Name-Surname : Rayene BECH **Email : l1118115@std.yildiz.edu.tr**

No :18011115 **Signature :**

HOME WORK 1 (Return by 20.12.2021)

BLM3590 – Statistical Data Analysis

T1(10)	T2(15)	T3(15)	T4(15)	T5(15)	T6(15)	T7(15)				Total(100)

The attached Excel file (**SdA-HW**) consists of two clases of data (embolic signals (**class 1**), and Doppler speckle (**class 2**)) recorded from stroke patients and some relevant numerical variables (**tpthrt**, **pkthrt**, **dfdrrt**, **time**, **rrt**, **frt**). Using this data file, implement the following tasks in **R**. You must include the **R** scripts in your answers.

==

T1: Show how to read this Excel datafile into **R** environment.

#First the package that allow us to read ".xls" files should be installed using the following instruction:

```
> install.packages("readxl")
```

#The following code is executed:

```
library("readxl")
df <- read_excel("2k21-SdA-HW1.xls")
```

#Note: The working directory should be selected prior to the execution of the program using the following instruction:

```
setwd("working_directory_path")
```

==

T2: This data file requires some preprocessing as it inludes a column with no value, some cells with no numerical value (divide by 0 error, etc.), and some cells with zero. Write required script in **R** to remove the empty column and correct the cells with no numerical value and zero by using simple interpolation.

#The empty column can be identified using the function sapply() :

```
empty_column <- sapply(df, function(x) all(is.na(x) | x == ""))
```

#This function returns True for the empty columns and False for non-empty columns as it can be seen bellow:

```
> empty_column
 class   tpthrt  pkthrt  dfdrrt   time   rrt     frt
 FALSE  FALSE  FALSE  FALSE   TRUE  FALSE  FALSE
```

#Now the empty column can be deleted:

```
df= df[, !empty_column]
```

#To get rid of zero valuesw, we turn them to NA and then To replace non numerical values the package "imputeTS" is installed and used:

```
df[df == 0] <- NA
install.packages("imputeTS")
library(imputeTS)
df = na_interpolation(df)
```

==

T3: Find **Five-number data summary** of the **variables** for each **data class** in this dataset.

Requirements: to use the pipeline operator %>% we need to install and import the "dplyr" package

```
install.packages("dplyr")
library("dplyr")
```

Then to access each class we use the function filter()
We finally call the function summary which will give us the five number summary
For class 1:

```
> summary(subset(df %>% filter(df$class==1), select = -c(class)))
    tpthrt             pkthrt           dfdrrt             rrt              frt
 Min.   : 0.3364   Min.   :-8.359   Min.   : 0.2601   Min.   :-59.765   Min.   : 0.9525
 1st Qu.:12.0774   1st Qu.: 3.320   1st Qu.:12.2683   1st Qu.:  2.925   1st Qu.: 4.5475
 Median :14.8535   Median : 5.949   Median :17.8565   Median :  5.655   Median : 6.5960
 Mean   :15.6507   Mean   : 5.793   Mean   :17.5927   Mean   :  4.236   Mean   : 7.5667
 3rd Qu.:19.4746   3rd Qu.: 8.319   3rd Qu.:22.4063   3rd Qu.:  9.469   3rd Qu.:10.1026
 Max.   :28.8640   Max.   :19.907   Max.   :45.4140   Max.   : 20.610   Max.   :24.7323
```

For class 2:

```
> summary(subset(df %>% filter(df$class==2), select = -c(class)))
    tpthrt               pkthrt           dfdrrt           rrt              frt
 Min.   : 0.008013   Min.   :-9.623   Min.   :-3.476   Min.   :-68.801   Min.   : 0.05729
 1st Qu.: 8.038797   1st Qu.:-1.003   1st Qu.: 7.022   1st Qu.: -7.168   1st Qu.: 2.16383
 Median :11.451826   Median : 1.277   Median :13.799   Median :  2.211   Median : 3.90122
 Mean   :11.093465   Mean   : 1.301   Mean   :14.419   Mean   : -3.131   Mean   : 4.93257
 3rd Qu.:14.265218   3rd Qu.: 4.161   3rd Qu.:21.877   3rd Qu.:  4.616   3rd Qu.: 6.30550
 Max.   :20.963047   Max.   : 7.324   Max.   :40.545   Max.   : 26.127   Max.   :32.28238
```

==

T4: Plot **boxplots** of the **variables** for each **data class** and determine if there is any outlier in these variables.

