Analyzing Time-Series Data using Exponential Smoothing Model

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June 2, 2018

Using the 20 years of daily high temperature data for Atlanta (file temps.txt), let's build and leverage an exponential smoothing model to help make a judgment of whether the unofficial end of summer has gotten later over the 20 years.

Let's first load the given data into a dataframe and set a seed value as best practice.

```
set.seed(42)
data_7<-read.table("7.2tempsSummer2018.txt",header=TRUE)
head(data_7)</pre>
```

```
##
       DAY X1996 X1997 X1998 X1999 X2000 X2001 X2002 X2003 X2004 X2005 X2006
## 1 1-Jul
               98
                     86
                            91
                                  84
                                         89
                                               84
                                                      90
                                                            73
                                                                          91
                                                                                93
                                                                   82
## 2 2-Jul
               97
                     90
                            88
                                  82
                                         91
                                               87
                                                      90
                                                            81
                                                                   81
                                                                          89
                                                                                93
## 3 3-Jul
               97
                     93
                            91
                                  87
                                         93
                                               87
                                                      87
                                                            87
                                                                   86
                                                                          86
                                                                                93
                     91
                            91
## 4 4-Jul
               90
                                  88
                                         95
                                               84
                                                      89
                                                            86
                                                                   88
                                                                          86
                                                                                91
## 5 5-Jul
               89
                            91
                                  90
                                         96
                                               86
                                                      93
                                                                   90
                                                                          89
                                                                                90
## 6 6-Jul
                            89
                                         96
                                                      93
                                                                   90
                                                                          82
                                                                                81
                                                            84
##
     X2007 X2008 X2009 X2010 X2011 X2012 X2013 X2014 X2015
## 1
        95
               85
                     95
                            87
                                  92
                                        105
                                               82
                                                      90
                                                            85
                                                            87
## 2
        85
               87
                     90
                            84
                                  94
                                         93
                                               85
                                                      93
        82
               91
                     89
                                  95
                                         99
                                               76
                                                      87
                                                            79
## 3
                            83
               90
                                               77
## 4
        86
                     91
                            85
                                  92
                                         98
                                                      84
                                                            85
## 5
        88
               88
                     80
                            88
                                  90
                                        100
                                               83
                                                      86
                                                            84
## 6
        87
               82
                     87
                            89
                                  90
                                         98
                                               83
                                                      87
                                                            84
```

For the HoltWinter (exponential smoothing) model, we require our data to be in a time series object rather than a dataframe.

```
data_7_vector<-as.vector(unlist(data_7[,2:21]))
data_ts<-ts(data_7_vector,start=1996, frequency=123)
class(data_ts)</pre>
```

```
## [1] "ts"
```

```
head(data_ts)
```

```
## [1] 98 97 97 90 89 93
```

Now that we have our time series object, let's call the HoltWinter method. By setting alpha, beta and gamma to NULL, R will find the optimal values for each of the parameters that gives our model the best fit. Further, as mentioned in the lectures, there are two ways exponential smoothing can deal with seasonality. One of the key

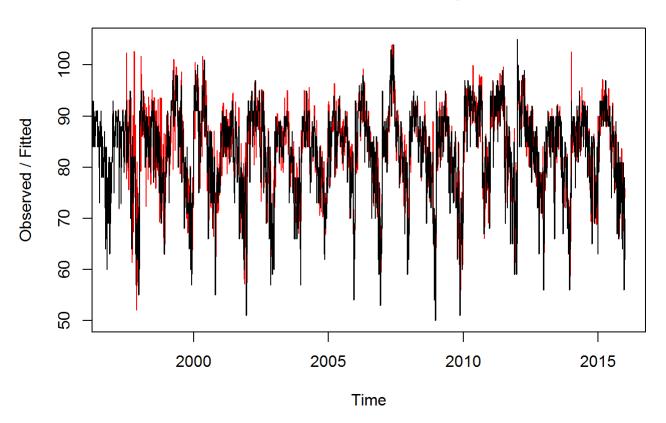
differences between the two is that for additive seasonality, the amplitude of the seasonal variation is independent of the level; contrarily, multiplicative seasonality is dependent on the level. Here we will utilize the multiplicative method as taught in the lectures.

```
HoltWinterModel<-HoltWinters(data_ts, alpha=NULL,beta=NULL,gamma=NULL, seasonal="multiplicative"
)</pre>
```

We can plot our HoltWinterModel to see how the smoothing works (the red shows the plot of calculated baseline values). The STR() function will also show us the alpha, beta and gamma used in the model.

plot(HoltWinterModel)

