Homework 2 - Week 2 - Karthick Krishna

Question 4.1

Describe a situation or problem from your job, everyday life, current events, etc., for which a clustering model would be appropriate. List some (up to 5) predictors that you might use.

```
I am an Analyst at Mindtree Limited. Currently, I work on Marketing Analytics and Ad Analyti
cs. I work for one of the world's largest Search Engine Platforms providers on the Advertise
r level data and User level data. I use Python for analysis and used the Scikit Learn packag
e in Python. In my current project, as one of the early steps, I segregate the Customers(als
o known as Advertisers) into different groups before I perform Quasi-experimental design to
 find a treatment group for my test advertisers. After trying out lots of different clusteri
ng methods such as K-means, Partitioning Around Medoids(PAM), Hierarchical Clustering, DBSCA
N, K-prototype, and K-Modes. I ended up using K-Modes since it gave good cluster separation
 for my dataset and I could also use Categorical data as my feature.


Few of the KPI's(predictors) are as follows,

 1. The Impression gained by the advertiser using the platform (Integer datatype)
 2. Click gained by the advertiser using the platform (Integer datatype)
 3. Spend/Revenue of the Advertiser on the Platform (Doubble datatype)
 4. Vertical (Example: Travel and Transport, Retail, B2C Services, et cetera) (Categorical d
ata)
 5. Country on the Advertiser has performed (Categorical data)
```

Question 4.2

Problem Statement: Use the R function kmeans to cluster the points as well as possible. Report the best combination of predictors, your suggested value of k, and how well your best clustering predicts flower type.

On an overall output of k =3 and using Petals as Predictors gave 96% accuracy

My approach to the given problem:

The problem is very straightforward, we have to Cluster the data into k numbers. In this problem, ***After the TA call(Mr. Siawpeng Er) I've scalled my data***, I've used ggplot to identify which feature (Sepal or Petal) can get better clustering of iris Dataset followed by identifying the number of clusters using the elbow curve, later I performed k-means using the number of k that we obtain from elbow curve and feature that I select. In the end, I use the output value to find the Accuracy.

My understanding of the output

```
The Petal feature looks good to separate the data into k clusters, later k = 3 for the petal
predictors looked good from the elbow curve. At last, the accuracy looks extremely good, i.e
k-means (for the selected feature and k value) has given a good output of separating the Spe
cies into different types.
```

I used the following link for this question:

1. `https://rpubs.com/AnanyaDu/361293`
2. `http://rstudio-pubs-static.s3.amazonaws.com/227726_134741628338405eaebcff73cc63abc6.html`

In [25]:
```
install.packages("dplyr", repos='http://cran.us.r-project.org')
install.packages("tidyverse", repos='http://cran.us.r-project.org')
install.packages("cluster", repos='http://cran.us.r-project.org')
install.packages("fpc", repos='http://cran.us.r-project.org')
install.packages("factoextra", repos='http://cran.us.r-project.org')
```

```
Installing package into 'C:/Users/v-balkar.REDMOND/Documents/R/win-library/3.6'
(as 'lib' is unspecified)
Installing package into 'C:/Users/v-balkar.REDMOND/Documents/R/win-library/3.6'
(as 'lib' is unspecified)
Installing package into 'C:/Users/v-balkar.REDMOND/Documents/R/win-library/3.6'
(as 'lib' is unspecified)
Installing package into 'C:/Users/v-balkar.REDMOND/Documents/R/win-library/3.6'
(as 'lib' is unspecified)
Installing package into 'C:/Users/v-balkar.REDMOND/Documents/R/win-library/3.6'
(as 'lib' is unspecified)
```

In [4]:
```
oldw <- getOption("warn")
options(warn = -1)
library(dplyr)
library(tidyverse)
library(cluster)
library(fpc)
library(factoextra)
require(gridExtra)
library(ggplot2)
```

In [189]:
```
# Loading the iris text dataset into a dataframe

iris <- read.table("iris.txt",header = TRUE)
```

In [190]:
```
head(iris)
```

Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Species
5.1	3.5	1.4	0.2	setosa
4.9	3.0	1.4	0.2	setosa
4.7	3.2	1.3	0.2	setosa
4.6	3.1	1.5	0.2	setosa
5.0	3.6	1.4	0.2	setosa
5.4	3.9	1.7	0.4	setosa

In [191]:
```
length(unique(iris$Species))
```

3

In [192]:
```
dim(iris)
```

150 5

In [193]:
```
summary(iris)
```

```
  Sepal.Length    Sepal.Width     Petal.Length    Petal.Width   
 Min.   :4.300   Min.   :2.000   Min.   :1.000   Min.   :0.100  
 1st Qu.:5.100   1st Qu.:2.800   1st Qu.:1.600   1st Qu.:0.300  
 Median :5.800   Median :3.000   Median :4.350   Median :1.300  
 Mean   :5.843   Mean   :3.057   Mean   :3.758   Mean   :1.199  
 3rd Qu.:6.400   3rd Qu.:3.300   3rd Qu.:5.100   3rd Qu.:1.800  
 Max.   :7.900   Max.   :4.400   Max.   :6.900   Max.   :2.500  
       Species  
 setosa    :50  
 versicolor:50  
 virginica :50  
```

Scalling the values after the TA call

In [196]:
```
normalize <- function(x){
  return ((x-min(x))/(max(x)-min(x)))
}

iris$Sepal.Length<- normalize(iris$Sepal.Length)
iris$Sepal.Width<- normalize(iris$Sepal.Width)
iris$Petal.Length<- normalize(iris$Petal.Length)
iris$Petal.Width<- normalize(iris$Petal.Width)
head(iris)
```

Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Species
0.22222222	0.6250000	0.06779661	0.04166667	setosa
0.16666667	0.4166667	0.06779661	0.04166667	setosa
0.11111111	0.5000000	0.05084746	0.04166667	setosa
0.08333333	0.4583333	0.08474576	0.04166667	setosa
0.19444444	0.6666667	0.06779661	0.04166667	setosa
0.30555556	0.7916667	0.11864407	0.12500000	setosa

Preprocessing the data

Clustering falls under Unsupervised Learning, so we don't need the output variable during execution of our algorithm. We will, therefore, remove Output variable “Species” and store it in another variable.

