National Institute Of Technology – Calicut Data Mining

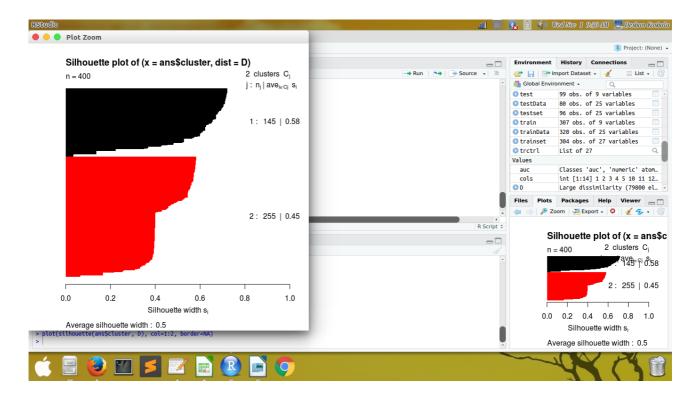
R programming

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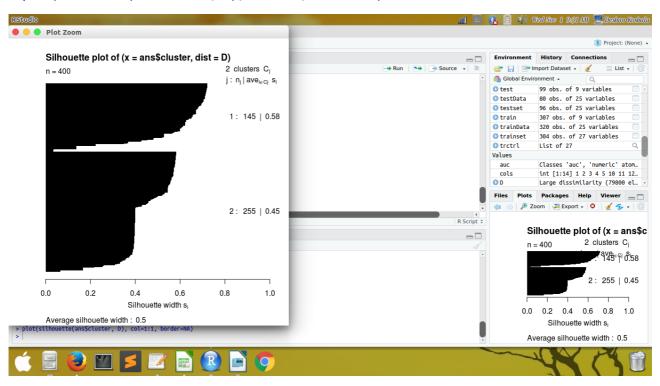
DATA-MINING ASSIGNMENT #02

A) K means clustering with k=actual number of classes

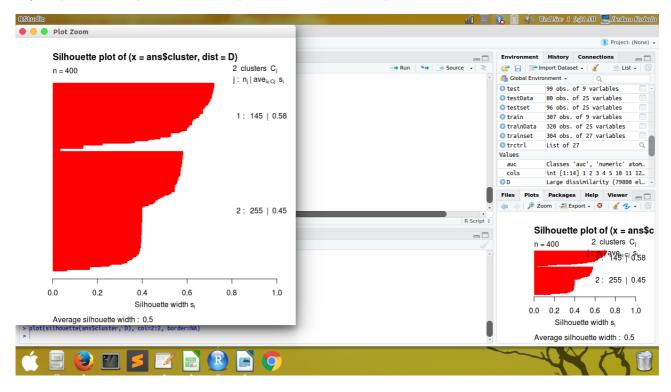
```
kidney_noc <- read.csv("/home/deshan/Desktop/clean_kidney_kmean.csv")</pre>
cols <- c(1:5, 10:18)
ans <- kmeans(kidney_noc[, cols], 2)</pre>
ans
K-means clustering with 2 clusters of sizes 145, 255
Cluster means:
                                                                                             al
                                                                                                                                                                  bu
                                                                                                                                          bgr
                                              ρp
                                                                                                                     su
                     age
                                                                    sq
sc
                    sod
                                           pot
                                                               hemo
1 48.05850604 75.09936011 1.019482759 0.7379310345 0.1862068966 135.4104223 55.08658160
2.961808759 137.0499835 4.759555779 13.09259612
2 53.43085101 77.24792803 1.016705882 0.9921568627 0.5137254902 155.2160608 58.75582112
3.135370384 137.8009961 4.552007388 12.20450309
                     pcv
                                          wbcc
1 40.46657582 6227.586207 4.771752345
2 37.98488574 9644.897959 4.670862333
Clustering vector:
    1 2 2 2 2 2 2 2 2 1 2 2 2 1 2 2 2 1 2 2 2 1 2 2 2 1
[199] 2 2 1 2 2 2 2 2 2 2 1 1 2 2 2 1 1 2 2 2 1 2 2 2 2 2 2 2 2 1 1 2 2 2 2 2 2 1 1 2 2 2 2 2 1 1 2 2 2 2 1
1 2 2 2 1 1 2 2 1 2 2 2 1 2 2 2 2 2 1 2 1 2 1 2
[265] 1 2 1 2 2 1 1 2 1 2 2 1 1 1 2 2 2 1 2 1 2 2 2 1 2 1 2 2 2 1 2 1 2 1 2 2 2 1 1 2 2 2 1 2 1 2 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2
\bar{2} 2 \bar{2} 2 1 1 1 1 1 1 1 2 2 1 1 2 1 1 1 1 1 2 1 [397] 1 1 1 1 1
Within cluster sum of squares by cluster:
[1] 199256539.1 1264972635.5
  (between_SS / total_SS = 42.4 %)
Available components:
[1] "cluster"
                                    "centers"
                                                                "totss"
                                                                                            "withinss"
                                                                                                                        "tot.withinss" "betweenss"
                            "iter"
 "size"
[9] "ifault"
** install.packages("cluster")
> library(cluster)
> D<- daisy(kidney_noc[, cols])</pre>
> plot(silhouette(ans$cluster, D), col=1:2, border=NA)
```