For class 1:

boxplot(subset(df %>% filter(df$class==1), select = -c(class)))

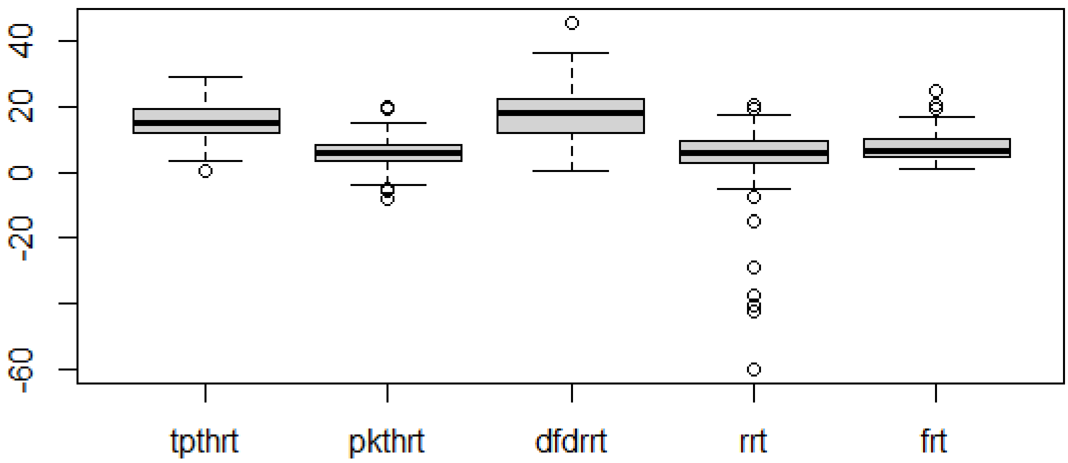


Figure 1: boxplot of class 1

Yes there are outliers for all variables shown by the circle

For class 2:

```
boxplot(subset(df %>% filter(df$class==2), select = -c(class)))
```

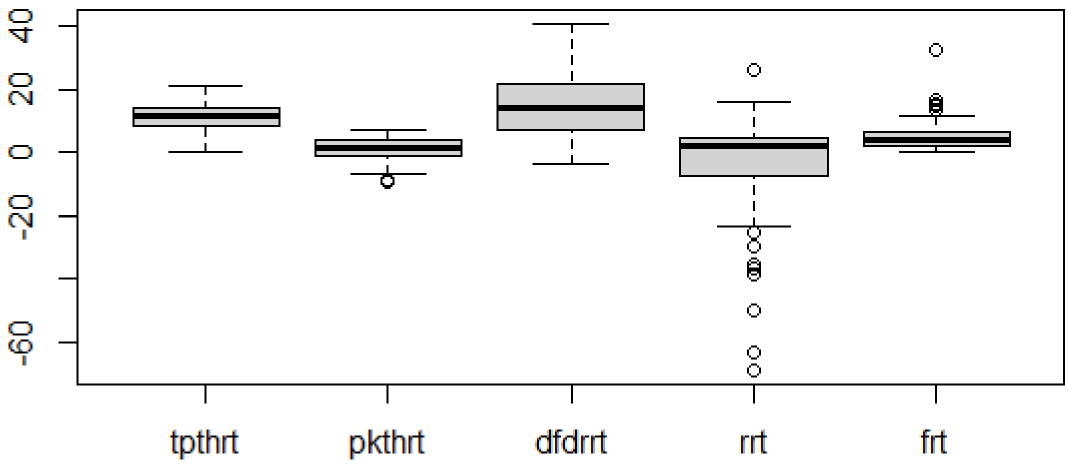


Figure 2: boxplot of class 2

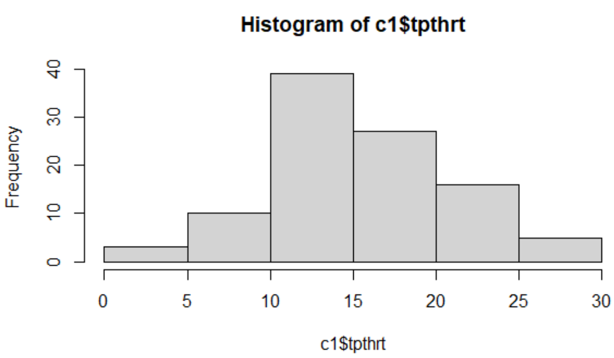
Yes there are outliers for the following variables: “pkthrt”, “rrt”, “frt”