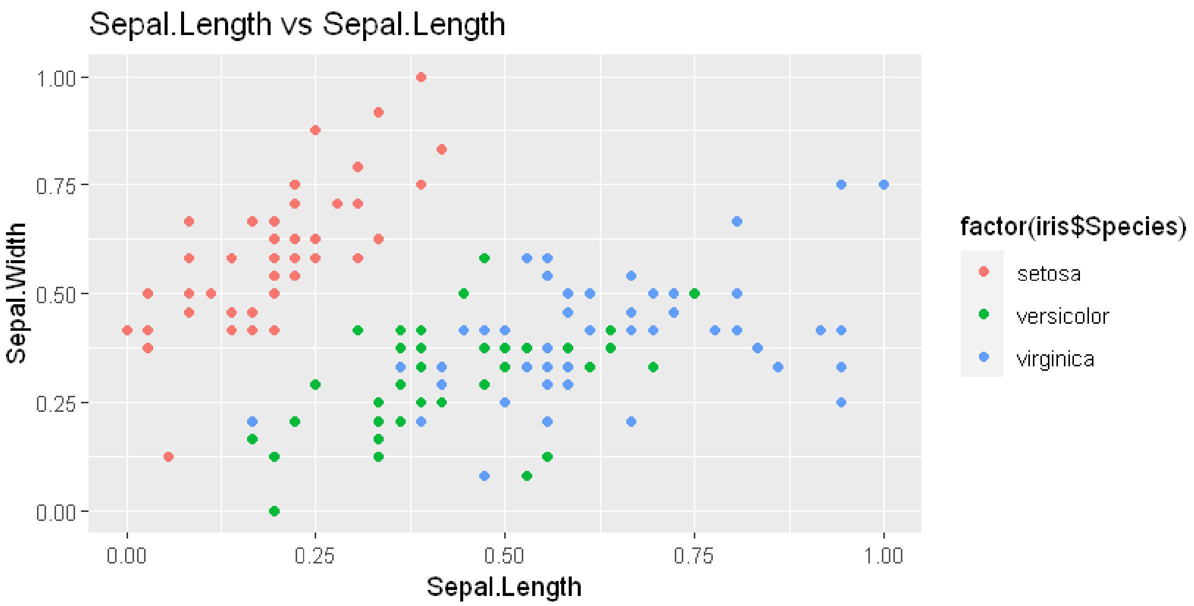
In [197]:
```
# Seperate the independent variables from the dependent variabe
df <- iris[,1:4]
df_Class <- iris[,"Species"]
head(df)
```

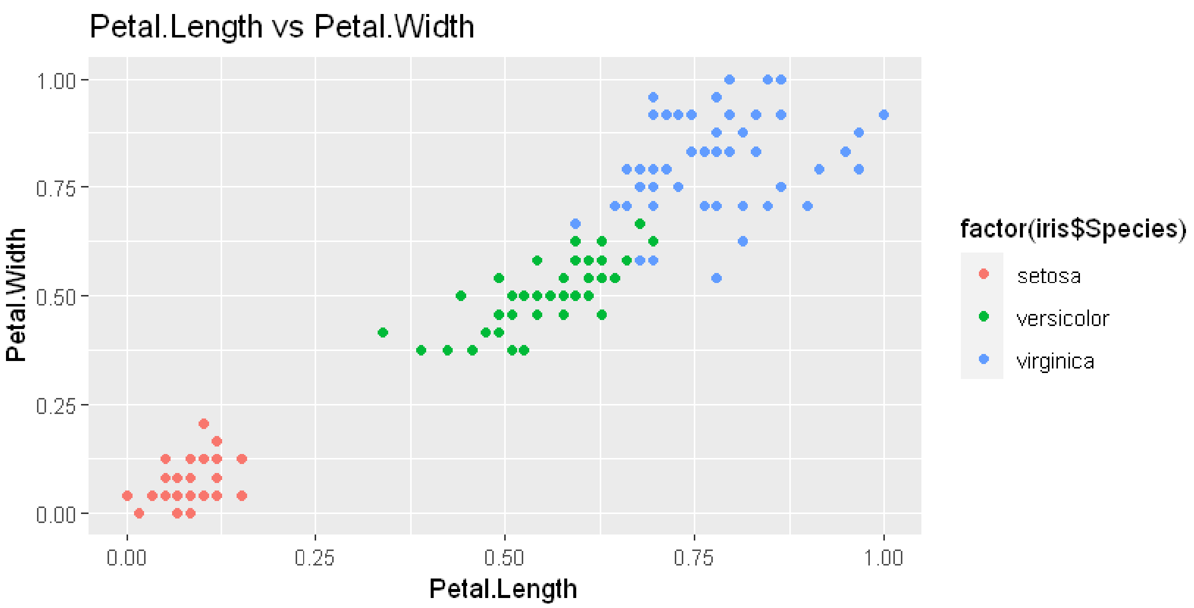
Sepal.Length	Sepal.Width	Petal.Length	Petal.Width
0.22222222	0.6250000	0.06779661	0.04166667
0.16666667	0.4166667	0.06779661	0.04166667
0.11111111	0.5000000	0.05084746	0.04166667
0.08333333	0.4583333	0.08474576	0.04166667
0.19444444	0.6666667	0.06779661	0.04166667
0.30555556	0.7916667	0.11864407	0.12500000

Now I see how different combinations have splitted.