> plot(silhouette(ans\$cluster, D), col=1:1, border=NA)



> plot(silhouette(ans\$cluster, D), col=2:2, border=NA)



B) K means clustering with k=actual number of classes-1

0.0%

(between_SS / total_SS =

```
cols <- c(1:5, 10:18)
ans <- kmeans(kidney_noc[, cols], 1)</pre>
ans
K-means clustering with 1 clusters of sizes 400
Cluster means:
         bp
            sg al
                su
                    bgr
                         bu
                             sc
                                 sod
    age
    hemo
        pcv
pot
1 51.48337596 76.46907216 1.0177125 0.9 0.395 148.0365169 57.4257218 3.072454295 137.528754
4.62724368 12.52643681 38.8844984
        rbcc
   wbcc
1 8406.122449 4.707434963
Clustering vector:
1111111111111111111111111111
[397] 1 1 1 1
Within cluster sum of squares by cluster:
[1] 2543757430
```

```
Available components:
[1] "cluster"
"size"
             "centers"
                        "totss"
                                  "withinss"
                                             "tot.withinss" "betweenss"
          "iter"
[9] "ifault"
C) K means clustering with k=actual number of classes+1
> cols <- c(1:5, 10:18)</pre>
> ans <- kmeans(kidney_noc[, cols], 3)</pre>
> ans
K-means clustering with 3 clusters of sizes 12, 111, 277
Cluster means:
                                  al
                                                             bu
                 bъ
                                                   bgr
                                            su
        age
                         sq
       sod
                       hemo
sc
                pot
1 52.25000000 71.66666667 1.012500000 2.4166666667 0.583333333 169.6697098 98.33333333
4.758333333 132.9214590 4.137874000 10.000000000
2 53.21591668 77.80068728 1.017162162 0.9459459459 0.6126126126 155.9489068 53.93742641
2.507565910 138.6257663 4.359782919 12.71987160
3 50.75589759 76.14351110 1.018158845 0.8158844765 0.2996389892 143.9286700 57.05138768
3.225783040 137.2887510 4.755621227 12.55837175
        pcv
                wbcc
1 29.41666667 17433.33333 3.667286250
2 38.84164405 10299.099099 4.659228378
3 39.31182985 7256.494511 4.771812996
Clustering vector:
 3 2 2 3 2 2 3 3 2 3 3 3 3 3 3 1 3 3 3 1 3 2
3 2 2 2 3 3 3 2 3 2 2 2 3 3 2 2 2 3 3 2 3 3 3
[265] 3 2 3 2 3 3 3 2 3 3 3 3 3 2
                         3 3 2 3 2 3 3 2 3 2 3 3 3 2 3 3 2 3 3 2 3 3 3 2 2 3 3 3 2 3
[397] 3 3 3 3
Within cluster sum of squares by cluster:
[1] 140094535.8 138132948.2 523753530.0
 (between SS / total SS = 68.5 %)
Available components:
[1] "cluster"
"size"
             "centers"
                        "totss"
                                             "tot.withinss" "betweenss"
                                  "withinss"
          "iter"
[9] "ifault"
D) Density based clustering with the radius parameter
** install.packages("dbscan")
library (cluster)
library (dbscan)
```

