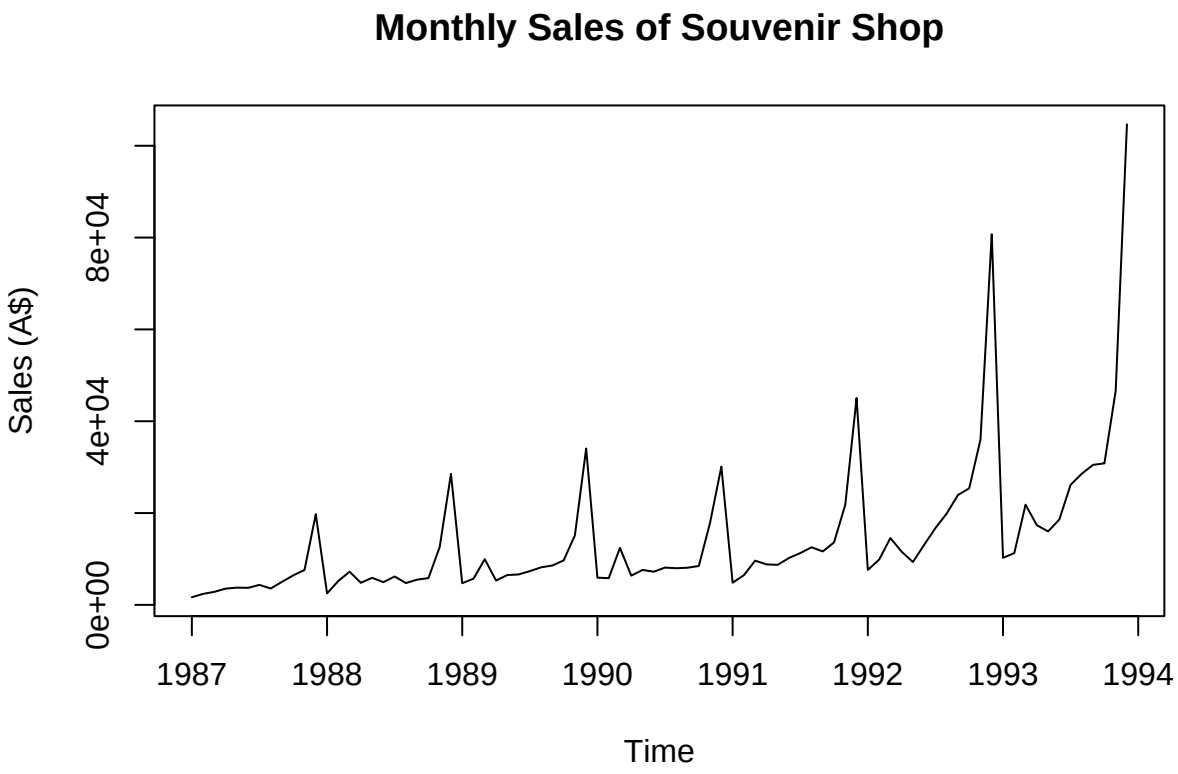
