STAT 443: Lab 8

Flora Zhang 52135365

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```
#import data
data = read_csv("souvenir.txt", col_names = FALSE)
```

```
##
## -- Column specification --------------------------------------------------------
## cols(
##   X1 = col_double()
## )
```

```
data
```

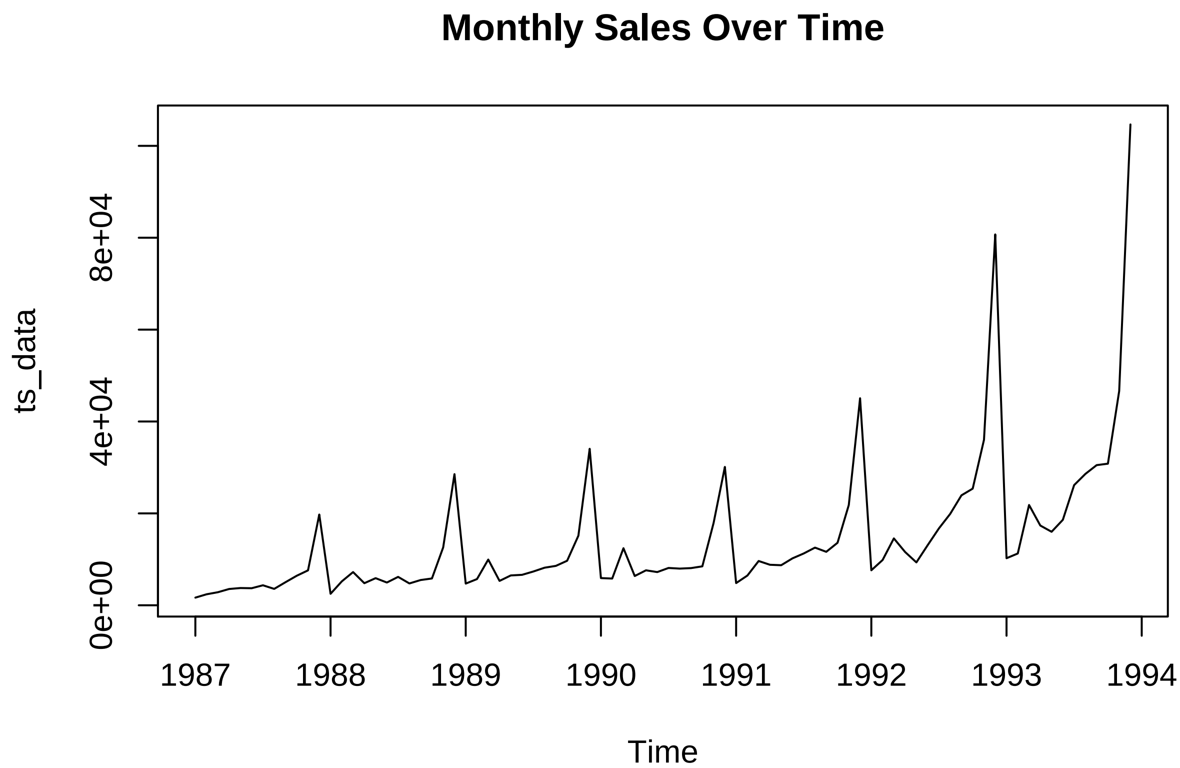
```
## # A tibble: 84 x 1
##       X1
##    <dbl>
##  1 1665.
##  2 2398.
##  3 2841.
##  4 3547.
##  5 3753.
##  6 3715.
##  7 4350.
##  8 3566.
##  9 5022.
## 10 6423.
## # ... with 74 more rows
```