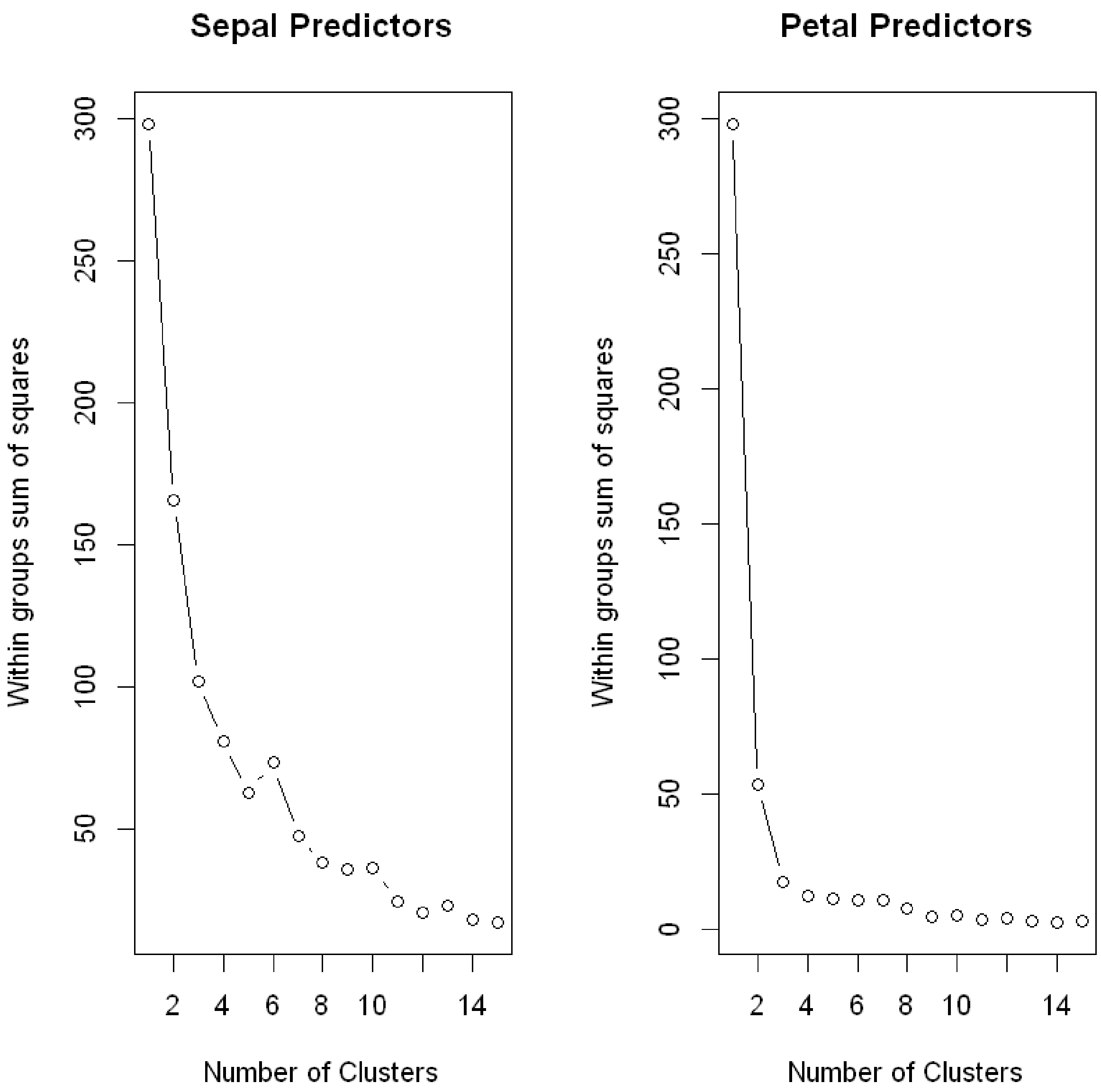
In [198]:

```
# plotting the petal and sepal features separately to view the different features.

plot1 <- ggplot(df, aes(x = df[,1], y = df[,2]))+geom_point(aes(color = factor(iris$Species)))+labs(x

plot2 <- ggplot(df, aes(x = df[,3], y = df[,4]))+geom_point(aes(color = factor(iris$Species)))+labs(x

grid.arrange(plot1, plot2, ncol=1)

# It is clear the petal features can get a better clustering of the iris dataset
```





In [199]:
```
# For the next step, I am going to try to determine the number of clusters using the elbow method.

# FROM THE ELBOW METHOD, I am going to be using 3 clusters as input to kmeans function.

sepals_df = df[,1:2]
petals_df = df[,3:4]
par(mfrow=c(1,2))                  # used to set or query graphical parameters (Get the 2 graphs sid

# Elbow method on Sepals
sepals_df <- scale(sepals_df)
wss <- (nrow(sepals_df)-1)*sum(apply(sepals_df,2,var))
for (i in 2:15) wss[i] <- sum(kmeans(sepals_df, centers=i)$withinss)
plot1 <- plot(1:15, wss, type="b", xlab="Number of Clusters", ylab="Within groups sum of squares", ma

# Elbow method on Petals
petals_df <- scale(petals_df)
wss <- (nrow(petals_df)-1)*sum(apply(petals_df,2,var))
for (i in 2:15) wss[i] <- sum(kmeans(petals_df, centers=i)$withinss)
plot2 <- plot(1:15, wss, type="b", xlab="Number of Clusters", ylab="Within groups sum of squares", ma
```



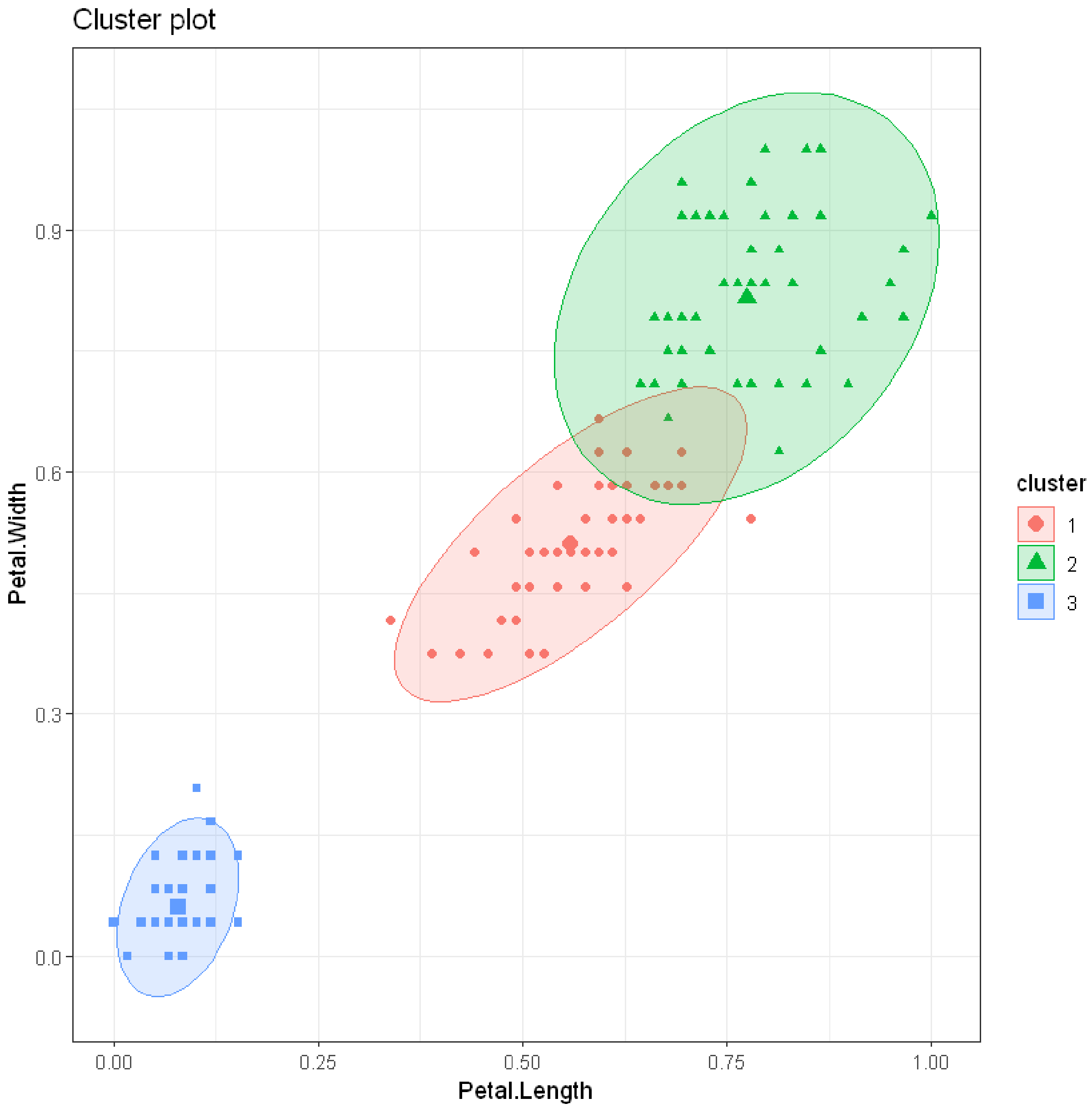
The plot above represents the variance within the clusters. It decreases as k increases, but we can see a bend or an elbow at k = 3 for the petal predictor. This bend indicates that additional clusters beyond the third have little value or not significant.

