Homework_Week2_GanapathyRaamanBalaji

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1 Homework - Week2 - Ganapathy Raaman Balaji

1.1 Problem 4.1

```
In a recent performance analysis of a fleet of mining trucks, I used GPS data
(latitude and longitude) recorded by the machine to cluster the turck operating in different f
I used this data to summarize truck operation and performance in different mine sites.
The predictors I used were
GPS coordinates,
Truck speed,
engine RPM,
operation hours and
aftertreatment (emission) performance values.
```

[ ]:

```

```

1.2 Problem 4.2

[20]:

```
# 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')
```

[9]:

```
oldw <- getOption("warn")
options(warn = -1)
library(dplyr)
library(tidyverse)
library(cluster)
library(fpc)
library(factoextra)
require(gridExtra)
```

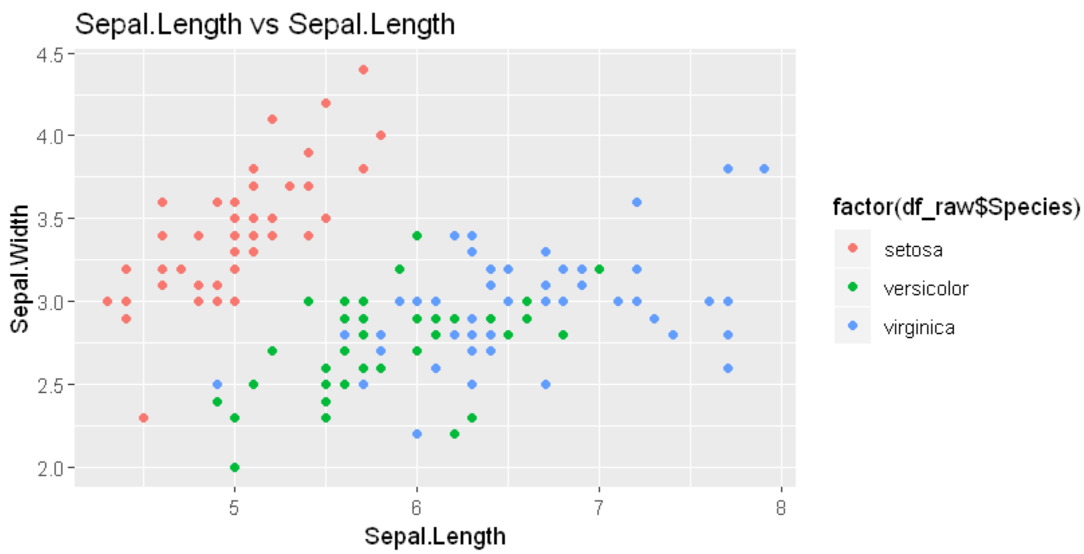
```
Welcome! Related Books: `Practical Guide To Cluster Analysis in R` at
https://goo.gl/13EFCZ
Loading required package: gridExtra
```

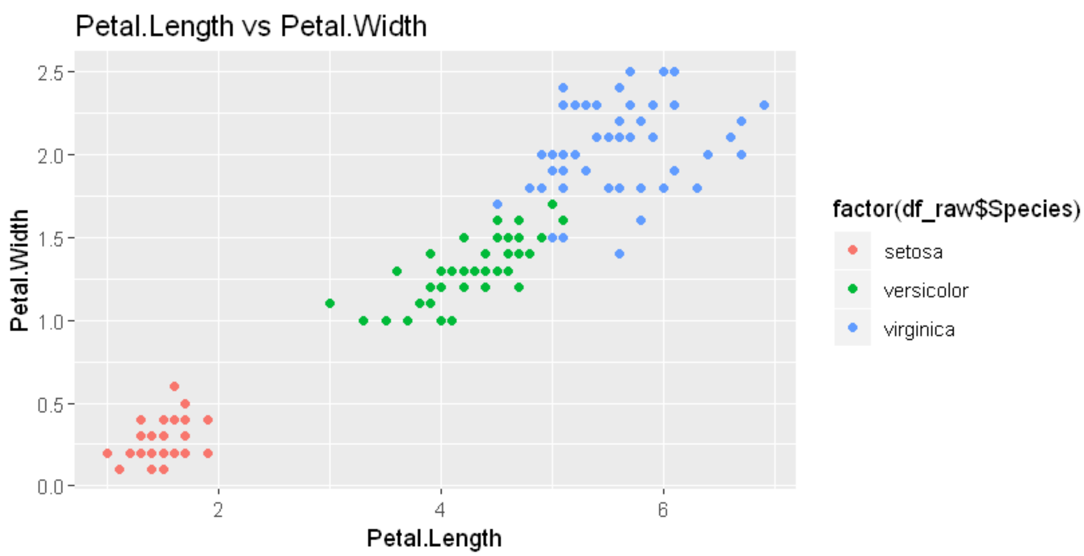
```
Attaching package: 'gridExtra'

The following object is masked from 'package:dplyr':

    combine
```