```
ts_data = ts(data=data$X1, start = c(1987, 1), frequency = 12)
```

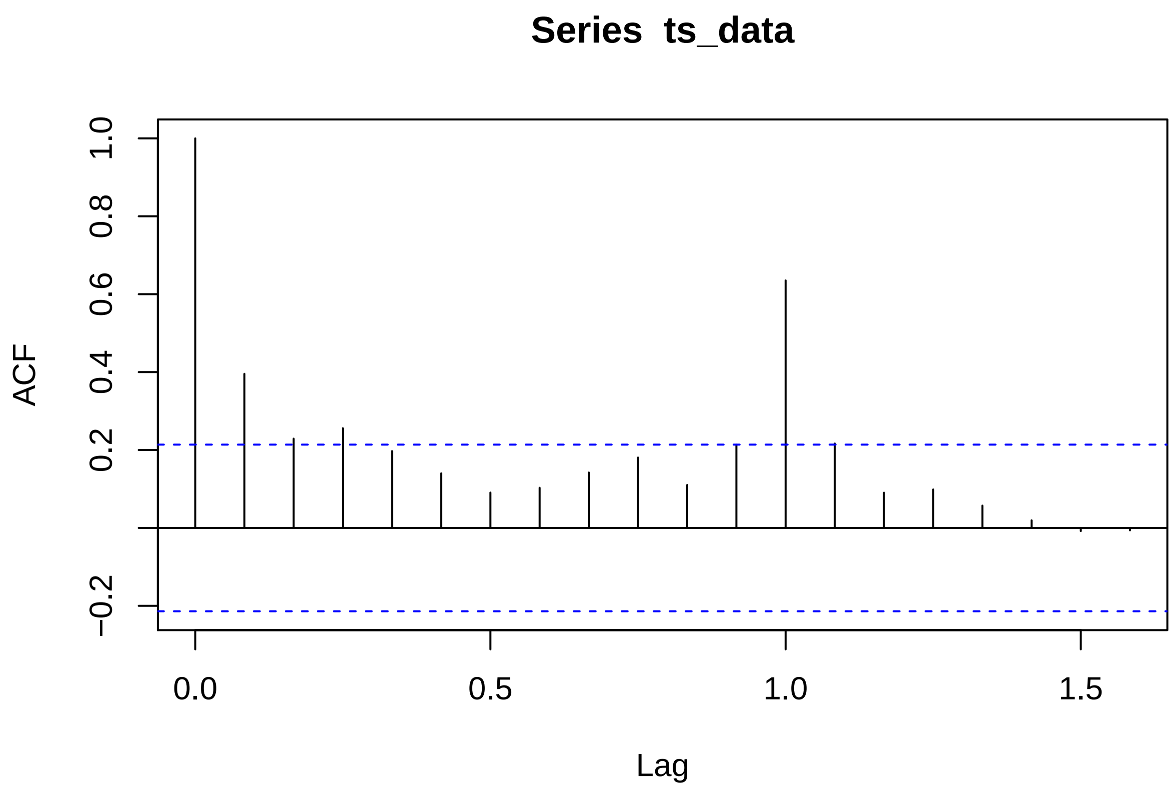
Data from January 1987–December 1993

1. Plot the time series and its acf and comment on what you see. If you deduce there is a seasonal effect, is it additive or multiplicative?

```
plot(ts_data, main = "Monthly Sales Over Time")
```


Monthly Sales Over Time
ts_data
0e+00
4e+04
8e+04
1987
1988
1989
1990
1991
1992
1993
1994
Time