cols <- c(1:5, 10:18)

ans

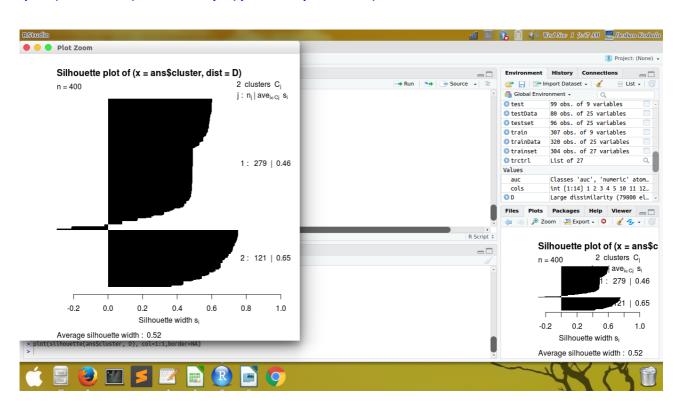
Call:

ans <- clara (x=kidney_noc[, cols], k=2)</pre>

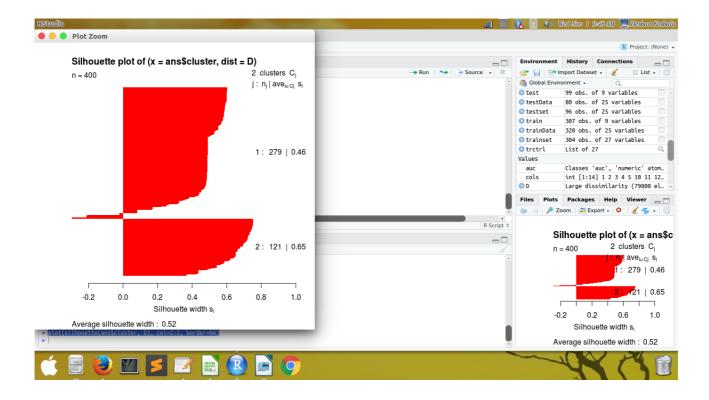
 $clara(x = kidney_noc[, cols], k = 2)$

```
Medoids:
     age bp
               sg al su bgr
                                   bu
                                                      sod
                                                               pot hemo
                                            sc
                                                                              pcv
wbcc
         гЬсс
     55 80 1.010 0 0 146 57.425722 3.072454 137.528754 4.627244 9.8 38.884498
[1,]
8406.122449 4.707435
[2,] 52 80 1.025 0 0 99 25.000000 0.800000 135.000000 3.700000 15.0 52.000000
6300.000000 5.300000
Objective function:
                         1136.183539
                         int [1:400] 1 2 1 2 2 1 1 2 1 1 1 2 1 1 1 2 1 1 ...
Clustering vector:
Cluster sizes:
                         279 121
Best sample:
 [1] 2 10 38 65 74 76 77 83 90 97 105 123 133 137 144 153 156 160 169 173 175 178
186 203 204 212 219 229 245 257 294 299 304
[34] 311 314 321 346 351 353 354 379 382 391 397
Available components:
                  "medoids"
                              "i.med"
 [1] "sample"
                                            "clustering" "objective" "clusinfo"
                                                                                   "diss"
"call"
            "silinfo"
                         "data"
ans[["clusinfo"]]
     size
             max_diss
                           av_diss
                                     isolation
     279 17994.21259 1251.2729450 8.540413057
[2,] 121 4100.26498 870.8120988 1.946067737
dbscan(kidney_noc[, cols], eps=11047, minPts = 121 )
DBSCAN clustering for 400 objects.
Parameters: eps = 11047, minPts = 121
The clustering contains 1 cluster(s) and 0 noise points.
  1
400
Available fields: cluster, eps, minPts
library(cluster)
 D<- daisy(kidney_noc[, cols])</pre>
```

plot(silhouette(ans\$cluster, D), col=1:1,border=NA)



plot(silhouette(ans\$cluster, D), col=2:2, border=NA)



The cluster with highest (between_SS / total_SS) would be the best cluser, accordingly out of the three cases A, B and C, C is the better cluster.