In [200]:
```
# ?kmeans

set.seed(123)
model <- kmeans(petals_df, 3, nstart = 25, iter.max = 10)
cluster_centroids <- aggregate(petals_df,by=list(model$cluster),FUN=mean)
cluster_centroids
```

Group.1	Petal.Length	Petal.Width
1	0.3048515	0.1648655
2	1.0245672	1.1242119
3	-1.3006301	-1.2507035

Showing the output graphically along with the cluster centroid

In [201]:
```
# ?fviz_cluster

fviz_cluster(object = model, data = df, geom = "point", choose.vars = c("Petal.Length", "Petal.Width"
             stand = FALSE, ellipse.type = "norm") + theme_bw()
```



Now to check how well the model has predicted

In [202]:
```
model$size # gives no. of records in each cluster
```

52 48 50

In [203]:
```
table(model$cluster,df_Class)
```

```
   df_Class
    setosa versicolor virginica
  1      0         48         4
  2      0          2        46
  3     50          0         0
```

The above result of table shows that Cluster 1 corresponds to Virginica, Cluster 2 corresponds to Versicolor and Cluster 3 to Setosa.

Total number of correctly classified instances are: 46 + 48 + 50= 144

Total number of incorrectly classified instances are: 2 + 4= 6

Accuracy = 144/(144+6) = 0.96 meaning our model has achieved 96% accuracy

Question 5.1

Problem Statement: Using crime data from the file uscrime.txt, test to see whether there are any outliers in the last column (number of crimes per 100,000 people). Use the grubbs.test function in the outliers package in R.

Grubbs Test:

It is a statistical test to identify Outliers. The value could be smallest or largest in the data. Grubbs test works by assuming that data is normally distributed, so we have to check the normality assumption first.

My approach to the given problem:

```
First I checked whether my data is normally distributed or not to perform Grubbs test. Later
I used grubbs.test() function to perform the test. Later I removed those values and I perfor
med the grubb test again and checked the P-value.
```

My understanding of the output

```
342 and 1993 are outliers, i.e these values are separated maximum from the mean. The p-value
measures how much evidence there is that the tested point is an Outlier or not (Values Near
 0 - Stronger evidence of an Outlier, Values Near 1 - Weaker evidence of an Outlier). Since
 I got P-value output of 1 this means the tested point should not be considered as an Outlie
r.
I continued the process till the value was some what near 0

That was not happening so as TA(Mr. Siawpeng Er) mentioned during the cass time if we contin
ue to do this we will end up in removing all the data.
```

I used the following link for this question:

```
1. rdocumentation.org/packages/outliers/versions/0.14/topics/grubbs.test
2. https://www.youtube.com/watch?v=kc9O5XfV2pc
```

In [63]:
```
# installing the required Package
# install.packages("outliers", repos = 'http://cran.us.r-project.org')
```

In [64]:
```r
crime_df <- read.table("uscrime.txt", header = TRUE)
```

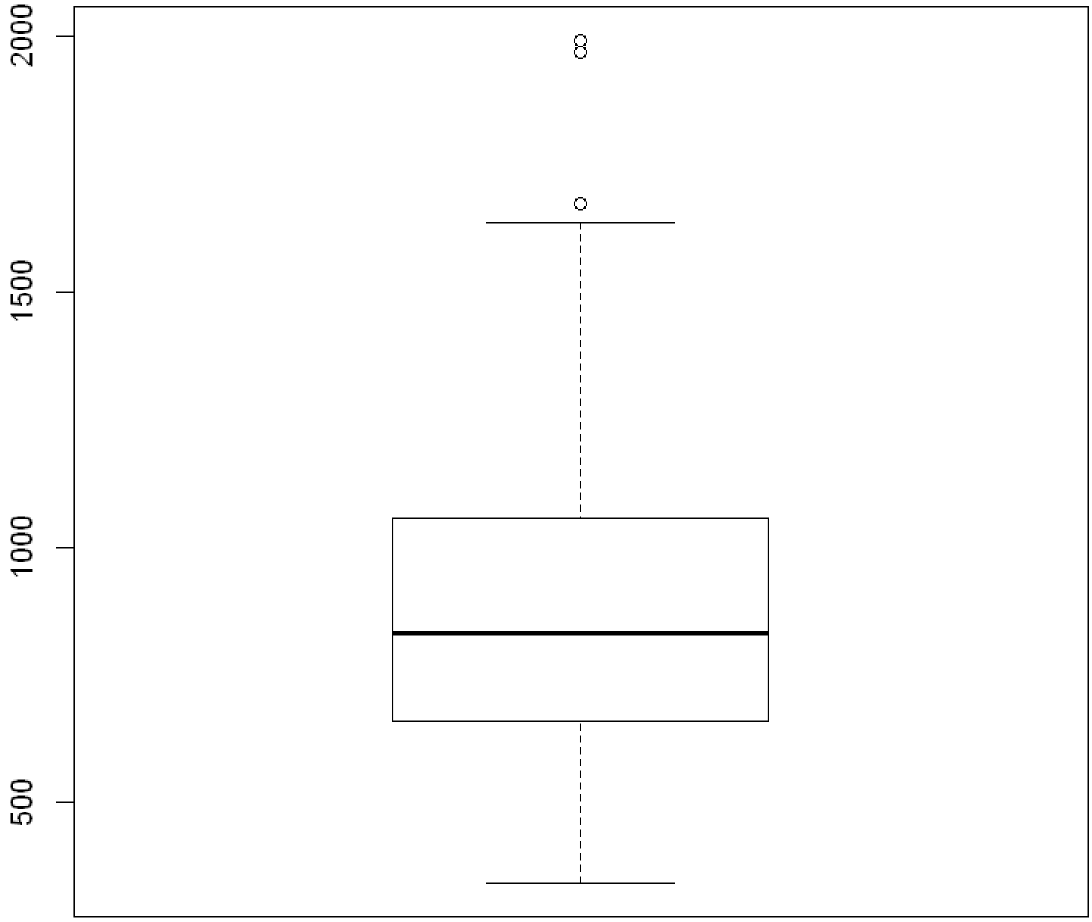
In [65]:
```r
head(crime_df,2)
```

M	So	Ed	Po1	Po2	LF	M.F	Pop	NW	U1	U2	Wealth	Ineq	Prob	Time	Crime
15.1	1	9.1	5.8	5.6	0.510	95.0	33	30.1	0.108	4.1	3940	26.1	0.084602	26.2011	791
14.3	0	11.3	10.3	9.5	0.583	101.2	13	10.2	0.096	3.6	5570	19.4	0.029599	25.2999	1635