```
acf(ts_data)
```



From the observed time series plot, we can see that there appears to be an exponential trend, which indicates a multiplicative seasonal effect. From the acf, we can observe a spike at lag 12, which indicates that there is a seasonal effect of period 12.

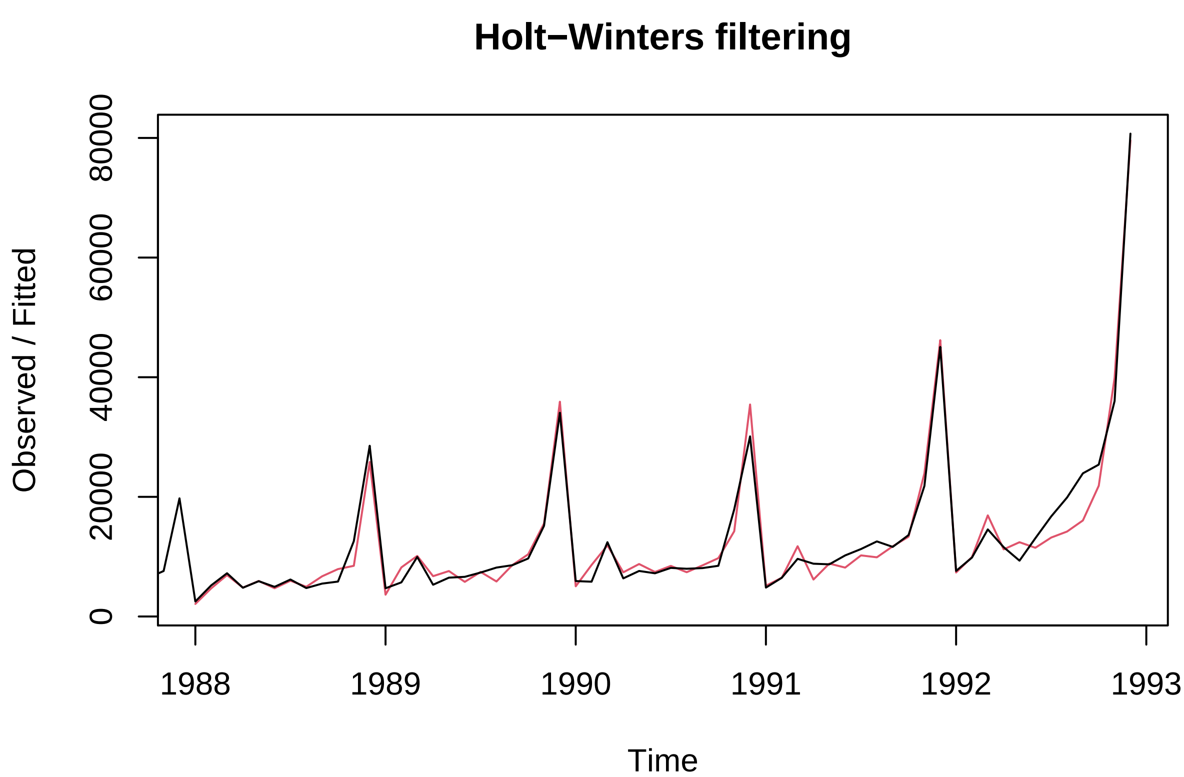
2. Extract the time series of sales figures between January 1987 to December 1992 (you can use the window command for this, or otherwise). Fit a prediction model based on the data from January 1987 to December 1992 using the R function HoltWinters(). Set the options according to what you decided above. Provide the parameter values for your smoothing model. Plot the fitted model.

```
extracted = window(ts_data, start = c(1987, 1), end = c(1992, 12))
Holtwinters = HoltWinters(extracted, alpha = NULL, beta = NULL, gamma = NULL, seasonal = "multiplicativ
Holtwinters
```

```
## Holt-Winters exponential smoothing with trend and multiplicative seasonal component.
##
## Call:
## HoltWinters(x = extracted, alpha = NULL, beta = NULL, gamma = NULL,     seasonal = "multiplicative")
##
## Smoothing parameters:
##  alpha: 0.3469842
##  beta : 0.07501578
##  gamma: 0.5711478
##
## Coefficients:
##             [,1]
## a   2.758252e+04
```