==

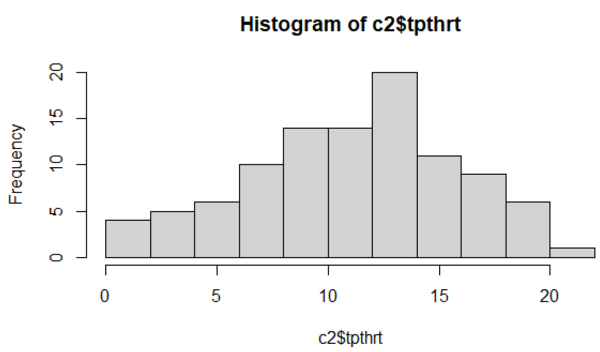
T5: Plot histograms of the **variables** for each **data class**, compare the histograms, and comment on the distributions.

Plotting “tpthrt”

```
c1 <- subset(df %>% filter(df$class==1), select = c(tpthrt))
hist(c1$tpthrt)
c2 <- subset(df %>% filter(df$class==2), select = c(tpthrt))
hist(c2$tpthrt)
```



Histogram of “tpthrt” for class 1

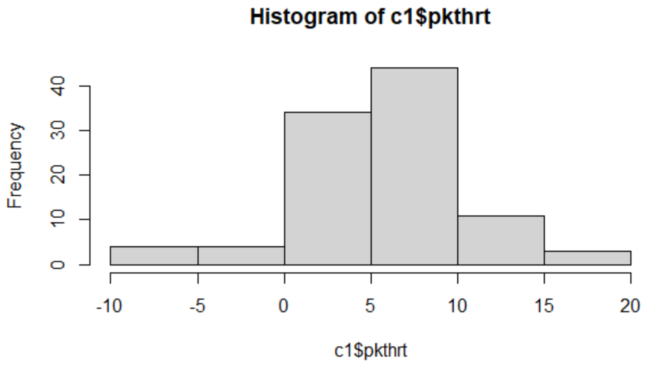


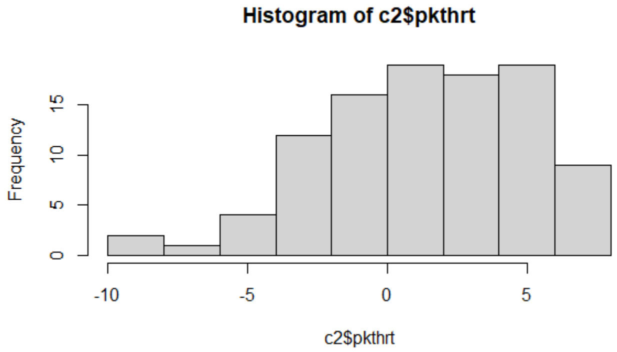
Histogram of “tpthrt” for class 2

Both distributions can be considered as normal distributions. Note that class 1 has greater range (from 0 to 30) comparing to class 2 (from 0 to 25) While class 2 has greater number of cells. Class 1 has greater mean and median (around 15) than class 2 has (around 12)

<u>Plotting "pkthrt"</u>

```
c1 <- subset(df %>% filter(df$class==1), select = c(pkthrt))
hist(c1$pkthrt)
c2 <- subset(df %>% filter(df$class==2), select = c(pkthrt))
hist(c2$pkthrt)
```