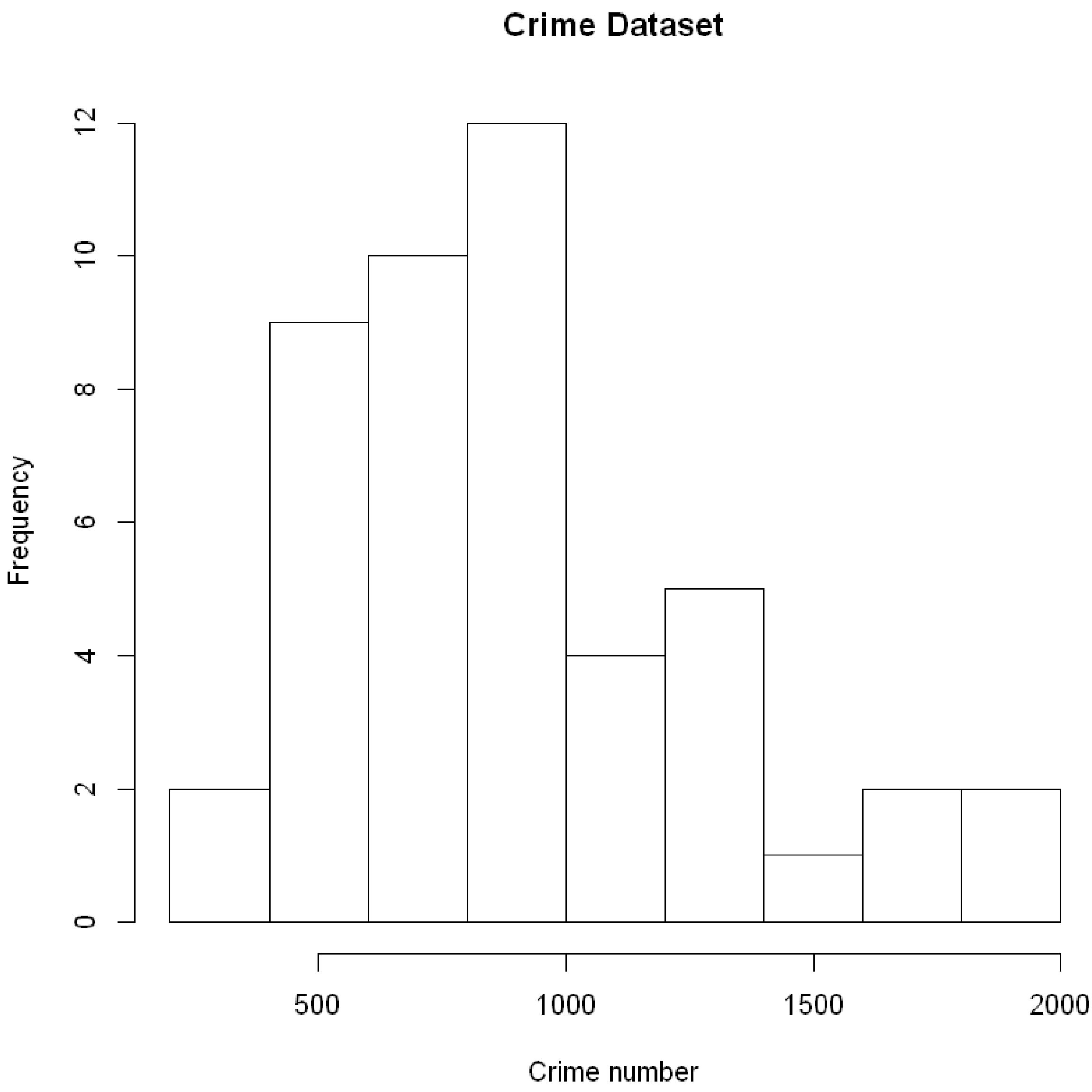
In [172]:
```r
dim(crime_df)
```

47 16

In [168]:
```r
# Using boxplot to visualize the Outliers
boxplot(crime_df$Crime)
```



In [83]:
```
# Checking Normality with Histogram

hist(crime_df$Crime, xlab = "Crime number", main = "Crime Dataset")
```



This looks fine, but if our data had more than a single peak then Grub test cannot be used. Now I'm continueing with the grub test.

In [84]:
```
library(outliers)
crime <- crime_df$Crime
```

In [188]:
```
# ?grubbs.test

grubbs.test(crime, type = 11, opposite = FALSE, two.sided = FALSE)
```

```
	Grubbs test for two opposite outliers

data:  crime
G = 4.26877, U = 0.78103, p-value = 1
alternative hypothesis: 342 and 1993 are outliers
```

p-value near 1 - Weaker evidence of an Outlier

In [239]:
```
crime_df <- crime_df[(!(crime_df$Crime == 342) & !(crime_df$Crime == 1993)),]
```

In [240]:
```
dim(crime_df)
```

45 16

In [241]:
```
grubbs.test(crime_df$Crime, type = 11, opposite = FALSE, two.sided = FALSE)
```

```
	Grubbs test for two opposite outliers

data:  crime_df$Crime
G = 4.56671, U = 0.73301, p-value = 0.6893
alternative hypothesis: 373 and 1969 are outliers
```

In [242]:
```
crime_df <- crime_df[(!(crime_df$Crime == 373) & !(crime_df$Crime == 1969)),]
```

In [243]:
```
dim(crime_df)
```

43 16

In [244]:
```
grubbs.test(crime_df$Crime, type = 11, opposite = FALSE, two.sided = FALSE)
```

```
	Grubbs test for two opposite outliers

data:  crime_df$Crime
G = 4.03257, U = 0.78992, p-value = 1
alternative hypothesis: 439 and 1674 are outliers
```

Kindly read "My understanding of the output" for this question as why I performed the process again

Question 6.1

Describe a situation or problem from your job, everyday life, current events, etc., for which a Change Detection model would be appropriate. Applying the CUSUM technique, how would you choose the critical value and the threshold?