[10]:
```r
# Read the iris.txt to a dataframe using read.table function.
# Writing the first four columns (containing the predictors) to a separate␣
↪dataframe.

df_raw <- read.table("iris.txt", header = TRUE)
df <- df_raw[,1:4]
head(df)
```

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

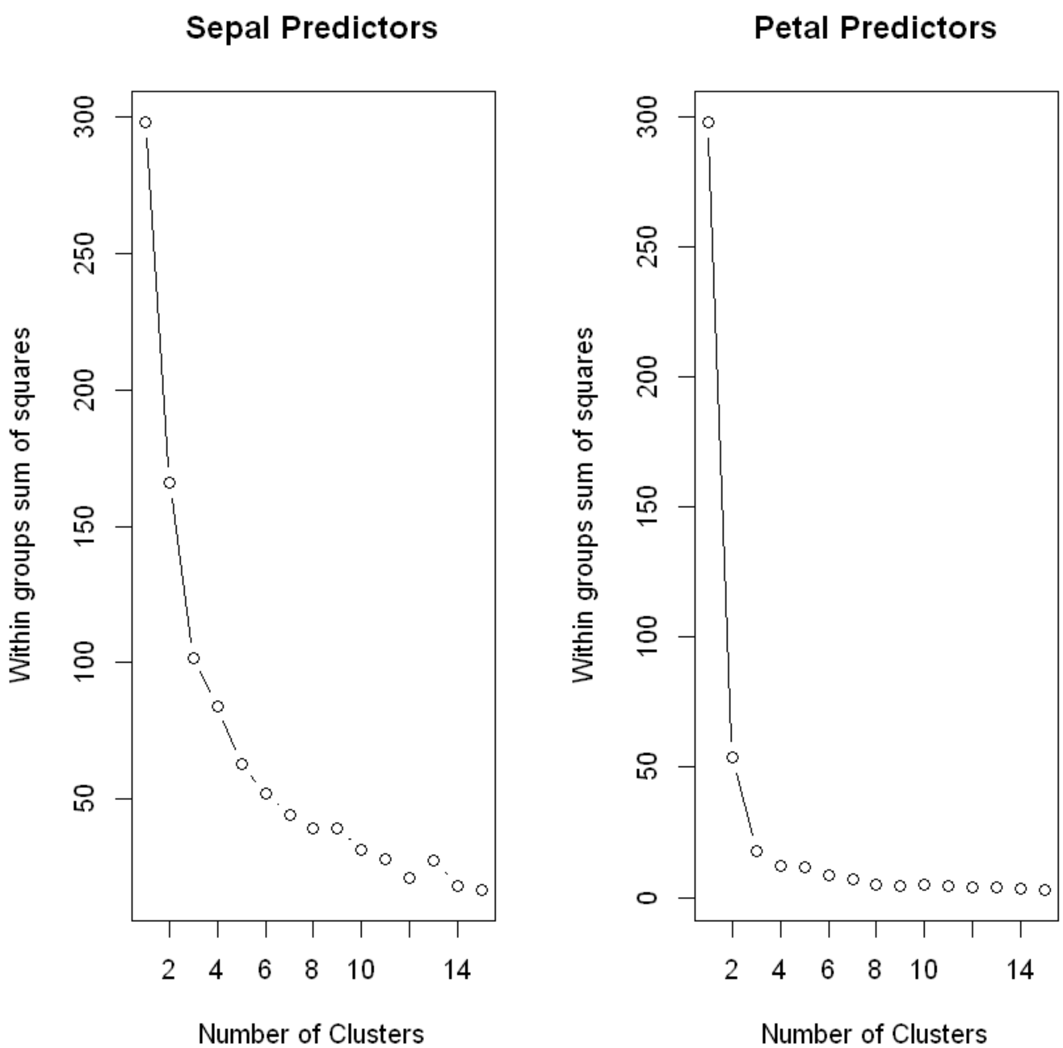
[11]:
```r
# plotting the petal and sepal features separately to view the different␣
↪features. This helps understand the distincr feature
# that will help cluster the data.

library(ggplot2)
plot1 <- ggplot(df, aes(x = df[,1], y = df[,2]))+geom_point(aes(color = factor
                                                                              ␣
↪(df_raw$Species)))+labs(x="Sepal.Length", y = "Sepal.Width",
                                                                              ␣
↪title="Sepal.Length vs Sepal.Length")
plot2 <- ggplot(df, aes(x = df[,3], y = df[,4]))+geom_point(aes(color = factor
                                                                              ␣
↪(df_raw$Species)))+labs(x="Petal.Length", y = "Petal.Width",
                                                                              ␣
↪title="Petal.Length vs Petal.Width")
grid.arrange(plot1, plot2, ncol=1)

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





[12]:
```
# For the next step, I am going to try to determine the number of clusters␣
↪using the elbow method. From the previous
# method, I determined that I am going to be using petal features as the input␣
↪for kmeans method. I am using the elbow
# method on both the petal and sepal features.