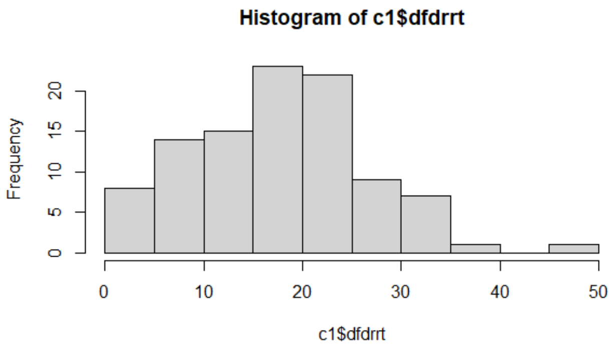
Histogram of "pkthrt" for class 1

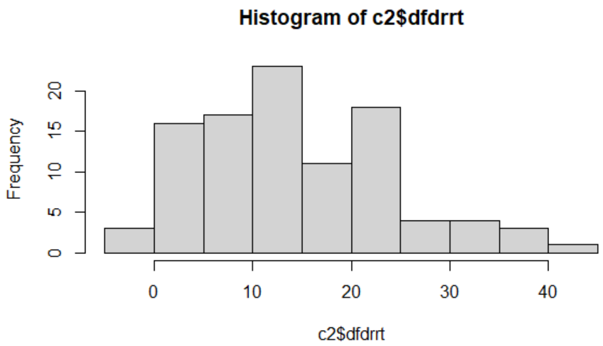
Histogram of "pkthrt" for class 2

The class 1 has normal distribution while class 2 has left-skewed distribution. Also class 1 has greater range (from -10 to 20) comparing to class 2 (from -10 to 10). We can also notice that the histogram of class 2 has greater number of cells. Class 1 has greater mean and median (around 5) than class 2 has (around 1)

<u>Plotting "dfdrrt"</u>

```
c1 <- subset(df %>% filter(df$class==1), select = c(dfdrrt))
hist(c1$dfdrrt)
c2 <- subset(df %>% filter(df$class==2), select = c(dfdrrt))
hist(c2$dfdrrt)
```





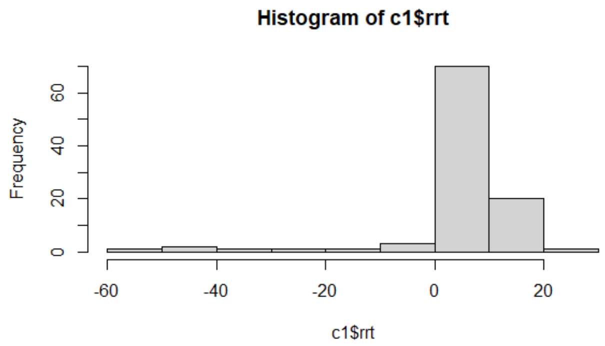
Histogram of "dfdrrt" for class 1

Histogram of "dfdrrt" for class 1

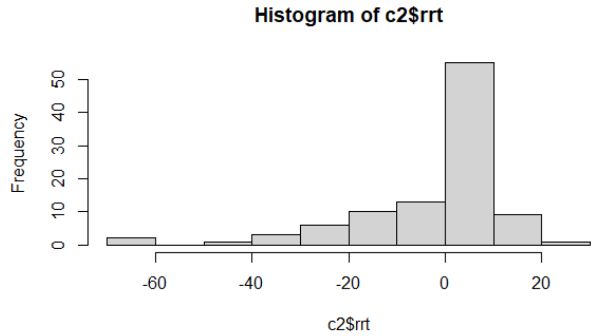
The class 1 has right-skewed distribution while class 2 seems to have bimodal distribution. Also class 1 has greater range (from 0 to 50) comparing to class 2 (from 0 to 40). That's because class 1 has an outlier at 50.

Plotting "rrt"

```
c1 <- subset(df %>% filter(df$class==1), select = c(rrt))
hist(c1$rrt)
c2 <- subset(df %>% filter(df$class==2), select = c(rrt))
hist(c2$rrt)
```