As an Analyst at Mindtree, I worked on a churn analytics project for my client where I had to analyze the Customers who tend to churn out of the system. For this I use lots of different performance metrics across a time period. One important note is that I consider the seasonality since some customers prefer to invest in the platform during a certain time of the yar. Depending on the importance of the metric, I vary the time window from weeks to months. After tabulating the time-weighted values, I compare the values to the threshold, which I decide on the data that is provided. The main objective of this project is to identify the time when the customer might leave the system, by doing so my client will get in touch with the customer and makes sure that the customer doesn't leave the system. So for this problem statement it's not definitive on selecting a Critical value or threshold.

Question 6.2 (a)

Problem Statement: Using July through October daily-high-temperature data for Atlanta for 1996 through 2015, use a CUSUM approach to identify when unofficial summer ends (i.e., when the weather starts cooling off) each year.

First I viewed the sum and average of temperatures by year and by month to see trends,if present, in this data.

In the Daily Temperature by Year output we want to see if climate has generally changed for the warmer as time goes on. It looks like temperature is stable throughout the years, but from 2010 there are a few abnormally with high mean temperatures. The mean temperatures for 2010 and 2011 are high.

In the Daily Temperature by Month output we want to see when we start transitioning out of summer. The output clearly explains what was expected. Starting in September temperatures start to cool down. CUSUM model would start to pick up changes as early as late August that temperatures are decreasing.

I set up a loop to run a cusum model on each individual year to determine which day start a string of temperature changes. To do this I set up a cusum model using the mean of all summer days as the center value, the standard deviation of all summer days as the target standard deviation. Detection standard deviation is set to 1.96 times the summer day standard deviation. Any value greater than 1.96 times the standard deviation will add to the cumulative sum model.

The dates for each year are listed in a data frame below. The earliest end of summer was 2013-08-15. The latest end of summer was 2005-10-06. Most end of summer days occur in early to mid-September.

In [118]:
```
# load libraries
# if (!require(lubridate)) install.packages("lubridate")
# library(lubridate)

# if (!require(qcc)) install.packages("qcc")
# library(qcc)

# if (!require(changepoint)) install.packages("changepoint")
# library(changepoint)

# if (!require(bda)) install.packages("bda")
# library(bda)
```

In [97]:
```
# setup cusum algorithm for changes over time
temps_df = read_delim('temps.txt', delim = '\t') %>%
        as_tibble() %>%
        gather(year, temp, -DAY) %>%
        mutate(year = as.factor(year),
               date = paste(DAY,year, sep = '-')) %>%
        mutate(date_val = dmy(date),
               color = ifelse(temp > mean(.$temp), 'Above', 'Below'),
               month = month(date_val),
               day = day(date_val)) %>%
        dplyr::select(date_val, DAY, year, temp,color, month, day)
```

```
Parsed with column specification:
cols(
  .default = col_double(),
  DAY = col_character()
)
See spec(...) for full column specifications.
```

In [133]:
```
# Truncating the data
head(temps_df)
```

date_val	DAY	year	temp	color	month	day
1996-07-01	1-Jul	1996	98	Above	7	1
1996-07-02	2-Jul	1996	97	Above	7	2
1996-07-03	3-Jul	1996	97	Above	7	3
1996-07-04	4-Jul	1996	90	Above	7	4
1996-07-05	5-Jul	1996	89	Above	7	5
1996-07-06	6-Jul	1996	93	Above	7	6

In [99]:
```
dim(temps_df)
```

2460 7

In [222]:
```
# This is the Standard Deviation of the whole output

sd(temps_df$temp)
```

8.62025319888611

In [218]:
```
# Group the data by year and summing it

aggregate(temps_df$temp ~ temps_df$year, temps_df, sum)
```

temps_df$year	temps_df$temp
1996	10297
1997	10046
1998	10364
1999	10253
2000	10336
2001	10031
2002	10281
2003	10022
2004	10057
2005	10253
2006	10215
2007	10504
2008	10149
2009	9962
2010	10727
2011	10489
2012	10412
2013	10045
2014	10325
2015	10246

In [213]:
```
# The mean temperaature across all the years

mean(temps_df$temp)
```

83.3390243902439

In [220]:
```
# Group the data by months and averaging it

aggregate(temps_df$temp ~ temps_df$year, temps_df, mean)
```

temps_df$year	temps_df$temp
1996	83.71545
1997	81.67480
1998	84.26016
1999	83.35772
2000	84.03252
2001	81.55285
2002	83.58537
2003	81.47967
2004	81.76423
2005	83.35772
2006	83.04878
2007	85.39837
2008	82.51220
2009	80.99187
2010	87.21138
2011	85.27642
2012	84.65041
2013	81.66667
2014	83.94309
2015	83.30081

In [216]:
```
# Group the data by months and summing it

aggregate(temps_df$temp ~ temps_df$month, temps_df, sum)
```

temps_df$month	temps_df$temp
7	55025
8	54942
9	49603
10	45444

In [217]:
```
# Group the data by months and averaging it

aggregate(temps_df$temp ~ temps_df$month, temps_df, mean)
```

temps_df$month	temps_df$temp
7	88.75000
8	88.61613
9	82.67167
10	73.29677

In [226]:
```
## Cusum Model
# setup cusum algorithm for changes over time
temps_model_df <- read_delim('temps.txt', delim = '\t') %>%
        as_data_frame() %>%
        gather(year, temp, -DAY) %>%
        mutate(year = as.factor(year),
               date = paste(DAY,year, sep = '-')) %>%
        mutate(date_val = dmy(date),
               color = ifelse(temp > mean(.$temp), 'Above', 'Below'),
               month = month(date_val),
               day = day(date_val)) %>%
        dplyr::select(date_val, DAY, year, temp,color, month, day)
print("Head of temp data")
head(temps_model_df)

print('Unique Years: ',)
unique(temps_model_df$year)

# grab only the summer dates for the cusum model
summer_df = temps_model_df %>%
        filter(month %in% c(as.Date(7), as.Date(8)))

# summer_df

# determine baseline mean and sd metrics in the summer months only
summer_mean = mean(summer_df$temp)
summer_sd = sd(summer_df$temp)

# summer_mean
# summer_sd

# list of years to loop through
years = as.list(unique(as.character(temps_model_df$year)))

# years

# empty list to store values of the for loop into
store_days <- list()


# cusum for loop
for (i in seq_along(years)) {

        # take a year subset
        year_index <- years[[i]]

        df <- temps_model_df %>%
                filter(as.character(year) == year_index) %>%
                dplyr::select(temp)

        # fit a cusum model to that year
        qsum <- qcc::cusum(
                data = df$temp,
                centervalue = summer_mean,
                std.dev = summer_sd,
                se.shift = 1.96,
                plot = F
           )
        # extract the first day that starts at least 4 consecutive days of temperature flagged by cus
        qsum_results <- qsum$neg %>%
                as_tibble() %>%
                rownames_to_column() %>%
                cbind(date = temps_model_df$DAY) %>%
                mutate( # current cusum value times the next and the fourth value cannot be 0!
                        consecutive = value * lead(value,1) * lead(value, 4) == 0
                        ) %>%
                filter(consecutive == F) %>%
                .[1,] %>%
                cbind(year_index) %>%
                dplyr::select(., -consecutive)

        # store the first day of a string of flagged temperatures into a list
        store_days[[i]] = qsum_results

}
```

```r
# reduce the list of stored temperatures and format into a readable format
end_summer <- reduce(store_days, rbind) %>%
        mutate(date = paste(date,year_index, sep = '-')) %>%
        mutate(date_val = dmy(date)) %>%
        dplyr::select(date_val, 'cusum_val' = value) %>%
        mutate(year_date = year(date_val)) %>%
        dplyr::select(year_date, date_val, cusum_val) %>%
        mutate(month_val = month(date_val),
               day_val = day(date_val))

# end_summer


# find the earliest end of summer
earliest_end <- end_summer %>%
        filter(month_val == min(month_val))

# earliest_end

# find the latest end of summer
latest_end <- end_summer %>%
        filter(month_val == max(month_val))

# latest_end

# print outputs
print("Outputs:")
print(paste('Earliest Summer End: ', earliest_end$date_val))
print(paste('Latest Summer End: ', latest_end$date_val))
end_summer
```

```
Parsed with column specification:
cols(
  .default = col_double(),
  DAY = col_character()
)
See spec(...) for full column specifications.
```

```
[1] "Head of temp data"
```

