Question 7.1

Over the past few weeks of being enrolled in OMSA, my stress levels have definitely fluctuated over time. One common way to measure stress involves heart rate variability (HRV) analysis. HRV records the variation in time between consecutive heartbeats, which is controlled by the autonomic nervous system. The autonomic nervous system is also responsible for the fight-or-flight response given by the sympathetic nervous system, and the relaxed response given by the parasympathetic nervous system. When in a chronic state requiring a fight-or-flight response the autonomic nervous system becomes unbalanced, and as a result lowers the HRV. In contrast, a relaxed state is associated with a higher HRV. By obtaining data from a chest strap monitor over the course of a few months including time during and away from the OMSA program (i.e a few weeks of OMSA followed by winter break), and applying exponential smoothing with regard to exam/homework due dates, the stress level can be effectively measured. I would expect the alpha parameter to be closer to 1 as I hypothesize the stress level to be tied directly to exam/homework dates which are all pre determined. This would induce the notion that there is not much randomness in the system and support the idea that the alpha value should be closer to 1.

Question 7.2

Based on the exponential smoothing model generated in Figures 2, 3, and 4. Each of these figures display important pieces of information that will be discussed. Figure 2 demonstrated the values obtained from the Holt-Winters exponential smoothing model in the absence of trend and seasonal factors. As such, only the alpha parameter was calculated and that was found to be 0.8396. This value displays that there is not a lot of randomness present within the temps dataset as it is far closer to 1 than 0. In Figure 3, an alpha and beta parameter were calculated, meaning that this model was generated with thought to the trend estimate. The alpha value remained close to a value of 1 with a weight of 0.8446, but the b value was extremely close to a value of 0, meaning that there is not a significant trend to be extracted from this dataset. Finally, Figure 4 illustrates a Holt-Winters model generated with respect to trend and seasonality. This model saw a fairly noteworthy decrease in the alpha value with it being 0.6611 but remained with a calculated beta value of exactly 0. The gamma value was found to be 0.6248 which tells us that the calculations were slightly weighted towards the latest value rather than the oldest ones. You can see the effect the decrease in alpha value had in the bottom graph of Figure 5. Comparing it with the almost identical above graphs, while it is clear that triple exponential smoothing that occurred in the final graph did alter it slightly, the same cyclic pattern detailing each time a new year started (see Figure 5 description for more details on segments present in the figure) was observed. And thus, we can conclude that the unofficial end of summer over the past 20 years has not changed.

```r
rm(list=ls())

set.seed(694)

data <- read.table("temps.txt", header=TRUE)
df <- data.frame(data)

newData <- as.matrix(data[,2:21])
tsData <- ts(newData, start=1996, frequency=123)

winter1 <- HoltWinters(tsData, beta=FALSE, gamma=FALSE)
winter2 <- HoltWinters(tsData, gamma=FALSE)
winter3 <- HoltWinters(tsData)

par(mfrow=c(3,1))

plot(winter1)
plot(winter2)
plot(winter3)

#print(winter3$fitted[,4], ncol=123)

cusumMatrix <- matrix(winter3$fitted[,4], ncol=123)
cusumObj <- cumsum(cusumMatrix)

plot(x=1:length(cusumObj), y=cusumObj, ylab="Cumulative Sum", xlab="Full Length of Data", type="o")

#print(winter1)
#print("|||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||")
#print(winter2)
#print("|||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||")
#print(winter3)
```

Figure 1. This figure represents the code used to determine the Holt-Winters filtering for the temps.txt dataset.

```
> print(winter1)
Holt-Winters exponential smoothing without trend and without seasonal component.

Call:
HoltWinters(x = tsData, beta = FALSE, gamma = FALSE)

Smoothing parameters:
 alpha: 0.8388021
 beta : FALSE
 gamma: FALSE

Coefficients:
      [,1]
a 63.30952
```

Figure 2. This is the output of the Holt-Winters filtering object “winter1” generated from the code used in Figure 1. Note that the beta and gamma values are both set to False.

```
> print(winter2)
Holt-Winters exponential smoothing with trend and without seasonal component.

Call:
HoltWinters(x = tsData, gamma = FALSE)

Smoothing parameters:
 alpha: 0.8445729
 beta : 0.003720884
 gamma: FALSE

Coefficients:
        [,1]
a 63.2530022
b -0.0729933
```

Figure 3. This is the output of the Holt-Winters filtering object “winter2” generated from the code used in Figure 1. Note that only the gamma value is set to False.

```
> print(winter3)
Holt-Winters exponential smoothing with trend and additive seasonal component.

Call:
HoltWinters(x = tsData)

Smoothing parameters:
 alpha: 0.6610618
 beta : 0
 gamma: 0.6248076

Coefficients:
             [,1]
a     71.477236414
b     -0.004362918
s1    18.590169842
s2    17.803098732
s3    12.204442890
s4    13.233948865
s5    12.957258705
s6    11.525341233
```

Figure 4. This is the output of the Holt-Winters filtering object “winter3” generated from the code used in Figure 1.