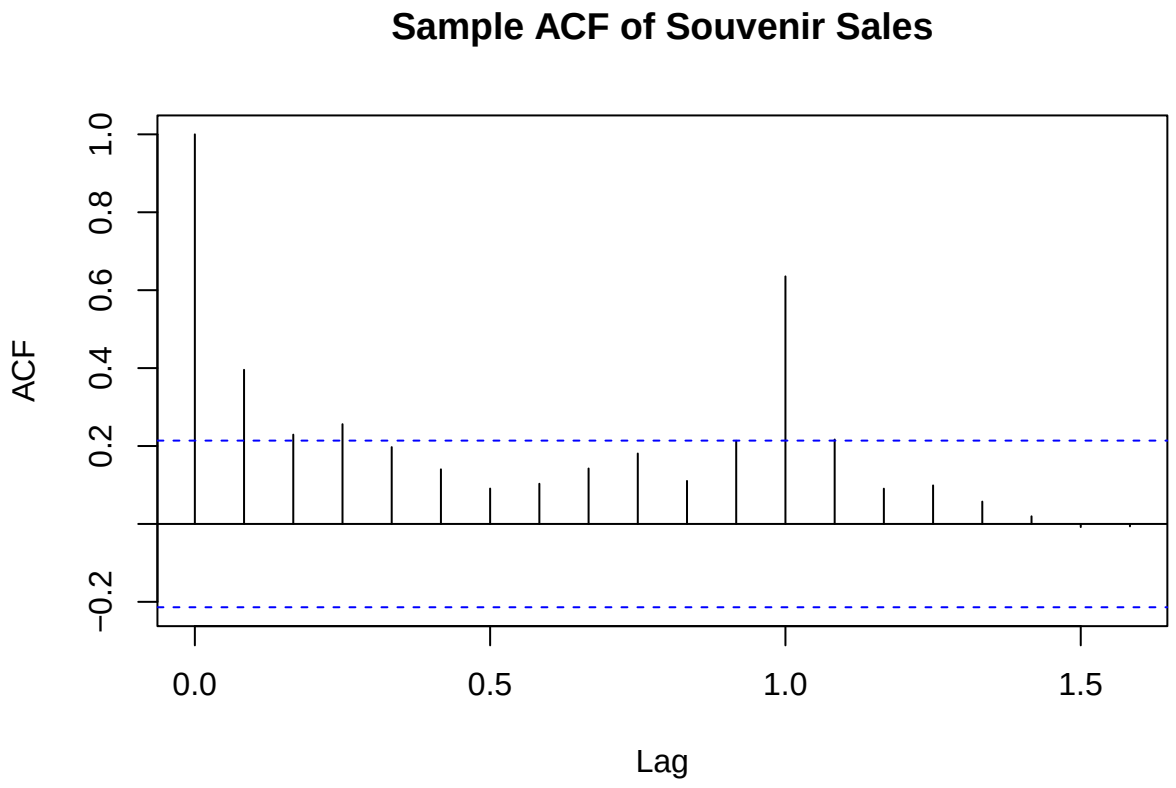
Question 1