Histogram of “rrt” for class 1

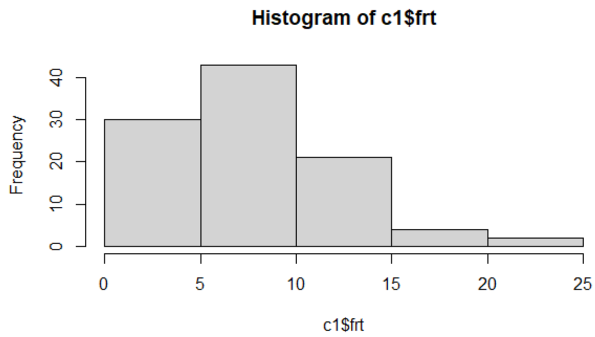


Histogram of “rrt” for class 2

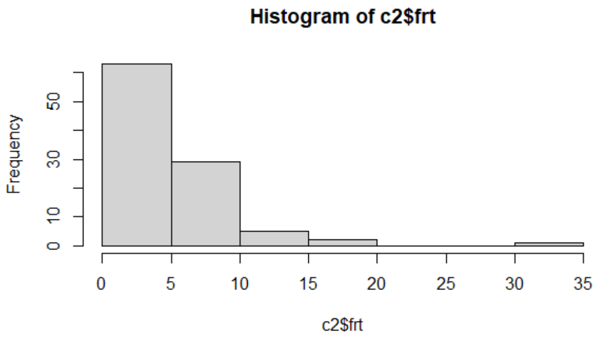
Both classes have left-skewed distributions and equal ranges. Class 2 has more standard deviation than class 1 .

Plotting “frt”

```
c1 <- subset(df %>% filter(df$class==1), select = c(frt))
hist(c1$frt)
c2 <- subset(df %>% filter(df$class==2), select = c(frt))
hist(c2$frt)
```



Histogram of “frt” for class 1



Histogram of “frt” for class 2

Both classes have right-skewed distributions. Class 2 has more standard deviation than class 1 . Also class 2 has greater range (from 0 to 35) comparing to class 2 (from 0 to 25). That’s because class 2 has an outlier at 35. Finally, Class 1 has greater mean and median (around 7) than class 2 has (around 4)

==

T6: First, normalize the **variables** for each **data class** so that the values of these variables range between **0** and **1**, and then line-plot (using different colors) each variables for both data classes in one figure (total 5 figures). Comment on the similarities of the variables for each plot.

To normalize we define the following function:

```
normalize <- function(x) {
  return ((x - min(x)) / (max(x) - min(x)))
}
```

To normalize the first class:

```
c1 <- subset(df %>% filter(df$class==1), select = -c(class))
for(i in 1:ncol(c1)) {       # for-loop over columns
  c1[ , i] <- normalize(c1[ , i])
}
```

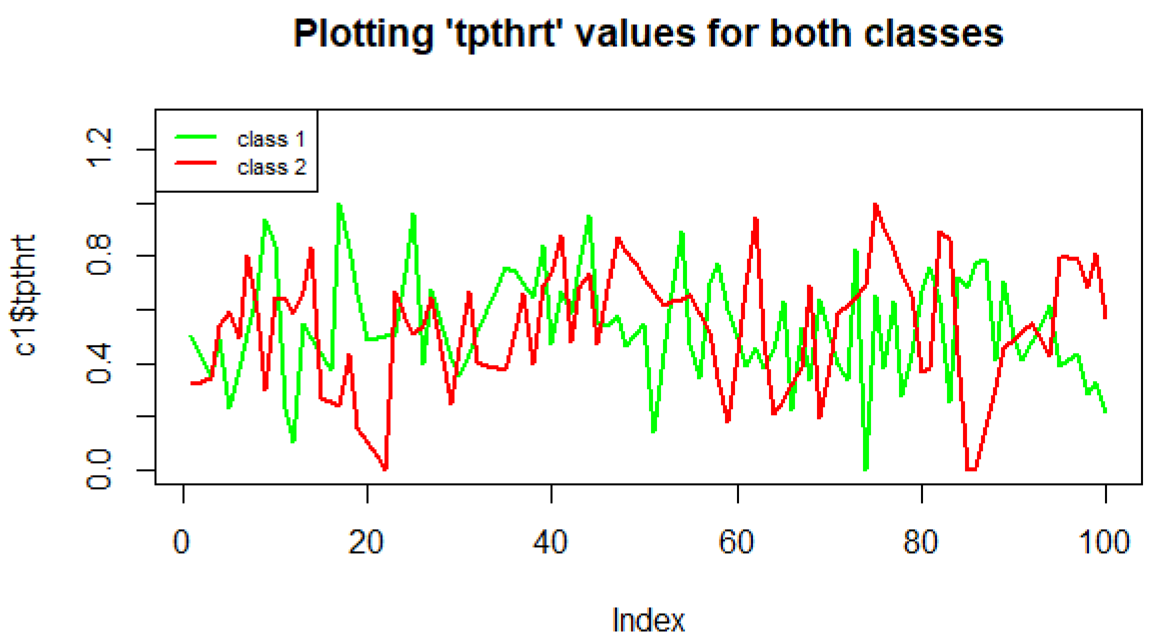
To normalize the second class:

```
c2 <- subset(df %>% filter(df$class==2), select = -c(class))
for(i in 1:ncol(c2)) {       # for-loop over columns
  c2[ , i] <- normalize(c2[ , i])
}
```

line-plot for “tpthrt”

```
plot(c1$tpthrt, type="l", col="green",lwd=2, ylim=c(0,1.3))
lines(c2$tpthrt, col="red", lwd=2)
title("Plotting 'tpthrt' values for booth classes")
legend("topleft", legend=c("class 1", "class 2"),col=c("green", "red"), lwd=c(2,2), cex=0.7)
```

