Homework 3 (ISYE 6501) — Questions 5.1 & 6.1 & 6.2

Sorry in advance to my peer reviewers! (— —) I like to write out my reasoning and can be... wordy... But I will try to be even more brief this time after taking the advice from HW2 peers!

I want to thank https://r-graphics.org/ for guiding me on how to create clear and effective graphs and plots. While I did not copy any specific lines of code, I used it as a helpful reference when creating the plots for Question 6.2.
I also want to thank R's built in help() function, which has been extremely useful for understanding things or functions I do not immediately get, and for providing examples that helped me write my own, more complex scripts.

Question 5.1 Answer

```r
dim(crime_data)
```

```
## [1] 47 16
```

```r
g <- grubbs.test(na.omit(crime_data$Crime))
#type = 20 was not working for .Rmd file,
#so I had to use this after already knowing the higher value was the possible outlier
g
```

```
##
##  Grubbs test for one outlier
##
## data:  na.omit(crime_data$Crime)
## G = 2.81287, U = 0.82426, p-value = 0.07887
## alternative hypothesis: highest value 1993 is an outlier
```

Even though they tell us exactly which test to run, I still wanted to know "why this test?"
So, from my understanding, this specific kind of test is just to see if there is one unusually large or small value compared to the rest of the data, which is perfect for the question we are being asked.

Analysis:
[1993] is was the most extreme value in the data, and is extreme in the sense this is the largest value.
I got [G = 2.81287], which is the Grubbs test statistic, this shows us that the largest value is [~2.81] standard deviations (distance) away from the mean.
I also got [U = 0.82426], I didn't know what this meant, so I used 'help(grubbs.test)' which essentially told me: 1. Smaller U corresponds to a more extreme observation
2. It can be ignored safely for this assignment
FInally, I got [p-value = 0.07887] (7.87%), This result says: If all the crime rates follow the same general pattern and there is no true outlier, results this extreme would show up about 8 times out of 100 just by chance.
So, in my personal opinion of this, there is no outlier in this dataset.

8 out of 100 is not insanely rare, rare enough to notice, but not rare enough I could confidently say "this can't occur"naturally."
This sentiment I believe is backed by the fact Grubbs is really good for catching the extremes, which could be the outlier, but not so good at catching multiple large values at once.
The next closest value is [1969], which is pretty close. So statistically, the upper tail has more than one large value, which also weakens the case that [1993] is a lone, aberrant point.

Question 6.1 Answer

I believe a change detection model would be appropriate for monitoring my heart rate during a semi long run, since heart rate is measured continuously over time and usually stays around a normal level when my pace and conditions are consistent.
During a recent 5 mile run at a 12:00 mile pace (I know I'm slow), my average heart rate was [159bpm], with a maximum of [169bpm]. So, a meaningful change to me would be when my heart rate starts to stay above my normal running level, which could be due to increased effort, fatigue, dehydration, or changes in terrain (uphill).
Using the CUSUM technique, the baseline mean would be set to my typical heart rate of [159bpm].
The threshold or reference value would be based on the smallest sustained increase I care about, maybe something like a prolonged [5/6bpm] rise above my average rather than short spikes.
The critical value would be larger to avoid false alarms, so the model only signals when my heart rate stays high over time instead of reacting to a single high reading like [169bpm].
This lets the model catch real changes while ignoring normal short term variation.