# 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))
```

```
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", main="Sepal Predictors")

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", main="Petal Predictors")
```



The plot above represents the variance within the clusters. It decreases as k increases, but it can be seen a bend (or “elbow”) at k = 3 for the petal predictor. This bend indicates that additional clusters beyond the third have little value. In the next section, we'll classify the observations into 3 clusters.

[14]:
```
# kmeans(x, centers, iter.max = 10, nstart = 1, algorithm = c("Hartigan-Wong",␣
↪"Lloyd", "Forgy", "MacQueen"), trace=FALSE)

set.seed(123)
model <- kmeans(petals_df, 3, nstart = 25, iter.max = 10)
```

[15]:
```
cluster_centroids <- aggregate(petals_df,by=list(model$cluster),FUN=mean)
cluster_centroids
```

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

[16]:
```
# Plotting the clusters and showing the location of the centroid in the cluster
fviz_cluster(object = model, data = df, geom = "point", choose.vars = c("Petal.
↪Length", "Petal.Width"),
             stand = FALSE, ellipse.type = "norm") + theme_bw()
```

1.3 Question 5.1

[17]:
```
install.packages("outliers", repos = 'http://cran.us.r-project.org')
```

```
package 'outliers' successfully unpacked and MD5 sums checked

The downloaded binary packages are in
        C:\Users\bgraa\AppData\Local\Temp\Rtmp4cz1Wh\downloaded_packages
```

[18]:
```
library(outliers)
crime_df <- read.table("uscrime.txt", header = TRUE)
head(crime_df, n=3)
```

M	So	Ed	Po1	Po2	LF	M.F	Pop	NW	U1	U2	Wealth	Ineq	Prob	Time
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
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
14.2	1	8.9	4.5	4.4	0.533	96.9	18	21.9	0.094	3.3	3180	25.0	0.083401	24.3006

[19]:

```
crime <- crime_df$Crime
grubbs.test(crime, type = 11, opposite = FALSE, two.sided = FALSE)
```

```
Grubbs test for two opposite outliers

data:  crime
G = 4.26880, U = 0.78103, p-value = 1
alternative hypothesis: 342 and 1993 are outliers
```

[ ]:

```
```

1.4 Problem 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 a Performance analytics engineer at CAT, I bin the engine and machine performance metrics to view as a 1D histogram or heat maps. To correlate these histograms, I often find time weighted values of key performance indicators. Depending on the importance of the metric, I vary the time window from minutes to days. After tabulating the time weighted values, I compare the values to the threshold to detect failures.

For example, I recently performed fatigue analysis where I had to calculate remaining life of a truck component based on stress-strain values. I chose my critical value based on varying the elastic and plastic constants of the material of component. The threshold is a million cycles (General rule of thumb when looking at cyclic fatigue life of a material). I identified trucks and instances where the component lasted over the million cycles threshold to summarize optimum performance.

[ ]:

```
```

1.5 Problem 6.2 (a)

In this problem, I varied the values of C from 0 through 3, keeping the threshold at 75 degrees Farenheit. I calculated average temperatures of each year. For different values of C, I used CUSUM approach, based on the following equation:

S(t) = max{0, S(t-1)+(mu - x(t) - C)}

to identify the day in each year when temperature (in Farenheit) decreased to unofficially end summer.

From my solution, I plotted the unofficial end of summer day per year for each value of C. October 8 seemed to be the average of all years when summer unofficially ended.

Summer unofficially ended earliest in the year 2000 across all values of C. (for C=0, the minimum day of end of summer was September 17).

The plot corroborates this data.

1.6 Problem 6.2 (b)

Using CUSUM approach for C=0,1,2,3, the values of temperature seems to rise above threshold of 3 degrees in the year 2011 (and onwards) for C = 0. For C=1, 2012 and 2013 seem to be hotter than the previous years by 3 degrees, but gets cooler from 2014. So, for C=0. Atalanta seems to get warmer from 2011 (the day is September 19 for C=0 - calculated from the previous part of the problem).

The answer seems to complement the average temperature trend plotted in the chart.

[ ]:

```

```