date_val	DAY	year	temp	color	month	day
1996-07-01	1-Jul	1996	98	Above	7	1
1996-07-02	2-Jul	1996	97	Above	7	2
1996-07-03	3-Jul	1996	97	Above	7	3
1996-07-04	4-Jul	1996	90	Above	7	4
1996-07-05	5-Jul	1996	89	Above	7	5
1996-07-06	6-Jul	1996	93	Above	7	6

```
[1] "Unique Years: "
```

1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015

▶ **Levels**:

```
[1] "Outputs:"
[1] "Earliest Summer End:  2013-08-15"
[1] "Latest Summer End:  2005-10-06"
```

year_date	date_val	cusum_val	month_val	day_val
1996	1996-09-18	-0.2128955	9	18
1997	1997-09-22	-1.4566970	9	22
1998	1998-09-29	-0.9527283	9	29
1999	1999-09-20	-2.2253764	9	20
2000	2000-09-06	-2.7836448	9	6
2001	2001-09-24	-1.6399583	9	24

year_date	date_val	cusum_val	month_val	day_val
2002	2002-09-24	-1.2293172	9	24
2003	2003-09-28	-0.7898293	9	28
2004	2004-09-15	-0.8492196	9	15
2005	2005-10-06	-1.3905193	10	6
2006	2006-09-21	-1.8172197	9	21
2007	2007-09-16	-0.9815750	9	16
2008	2008-09-17	-1.8401883	9	17
2009	2009-09-29	-0.8967318	9	29
2010	2010-09-26	-1.3599757	9	26
2011	2011-09-04	-0.1212649	9	4
2012	2012-09-30	-1.6603207	9	30
2013	2013-08-15	-0.8288572	8	15
2014	2014-09-23	-0.4691220	9	23
2015	2015-09-12	-0.1263554	9	12

Question 6.2 (b)

Use a CUSUM approach to make a judgment of whether Atlanta's summer climate has gotten warmer in that time (and if so, when).

To answer this question we will use the a cusum model to see if any year's summer days have been hotter than the overall average of the summer months. To do this we will filter the data set to only the summer months, then set up a cusum model with center value as the mean temperature of all summer months. We will use the standard deviation for the same time period.

Examining the cusum plot - there is an extreme amount of positive change around the mid 2000s, with another run of hot summers following close to the end of our data set.

2007 looks to be the peak of the hot summers shown in the cusum chart. In particular, 8-25-2007, shows the highest cummulative sum total of any of the years summer days.

To get the CUSUM chart I used :

1. `https://cran.r-project.org/web/packages/qcc/vignettes/qcc_a_quick_tour.html`
2. `http://www.stat.unipg.it/luca/misc/Rnews_2004-1-pag11-17.pdf`
3. `https://rdrr.io/cran/qcc/man/qcc.html`

In [227]:

```r
# setup cusum algorithm for changes over time
temps_df2 <- read_delim('temps.txt', delim = '\t') %>%
        as_data_frame() %>%
        gather(year, temp, -DAY) %>%
        mutate(year = as.factor(year),
               date = paste(DAY,year, sep = '-')) %>%
        mutate(date_val = dmy(date),
               month = month(date_val),
               day = day(date_val)) %>%
        filter(month %in% c(7, 8)) %>%
        dplyr::select(date_val, DAY, year, temp)
```

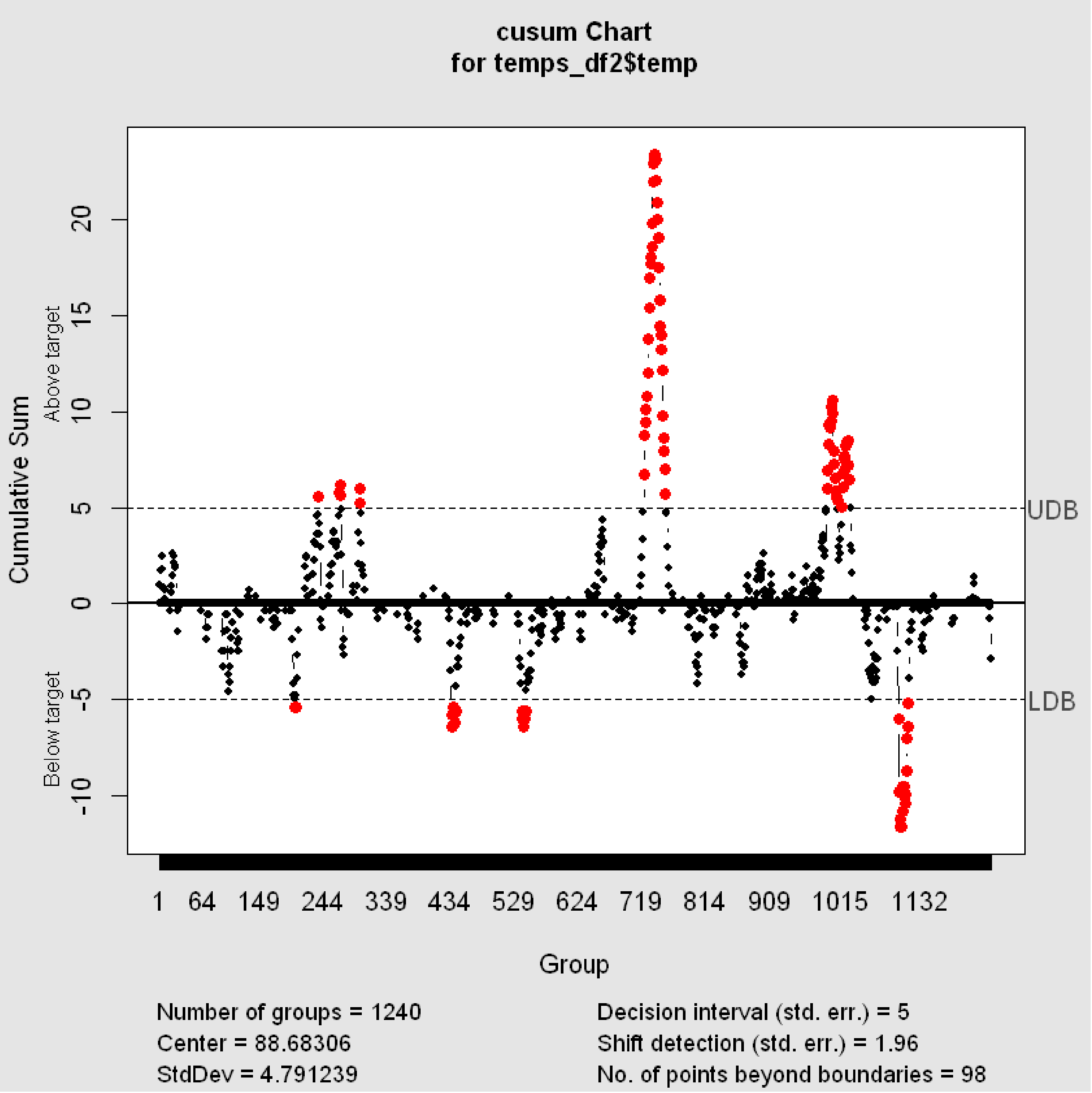
```
Parsed with column specification:
cols(
  .default = col_double(),
  DAY = col_character()
)
See spec(...) for full column specifications.
```