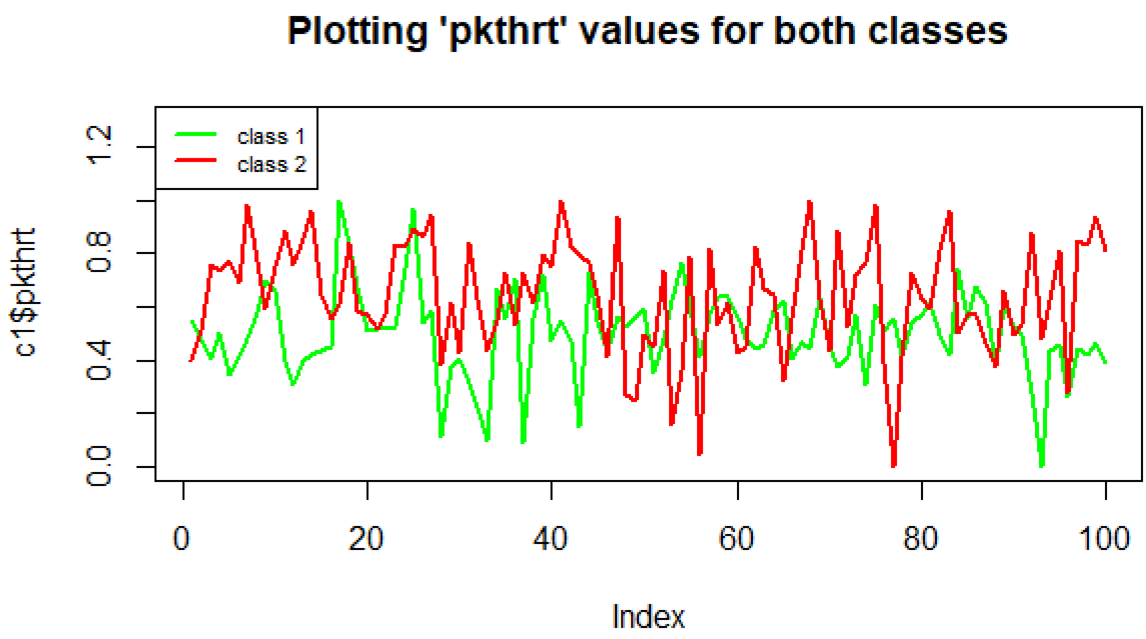
We can notice that the graphs are almost negatively corelated. Class 1 has values that are almost the opposite of Class 2:



line-plot for “pkthrt”

```
plot(c1$pkthrt, type="l", col="green",lwd=2, ylim=c(0,1.3))
lines(c2$pkthrt, col="red", lwd=2)
title("Plotting ' pkthrt ' values for booth classes")
legend("topleft", legend=c("class 1", "class 2"),col=c("green", "red"), lwd=c(2,2), cex=0.7)
```