(a)

```
# this is where your R code goes
souvenir <- scan("souvenir.txt")

souvenir_ts <- ts(souvenir,
                  start = c(1987, 1),
                  end = c(1993, 12),
                  frequency = 12)

train_data <- window(souvenir_ts,
                     start = c(1987, 1),
                     end = c(1993, 1))

test_data <- window(souvenir_ts,
                    start=c(1993, 2),
                    end=c(1993, 12))



plot(souvenir_ts,
     main = "Monthly Sales of Souvenir Shop",
     ylab = "Sales (A$)",
     xlab = "Time")
```




```
acf(souvenir_ts, main = "Sample ACF of Souvenir Sales")
```



There is a seasonal effect as we can see consistent periodic spikes in the monthly sales. We also see that the size of the spikes increase over time and is not consistently the same size which suggests a multiplicative model.

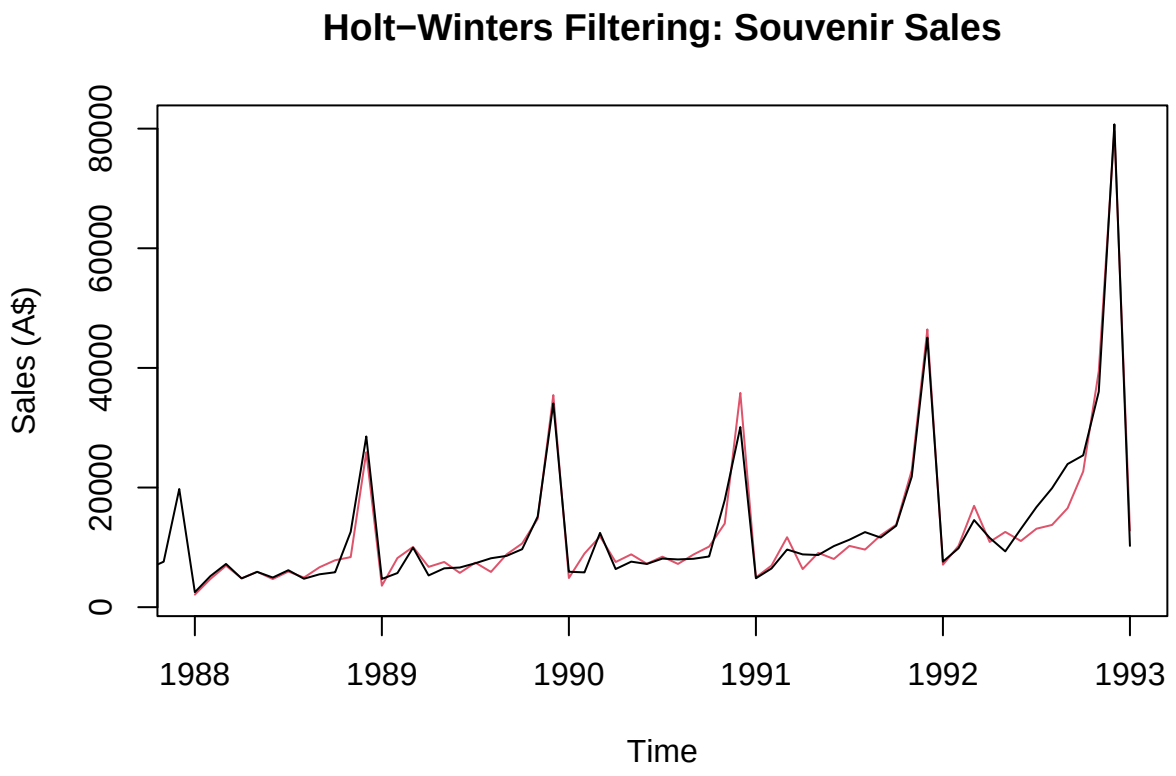
(b)

```
# this is where your R code goes
holt_model <- HoltWinters(train_data,
                          seasonal = "multiplicative")
holt_model
```

```
## Holt-Winters exponential smoothing with trend and multiplicative seasonal component.
##
## Call:
## HoltWinters(x = train_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
```