Figure 5. This figure is a graphical representation of winter1, winter2, and winter3 from top to bottom, respectively. The graphs can be interpreted such that each time a low peak was followed by a very substantial increase, that would account for the ending a year. Meaning, that each time that occurs, the segment right before it would be a year described in the temps dataset.

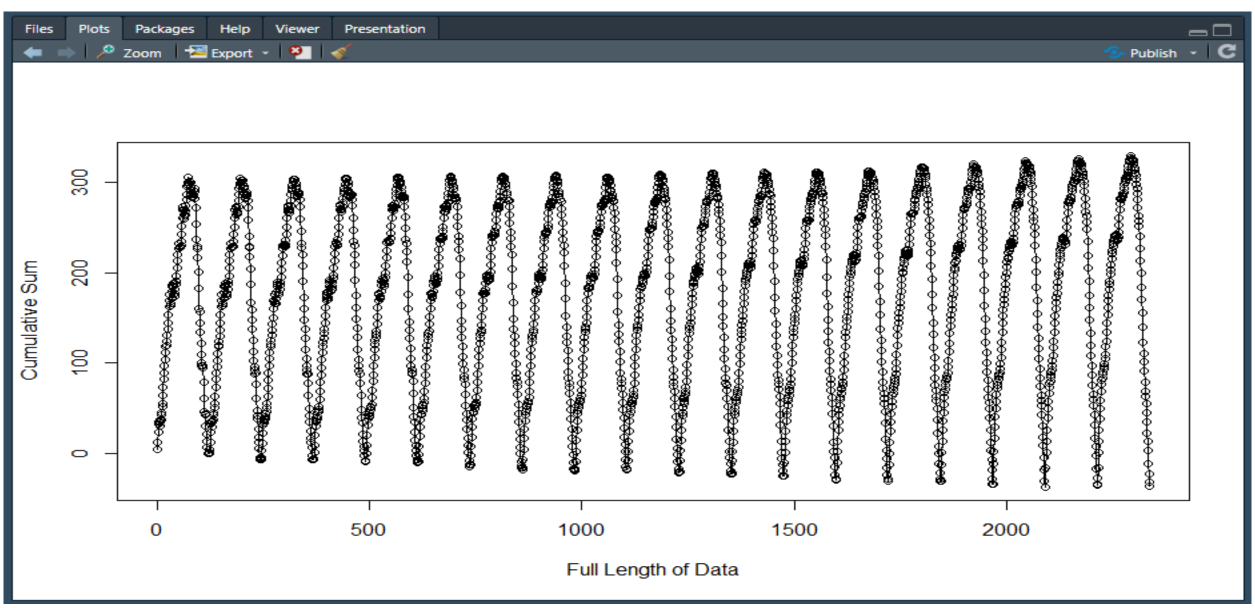

Figure 6. CUSUM chart generated by the code in Figure 1.