```
## b   8.079173e+02
## s1  4.676809e-01
## s2  6.030877e-01
## s3  9.592971e-01
## s4  7.056491e-01
## s5  6.754072e-01
## s6  7.911595e-01
## s7  8.912119e-01
## s8  8.937350e-01
## s9  8.856460e-01
## s10 9.134738e-01
## s11 1.392572e+00
## s12 2.915102e+00
```

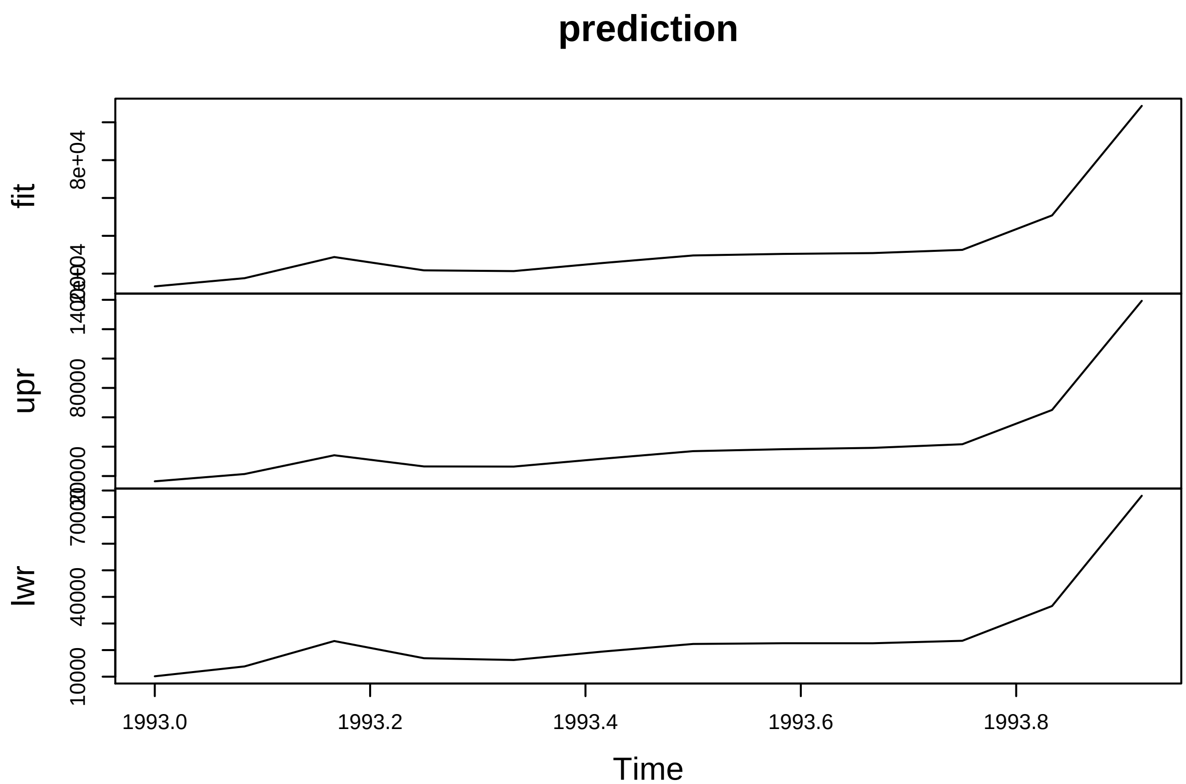
```
plot(Holtwinters)
```



The smoothing parameters are: alpha: 0.3469842 beta : 0.07501578 gamma: 0.5711478

3. Now use the prediction model from above to predict monthly sales from January 1993 to December 1993 via the predict function. Plot the predicted values along with 95% prediction intervals. Provide the forecast values for the first three months of 1993.