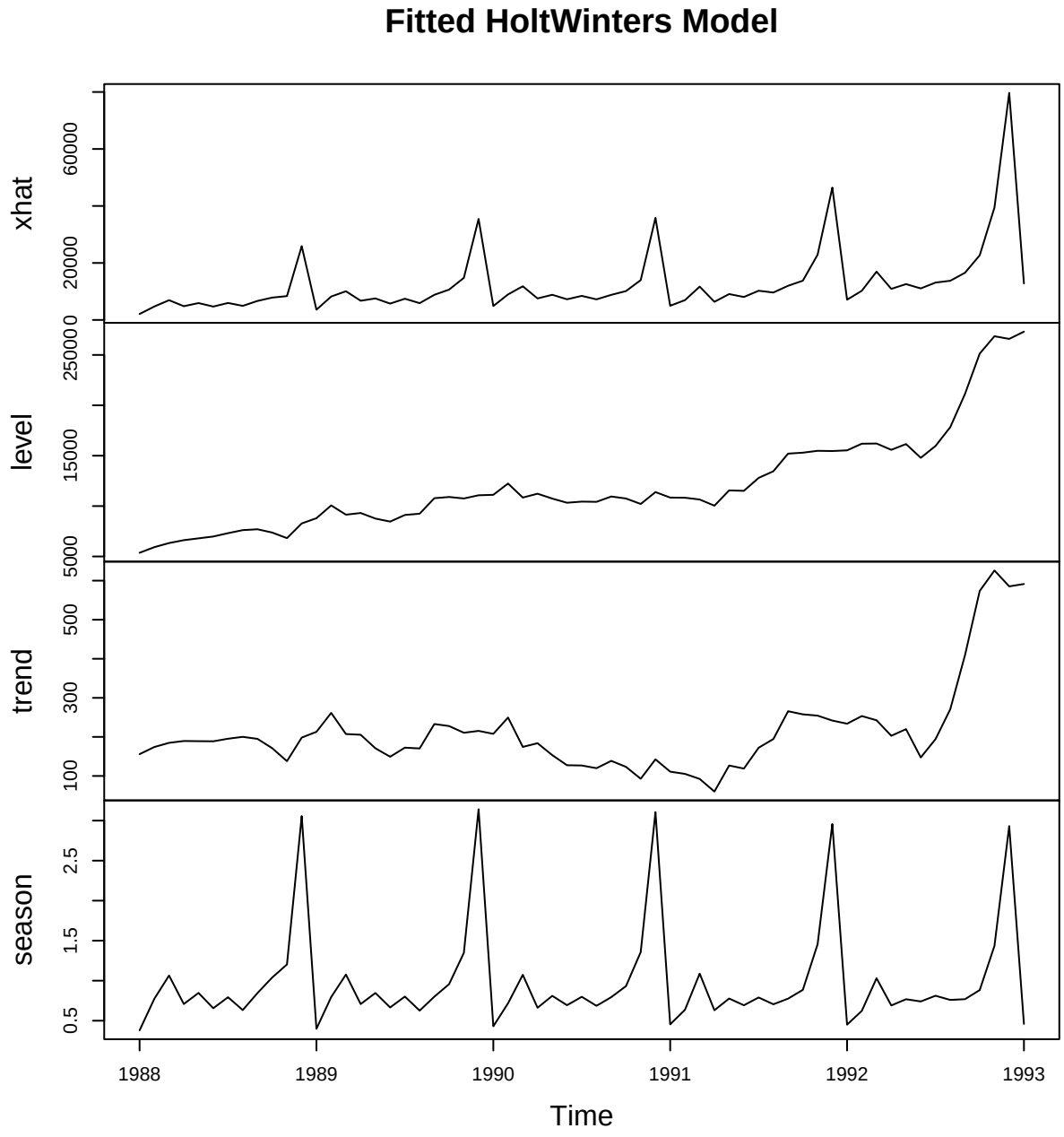
```r
plot(holt_model,
     main = "Holt-Winters Filtering: Souvenir Sales",
     ylab = "Sales (A$)",
     xlab = "Time")
```