Note: I did try to run CUSUM in R for the first time, but I could figure out exactly what my results were displaying in Figure 6. As a result, I did not include it in reaching the conclusion in question 7.2. However, I did include it in the final report just in case one of my peer reviewers was able to shine some light onto why my chart came out the way it did, and possible things I could have done wrong. I extracted the data points from the winter3 model, where each point is described by the cyclic factor generated from the winter3 model. The problem with this is that each point on the graph is a data value that should correspond to a point on the temp dataset, but the x-axis is equal to 123*19 rather than 123*20 (i.e number of features in column * num of columns). If you have any idea as to how I could improve this existing code or maybe try something entirely new, please feel free to comment or drop a link to somewhere where I could find more information. Below is a snippet of the data gathered from winter$3:

```
> print(winter3$fitted[,4], ncol=123)
Time Series:
Start = c(1997, 1)
End = c(2015, 123)
Frequency = 123
   [1]   4.303159495   8.238118845  11.091777381   9.042996893   2.067387137   2.116167625  -6.826921806
   [8]   5.197468438   2.205598519   5.262509089   2.295029414   6.327549739   4.343809902   8.270639170
  [15]   9.205598519   9.189338357   7.140557869   7.075517219   6.994216406   7.896655430   6.766574129
  [22]   1.677143235   4.766574129   5.799094454   6.815354617   6.986086324   9.099907462   9.221858682
  [29]   7.278769251   6.238118845  -9.940742944  -2.013913676   1.977956243   6.051126975   6.986086324
  [36]   5.864135105   1.717793641   1.538931853  -2.493588472  -9.574889285  -2.656190098   3.238118845
  [43]   5.156818032   5.099907462   4.189338357   5.335679820   8.522671690   8.652752991   6.669013154
  [50]   6.620232666   5.603972503  -0.322856765  -3.168385220  -1.119604733  -0.030173838   1.953565999
  [57]   4.986086324   8.132427788   8.343809902   9.490151365   9.620232666   2.770639170  -3.152125058
  [64] -10.095214489   3.937305836   0.929175755   3.969826162   6.042996893   6.189338357   6.221858682
  [71]   8.295029414   1.343809902   3.392590389   5.416980633  -4.526108798  -3.501718554   3.425110715
  [78]  -0.574889285  -0.517978716  -4.469198229  -3.412287659  -3.339116928  -4.322856765  -1.233425871
  [85]   1.799094454   1.839744861   4.799094454   1.758444048  -3.314726684  -7.412287659 -10.404157578
  [92] -18.379767334 -16.257816115 -10.209035627   1.839744861 -12.192775464 -16.176515302 -18.135864895
  [99] -22.103344570  -4.046434001 -12.013913676  -9.875702294 -12.802531562 -12.786271399  -8.802531562
 [106]  -2.835051887  -0.843181968  -1.835051887   0.156818032 -15.843181968 -18.826921806 -13.818791725
 [113]  -2.810661643  -0.745620993 -12.648060017  -8.566759204  -8.493588472  -6.493588472  -6.485458391
 [120]  -0.534238879   0.433240796   0.408850552  -0.648060017   4.054077068   8.168392961  11.100059460
 [127]   9.057058249   2.067911858   2.106939111  -6.841177781   5.188395332   2.201725520   5.250068302
 [134]   2.284849827   6.318136560   4.338099921   8.285123233   9.225205399   9.200351253   7.155544803
 [141]   7.095294541   7.019060807   7.926660693   6.805215474   1.710103092   4.759730538   5.790811972
 [148]   6.810027873   6.949048769   9.064173920   9.184845402   7.255095956   6.239627585  -9.901429858
 [155]  -1.984169574   1.990683314   6.040869153   6.997307233   5.894687996   1.760064032   1.592060621
 [162]  -2.467770293  -9.547997406  -2.628934301   3.270663139   5.185989649   5.122770799   4.179072669
 [169]   5.302133419   8.472625980   8.609167053   6.651720718   6.625625841   5.610167831  -0.335328445
 [176]  -3.204401034  -1.141218231  -0.055514427   1.949344479   4.978692562   8.099854792   8.288928964
 [183]   9.441483149   9.577113613   3.572181444  -1.625256904  -7.471116566   2.279495667  -1.536014647
 [190]   2.491280611   5.315518547   6.759785951   6.832784658   7.216896886   1.604296789   3.471472996
 [197]   5.863018152  -2.056574515  -2.880711347   2.381386008  -0.080638770   0.061956005  -3.858500136
 [204]  -2.792884401  -2.296664192  -5.030905152  -6.150391872   1.608982090   2.191166262   0.904084354
 [211]   1.930207077  -3.451861429  -5.743013733  -7.297920193 -13.731075515 -17.460124068 -12.320119728
 [218]  -1.002900631  -9.548335550 -13.800334579 -16.702857419 -20.776521663  -7.419732632 -11.892589329
 [225]  -9.862926082 -12.177459132 -13.212243537  -9.577856033  -6.901909774  -3.701348379  -3.863447567
 [232]   0.954361209 -12.607143359 -16.038454460 -13.721556068  -5.107985725  -3.654833771 -10.900814570
 [239]  -9.049700123  -5.918821548  -6.890604742  -9.585616950  -3.267916530   1.208673289   1.101305770
 [246]  -1.459240495   9.349190878   8.457426279  11.213418913   9.529052859   3.708912733   2.232253763
 [253]  -4.055741675   4.009435376   2.435545488   3.837606771   2.434984406   4.456956890   4.551056020
 [260]   7.310589082   9.543824913   8.467446129   7.976403877   7.598969484   8.053928354   7.239052512
```