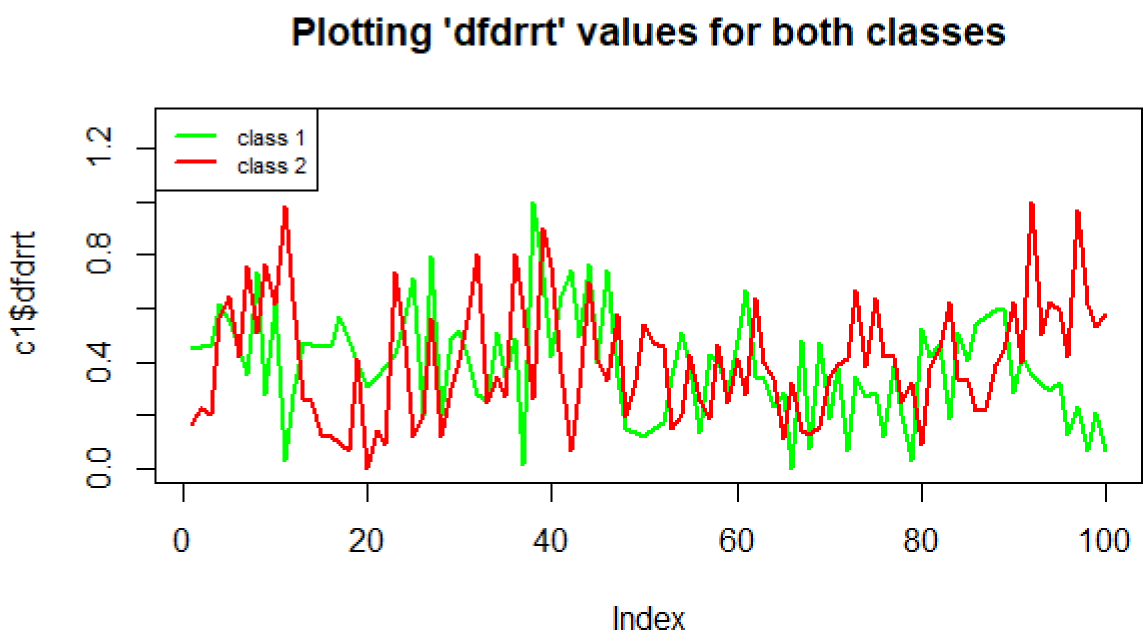
We can notice that the graphs are almost negatively corelated. Class 1 has values that are almost the opposite of Class 2. But the are a bit similar in the interval [50-80]:



line-plot for "dfdrrt"

plot(c1$dfdrrt, type="l", col="green",lwd=2, ylim=c(0,1.3))
lines(c2$dfdrrt, col="red", lwd=2)
title("Plotting 'dfdrrt' values for both classes")
legend("topleft", legend=c("class 1", "class 2"),col=c("green", "red"), lwd=c(2,2), cex=0.7)

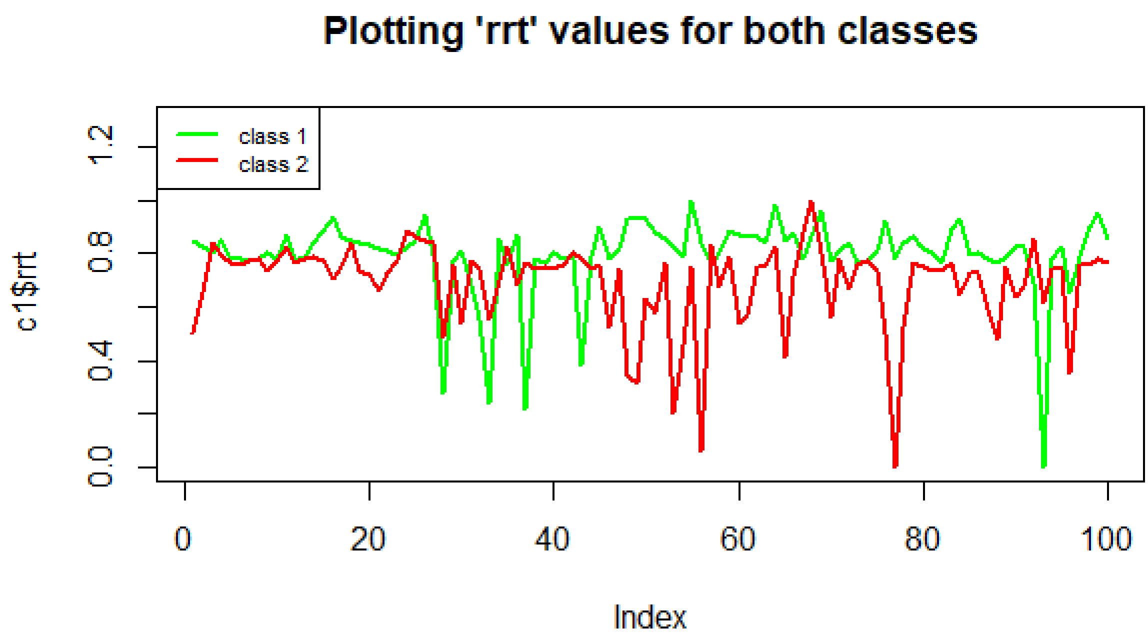
Again we can notice that the graphs are a little bit similar. But generally the values the classes have opposite values:



line-plot for “rrt”