Question 6.2 Answer

```
## [1] 123  21
```

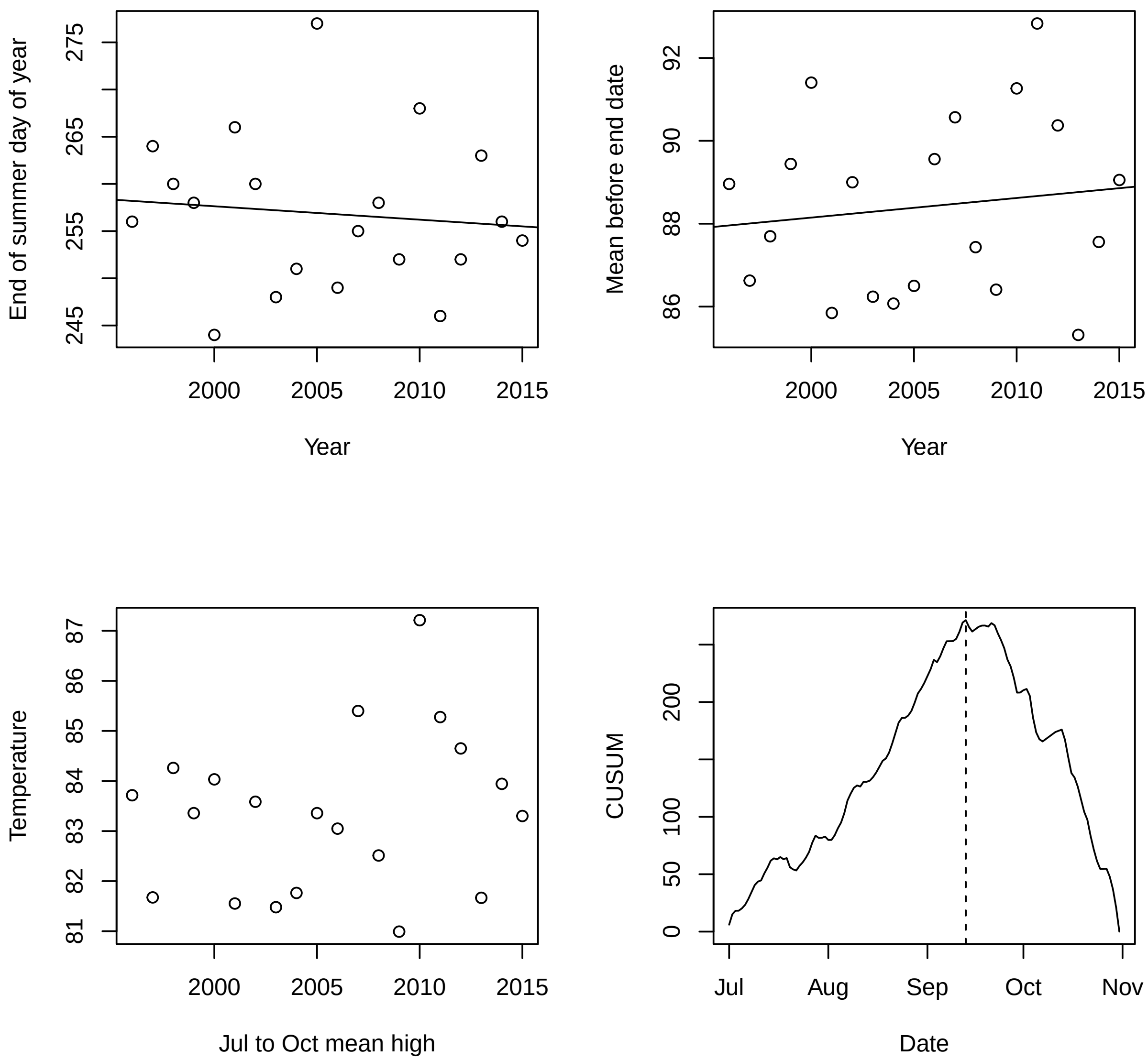
```r
summary(lm(mean_before ~ year, data = R))
```

```
##
## Call:
## lm(formula = mean_before ~ year, data = R)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.4454 -1.9256 -0.0794  1.4201  4.1629
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -6.47092  170.43134  -0.038    0.970
## year          0.04731    0.08498   0.557    0.585
##
## Residual standard error: 2.191 on 18 degrees of freedom
## Multiple R-squared:  0.01693,    Adjusted R-squared:  -0.03769
## F-statistic: 0.3099 on 1 and 18 DF,  p-value: 0.5846
```

```r
summary(lm(end_doy ~ year, data = R))
```

```
##
## Call:
## lm(formula = end_doy ~ year, data = R)
```

```
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -13.6316  -4.7803  -0.6368   3.4750  20.0789
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 541.8421   642.6503   0.843    0.410
## year         -0.1421     0.3204  -0.443    0.663
##
## Residual standard error: 8.263 on 18 degrees of freedom
## Multiple R-squared:  0.01081,    Adjusted R-squared:  -0.04415
## F-statistic: 0.1967 on 1 and 18 DF,  p-value: 0.6627
```



```r
dim(w)
```

```
## [1] 123  21
```

```r
dim(L)
```

```
## [1] 2460    3
```

```r
dim(R)
```

```
## [1] 20  6
```

```r
head(R,20) #just want to ensure it all loaded as expected
```

```
##      year   end_date end_doy mean_before mean_after drop_after
## 1996 1996 1996-09-12     256    88.95946   75.79592 -13.163541
## 1997 1997 1997-09-21     264    86.62651   71.40000 -15.226506
## 1998 1998 1998-09-17     260    87.69620   78.09091  -9.605293
## 1999 1999 1999-09-15     258    89.44156   73.17391 -16.267645
## 2000 2000 2000-08-31     244    91.40323   76.54098 -14.862242
## 2001 2001 2001-09-23     266    85.84706   71.94737 -13.899690
## 2002 2002 2002-09-17     260    89.00000   73.86364 -15.136364
## 2003 2003 2003-09-05     248    86.23881   75.78571 -10.453092
## 2004 2004 2004-09-07     251    86.07246   76.25926  -9.813205
## 2005 2005 2005-10-04     277    86.50000   72.18519 -14.314815
## 2006 2006 2006-09-06     249    89.55882   75.00000 -14.558824
## 2007 2007 2007-09-12     255    90.56757   77.59184 -12.975731
## 2008 2008 2008-09-14     258    87.43421   74.55319 -12.881019
## 2009 2009 2009-09-09     252    86.40845   73.59615 -12.812297
## 2010 2010 2010-09-25     268    91.26437   77.41667 -13.847701
## 2011 2011 2011-09-03     246    92.83077   76.81034 -16.020424
## 2012 2012 2012-09-08     252    90.37143   77.09434 -13.277089
## 2013 2013 2013-09-20     263    85.31707   74.36585 -10.951220
## 2014 2014 2014-09-13     256    87.56000   78.29167  -9.268333
## 2015 2015 2015-09-11     254    89.05479   74.90000 -14.154795
```

Using CUSUM, I centered each year's daily high temperatures around that year's July to October average and defined the CUSUM maximum as the end of summer.
With this method, I found that summer in Atlanta typically ends in early to mid September, most often between about [September 5] and [September 20].
Before the CUSUM peak, average daily highs were usually in the upper [80s] to low [90s], and after the peak they dropped to the mid [70s], a decrease of about [10 to 15] degrees.

Analysis:
To check whether summers have been lasting longer over time, I looked at the trend in the calendar day of year for the CUSUM end of summer date across years.
The estimated temperature trend was about [0.05] degrees per year with a p value of about [0.58], and the trend in the end of summer date was about [-0.14] days per year with a p value of about [0.66].
Both p values are fairly large, which means these trends are not statistically significant and could easily be due to random variation rather than a real change over time.
Based on these results from [1996] to [2015], there is no strong statistical evidence that Atlanta's summers became warmer or lasted longer over this period.