$\alpha = 0.3746875$ $\beta = 0.04573451$ $\gamma = 0.4522636$

Question 3

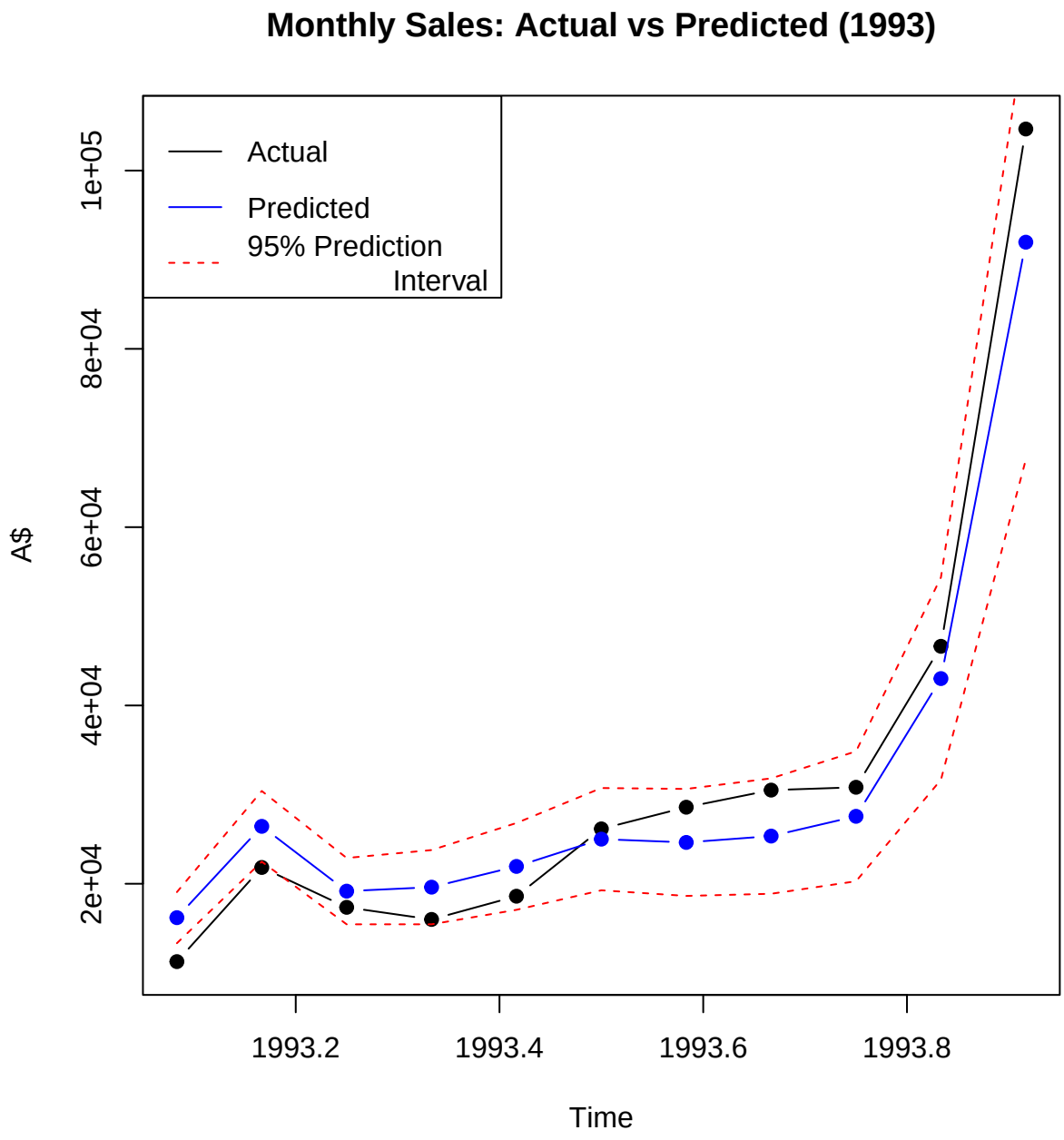
```r
# this is where your R code goes
plot(fitted(holt_model), main = "Fitted HoltWinters Model")
```



Question 4

```
# this is where your R code goes
predictions <- predict(holt_model,
                       n.ahead = length(test_data),
                       prediction.interval = TRUE)

plot(test_data,
     col = "black",
```

```
     type="b",
     pch=19,
     main = "Monthly Sales: Actual vs Predicted (1993)",
     ylab = "A$", xlab = "Time")


lines(predictions[, "fit"],
      type="b",
      pch=19,
      col = "blue",
      lty = 1)

lines(predictions[, "lwr"],
      type = "l",
      col = "red",
      lty = 2)

lines(predictions[, "upr"],
      type = "l",
      col = "red",
      lty = 2)

legend("topleft",
       legend = c("Actual", "Predicted", "95% Prediction
                  Interval"),
       col = c("black", "blue", "red"),
       lty = c(1, 1, 2))
```



model follows the data fairly well and the real value is usually within the prediction interval except for the first data point (February 1993). Some data points were on the edge of the prediction intervals where the prediction wasn't as accurate: March 1993, May 1993.

Question 5

```
# this is where your R code goes
head(predictions, 3)
```

```
##              fit      upr      lwr
```

```
## Feb 1993 16196.15 19063.13 13329.18
## Mar 1993 26440.10 30404.18 22476.02
## Apr 1993 19170.49 22890.22 15450.75
```

Question 6

I would take the natural logarithm of the data so that we can convert it to a additive model then difference the model to remove trend/seasonal components to make the process stationary.