Holt-Winters filtering



str(HoltWinterModel)

```
## List of 9
##
   $ fitted
                  : Time-Series [1:2337, 1:4] from 1997 to 2016: 87.2 90.4 93 90.9 84 ...
##
     ... attr(*, "dimnames")=List of 2
     .. ..$ : NULL
##
##
     .. ..$ : chr [1:4] "xhat" "level" "trend" "season"
                  : Time-Series [1:2460] from 1996 to 2016: 98 97 97 90 89 93 93 91 93 93 ...
##
   $ x
##
   $ alpha
                  : Named num 0.615
##
     ... attr(*, "names")= chr "alpha"
##
   $ beta
                 : Named num 0
    ... attr(*, "names")= chr "beta"
##
##
   $ gamma
                 : Named num 0.55
    ... attr(*, "names")= chr "gamma"
##
##
   $ coefficients: Named num [1:125] 73.67952 -0.00436 1.23902 1.23434 1.15951 ...
     ... attr(*, "names")= chr [1:125] "a" "b" "s1" "s2" ...
##
                  : chr "multiplicative"
##
   $ seasonal
##
   $ SSE
                  : num 68905
##
   $ call
                  : language HoltWinters(x = data ts, alpha = NULL, beta = NULL, gamma = NULL,
    seasonal = "multiplicative")
   - attr(*, "class")= chr "HoltWinters"
##
```

In regards to the original question of whether the unofficial end of summer has gotten later over the 20 years, there are many ways to answer this. For example, we could simply conduct CUSUM on the temperature data, as we did in last week's homework. Instead, here, we will run a CUSUM change detection analysis on the seasonality coefficient (which acts as a proxy) to determine our last day of summer for each year. The seasonality coefficient signifies that the baseline is expected to change solely because of the current time period in the cycle.

Below, we will extract the seasonality coefficients from the Holt-Winter model we developed and store it in a matrix

```
seasonality<-matrix(HoltWinterModel$fitted[,4],123)
head(seasonality)</pre>
```

```
##
                                       [,4]
            [,1]
                     [,2]
                              [,3]
                                                 [,5]
                                                          [,6]
                                                                   [,7]
## [1,] 1.052653 1.049468 1.120607 1.103336 1.118390 1.108172 1.140906
## [2,] 1.100742 1.099653 1.108025 1.098323 1.110184 1.116213 1.126827
## [3,] 1.135413 1.135420 1.139096 1.142831 1.143201 1.138495 1.129678
## [4,] 1.110338 1.110492 1.117079 1.125774 1.134539 1.126117 1.130758
## [5,] 1.025231 1.025233 1.044684 1.067291 1.084725 1.097239 1.115055
## [6,] 1.025838 1.025722 1.028169 1.042340 1.053954 1.067494 1.080203
##
            [8,]
                     [,9]
                             [,10]
                                       [,11]
                                                [,12]
                                                         [,13]
                                                                  \lceil,14\rceil
## [1,] 1.140574 1.125438 1.122063 1.161415 1.198102 1.198910 1.243012
## [2,] 1.154074 1.142187 1.131889 1.144549 1.134661 1.153433 1.165431
## [3,] 1.156092 1.165657 1.147982 1.149459 1.135756 1.153310 1.155197
## [4,] 1.137722 1.150639 1.146992 1.142497 1.150162 1.151169 1.157751
## [5,] 1.103877 1.120818 1.133733 1.132167 1.142714 1.139244 1.112909
## [6,] 1.094312 1.102680 1.092178 1.075766 1.088547 1.082185 1.103092
##
           [,15]
                    [,16]
                             [,17]
                                       [,18]
## [1,] 1.243781 1.238435 1.300204 1.290647 1.254521
## [2,] 1.172935 1.190735 1.191956 1.219190 1.228826
## [3,] 1.157286 1.169773 1.189915 1.172309 1.169045
## [4,] 1.163844 1.159343 1.166605 1.167993 1.158956
## [5,] 1.132435 1.132045 1.145230 1.168161 1.170449
## [6,] 1.115071 1.118575 1.121598 1.134962 1.145475
```

We can now export our seasonality into Excel to conduct our CUSUM change detection analysis.

#sheet<-sheets[[1]]</pre>

write.csv(seasonality, "CUSUM.csv")

```
library(xlsx)

## Loading required package: rJava

## Loading required package: xlsxjars

#workbook<-LoadWorkbook("CUSUM.xlsx")
#sheets<-getSheets(workbook)</pre>
```

#addDataFrame(seasonality, sheet, col.names=FALSE, row.names=FALSE, startRow=2, startColumn=3)