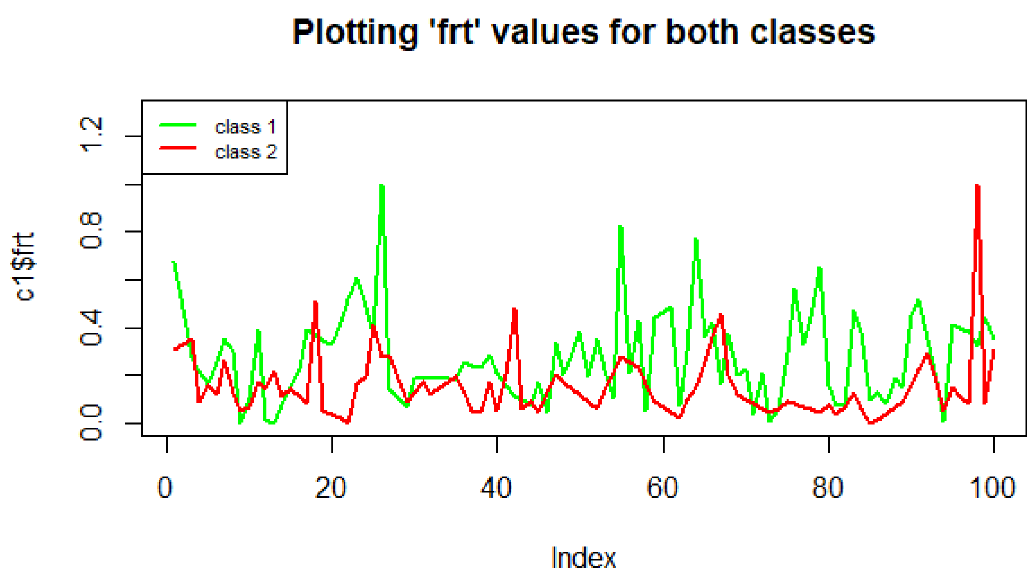
plot(c1$rrt, type="l", col="green",lwd=2, ylim=c(0,1.3))
lines(c2$rrt, col="red", lwd=2)
title("Plotting 'rrt' values for both classes")
legend("topleft", legend=c("class 1", "class 2"),col=c("green", "red"), lwd=c(2,2), cex=0.7)

We can notice that the graphs are a little bit similar in the range [5-20]. But values of class 2 has opposite values of class 1 in the range [30-100]



line-plot for “frt”

plot(c1$frt, type="l", col="green",lwd=2, ylim=c(0,1.3))
lines(c2$frt, col="red", lwd=2)
title("Plotting 'frt' values for both classes")
legend("topleft", legend=c("class 1", "class 2"),col=c("green", "red"), lwd=c(2,2), cex=0.7)
Again we can notice that the graphs are a little bit similar. But the values of class 1 are much bigger.



==

T7: First, determine how similar the variables **tpthrt** and **pkthrt** are for each **data class**, and then determine how similar **tpthrt of data class 1** and **tpthrt of data class 2** by using similarity metric (correlation).

For class 1:

```
c1 <- subset(df %>% filter(df$class==1), select = -c(class))
cor(subset(c1,select= c(tpthrt,pkthrt)))
```

output:

	tpthrt	**pkthrt**
tpthrt	**1.0000000**	**0.6007039**
pkthrt	**0.6007039**	**1.0000000**

This means the variables “tpthrt” and “pkthrt” of class 1 are 60.07039% similar

For class 2:

```
c2 <- subset(df %>% filter(df$class==2), select = -c(class))
cor(subset(c2,select= c(tpthrt,pkthrt)))
```

output:

	tpthrt	**pkthrt**
tpthrt	**1.0000000**	**0.2726601**
pkthrt	**0.2726601**	**1.0000000**

This means the variables “tpthrt” and “pkthrt” of class 2 are 27.26601% similar

Comparing “tpthr” of both classes:

```
cor(subset(c1,select= c(tpthrt)),subset(c2,select= c(tpthrt)))
```

output:

	tpthrt
tpthrt	**-0.1982791**

This means the variable “tpthrt” has similarity value of -0.1982791 between both classes.