In [228]:
```
# center value and std.dev
summer_center2 <- mean(temps_df2$temp)
summer_sd2 <- sd(temps_df2$temp)
```

In [229]:
```
# print outputs
print(paste('Overall Summer  Mean: ', summer_center2))
print(paste('Overall Summer Standard Deviation: ', summer_sd2))
```

```
[1] "Overall Summer  Mean:  88.683064516129"
[1] "Overall Summer Standard Deviation:  4.79123867097968"
```

In [230]:
```
# plot the cusum chart for all summer days
cusum_chart <- qcc::cusum(
        data = temps_df2$temp,
        centervalue = summer_center2,
        std.dev = summer_sd2,
        se.shift = 1.96,
        plot = T
        )
```



In [231]:
```
# extract the cusum results to see exactly when summers get hotter than normal
cusum_results <- qcc::cusum(
        data = temps_df2$temp,
        centervalue = summer_center2,
        std.dev = summer_sd2 ,
        se.shift = 1.96,
        plot = F
        )
```

In [232]:
```
cusum_results
```

```
List of 14
 $ call             : language qcc::cusum(data = temps_df2$temp, std.dev = summer_sd2, se.shift = 1.
96,      plot = F, centervalue = summer_center2)
 $ type             : chr "cusum"
 $ data.name        : chr "temps_df2$temp"
 $ data             : num [1:1240, 1] 98 97 97 90 89 93 93 91 93 93 ...
  ..- attr(*, "dimnames")=List of 2
 $ statistics       : Named num [1:1240] 98 97 97 90 89 93 93 91 93 93 ...
  ..- attr(*, "names")= chr [1:1240] "1" "2" "3" "4" ...
 $ sizes            : int [1:1240] 1 1 1 1 1 1 1 1 1 1 ...
 $ center           : num 88.7
 $ std.dev          : num 4.79
 $ pos              : num [1:1240] 0.965 1.72 2.476 1.771 0.857 ...
 $ neg              : num [1:1240] 0 0 0 0 0 0 0 0 0 0 ...
 $ head.start       : num 0
 $ decision.interval: num 5
 $ se.shift         : num 1.96
 $ violations       :List of 2
 - attr(*, "class")= chr "cusum.qcc"
```

In [233]:
```
cusum_positive <- cusum_results$pos %>%
        as_tibble() %>%
        rownames_to_column() %>%
        cbind(date = temps_df2$date_val) %>%
        left_join(., temps_df2, by = c('date' = 'date_val')) %>%
        dplyr::select(date, value, temp) %>%
        filter(value != 0) %>%
        arrange(date)
```

In [234]:
```
head(cusum_positive,15)
```

date	value	temp
1996-07-01	0.96457762	98
1996-07-02	1.72044094	97
1996-07-03	2.47630427	97
1996-07-04	1.77116753	90
1996-07-05	0.85731649	89
1996-07-06	0.77832264	93
1996-07-07	0.69932878	93
1996-07-08	0.20290634	91
1996-07-09	0.12391248	93
1996-07-10	0.04491863	93
1996-07-17	0.54714903	96
1996-07-18	0.88558376	95
1996-07-19	1.43273279	96
1996-07-20	2.60602471	99
1996-07-21	2.10960226	91

In [235]:
```
highest_cusum <- cusum_positive %>% filter(value == max(value)) %>%
        dplyr::select(date)
```

In [236]:
```
highest_cusum
```

date
2007-08-25

In [237]:
```
print(paste('Date with Highest Cusum: ', as.character(highest_cusum$date)))
```

```
[1] "Date with Highest Cusum:  2007-08-25"
```

In [238]:
```
# look at the actual temps in August 2007 - 18 days above 95 degrees!
(summer_2018 <- cusum_positive %>%
        filter(month(date) %in% as.Date(8),
               year(date) %in% as.Date(2007))
)
```

date	value	temp
2007-08-03	0.1297204	94
2007-08-04	0.8855838	97
2007-08-05	1.4327328	96
2007-08-06	2.3973104	98
2007-08-07	3.3618880	98
2007-08-08	4.7438942	100
2007-08-09	6.7520433	103
2007-08-10	8.7601924	103
2007-08-11	10.1421986	100
2007-08-12	9.4370619	90
2007-08-13	10.8190681	100
2007-08-14	11.9923600	99
2007-08-15	13.7917948	102
2007-08-16	15.3825153	101
2007-08-17	16.9732358	101
2007-08-18	17.7290991	97
2007-08-19	18.0675339	95
2007-08-20	18.6146829	96
2007-08-21	19.7879748	99
2007-08-22	22.0048382	104
2007-08-23	22.9694158	98
2007-08-24	23.3078506	95
2007-08-25	23.4375710	94
2007-08-26	23.1498628	92
2007-08-27	22.0272975	88
2007-08-28	20.9047322	88
2007-08-29	19.9908811	89
2007-08-30	19.0770301	89
2007-08-31	17.5370362	86