```
prediction = predict(Holtwinters, n.ahead=12, prediction.interval = TRUE, level=0.95)
plot(prediction)
```

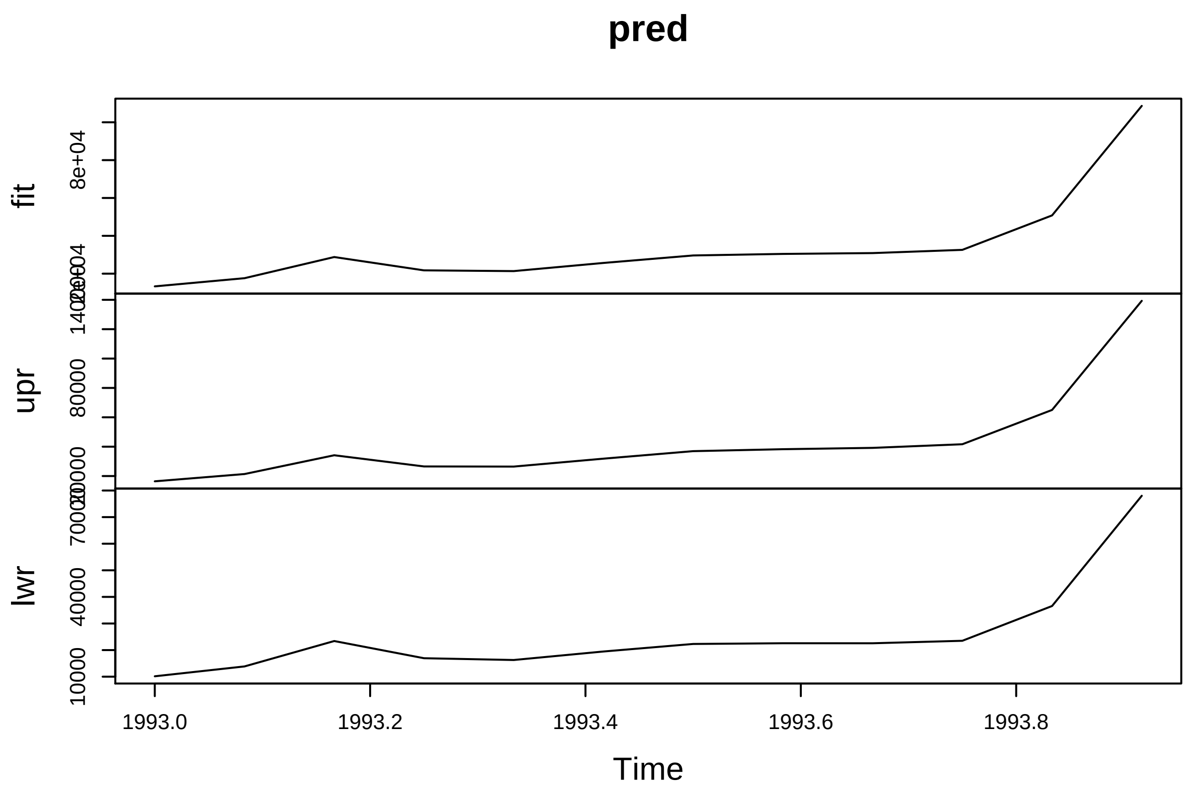



```
prediction
```

```
##                fit       upr      lwr
## Jan 1993  13277.67  16397.24 10158.10
## Feb 1993  17609.17  21360.94 13857.41
## Mar 1993  28784.94  34162.65 23407.23
## Apr 1993  21744.01  26535.79 16952.23
## May 1993  21357.80  26440.12 16275.49
## Jun 1993  25657.32  31837.00 19477.65
## Jul 1993  29622.05  36940.18 22303.93
## Aug 1993  30427.98  38276.06 22579.90
## Sep 1993  30868.11  39171.61 22564.62
## Oct 1993  32576.03  41649.05 23503.01
## Nov 1993  50786.55  65002.41 36570.70
## Dec 1993 108667.82 139313.85 78021.79
```

The first three forecast values are 13277.67, 17609.17, and 28784.94 for Jan, Feb and March.

```
pred = predict(Holtwinters, n.ahead=12, prediction.interval = TRUE, level=0.95)
plot(pred)
```



4. Do the observed values for the first three months of 1993 fall inside their corresponding 95% prediction intervals?

```
window(x =ts_data, start = c(1993,1), end = c(1993,12)) #observed values
```

```
##            Jan       Feb       Mar       Apr       May       Jun       Jul
## 1993  10243.24  11266.88  21826.84  17357.33  15997.79  18601.53  26155.15
##            Aug       Sep       Oct       Nov       Dec
## 1993  28586.52  30505.41  30821.33  46634.38 104660.67
```

The observed value for January falls inside the 95% prediction interval, but not February and March.

5. If you were to perform a transformation on the time series, what would you consider and why?

For Holt Winters forecasting, prediction intervals are easier to calculate when working with an additive model. We can use a log transform to turn this multiplicative seasonal effect model into an additive one.