Les pays à aider

Projet de apprentissage non suppervisé
Classification
Université de Rennes II : Master Mathématiques Appliquées, Statistiques

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15 April, 2023

Contents

1 Compréhension et pré-traitement des données

```
donnee <- read.csv("Pays_donnees.csv", sep = ',', row.names = 1)
head(donnee,3)
```

```
##             enfant_mort exports sant. imports revenu inflation esper_vie fert
## Afghanistan        90.2    10.0  7.58    44.9   1610      9.44      56.2 5.82
## Albania            16.6    28.0  6.55    48.6   9930      4.49      76.3 1.65
## Algeria            27.3    38.4  4.17    31.4  12900     16.10      76.5 2.89
##             pib_h
## Afghanistan   553
## Albania      4090
## Algeria      4460
```

```
str(donnee)
```

Nous observons que toutes les colonnes ont des données qui sont en cohérence avec leur type.

```
dim(donnee)
```

Nous avons 167 individus et 9 variables

1.1 Statistiques descriptives

```
summary(donnee)
```

```
##   enfant_mort        exports            sant.           imports
##  Min.   :  2.60   Min.   :  0.109   Min.   : 1.810   Min.   :  0.0659
##  1st Qu.:  8.25   1st Qu.: 23.800   1st Qu.: 4.920   1st Qu.: 30.2000
##  Median : 19.30   Median : 35.000   Median : 6.320   Median : 43.3000
##  Mean   : 38.27   Mean   : 41.109   Mean   : 6.816   Mean   : 46.8902
##  3rd Qu.: 62.10   3rd Qu.: 51.350   3rd Qu.: 8.600   3rd Qu.: 58.7500
##  Max.   :208.00   Max.   :200.000   Max.   :17.900   Max.   :174.0000
##      revenu         inflation         esper_vie          fert
##  Min.   :   609   Min.   : -4.210   Min.   :32.10   Min.   :1.150
##  1st Qu.:  3355   1st Qu.:  1.810   1st Qu.:65.30   1st Qu.:1.795
##  Median :  9960   Median :  5.390   Median :73.10   Median :2.410
##  Mean   : 17145   Mean   :  7.782   Mean   :70.56   Mean   :2.948
##  3rd Qu.: 22800   3rd Qu.: 10.750   3rd Qu.:76.80   3rd Qu.:3.880
##  Max.   :125000   Max.   :104.000   Max.   :82.80   Max.   :7.490
##      pib_h
##  Min.   :   231
##  1st Qu.:  1330
##  Median :  4660
##  Mean   : 12964
##  3rd Qu.: 14050
##  Max.   :105000
```

1.2 Pre-traimement

Donnees manquantes ? Outliers

```
table(is.na(donnee))
```

```
##
## FALSE
##  1503
```

Aucune donnée manquante.

Valeur aberrante

Exports max à 200 ? Bizarre

Ce sont à première vue des pays riche comme malte, luxembourg, singapour

Imports max à 174 ? Idem, finalement c'est logique Aucune valeur aberrante

Mais y a des valeurs "leviers", certains pays comme malte, singapour se dégagent des valeurs moyennes

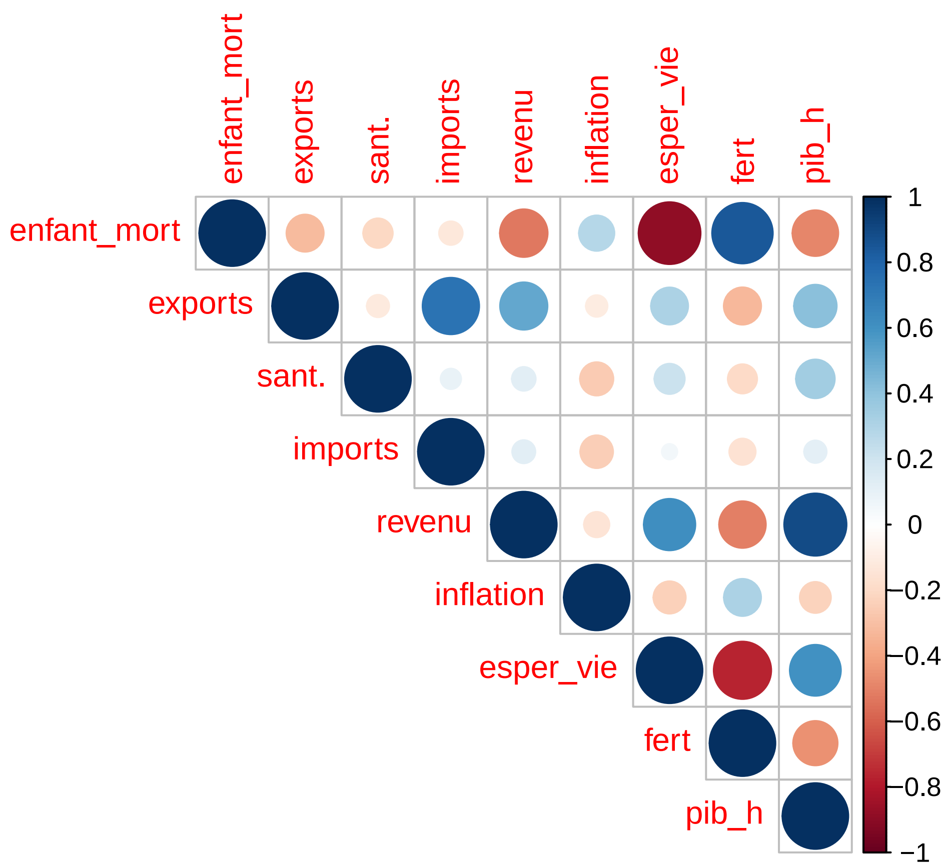
Standardisation ?

Lorsque l'on a des données avec des unités différentes (par exemple des pourcentages, des espérances de vie, des PIB par habitant), il est recommandé de centrer et de réduire ces données. Centrer les données signifie soustraire la moyenne de la variable de toutes les observations, ce qui permet d'avoir une moyenne égale à zéro. Réduire les données signifie diviser chaque observation par l'écart-type de la variable, ce qui met toutes les variables à la même échelle. Cela facilite la comparaison entre les différentes variables et permet des analyses statistiques plus fiables. Il est cependant important de garder à l'esprit que la signification des résultats dépend toujours du contexte et de la validité des données utilisées

```
donnee <- data.frame(scale(donnee))
```

Matrice de corrélation

```
var <- donnee[,1:9]
corrplot(cor(var), type = "upper")
```



La matrice de corrélation nous aide à mieux comprendre les relations entre chaque variable et pourra nous aider à interpréter plus tard.

Nous allons alors classifier les pays en fonction de NOMS DE COLONNES.

2 Classification des pays en utilisant les différents algorithmes abordés en cours

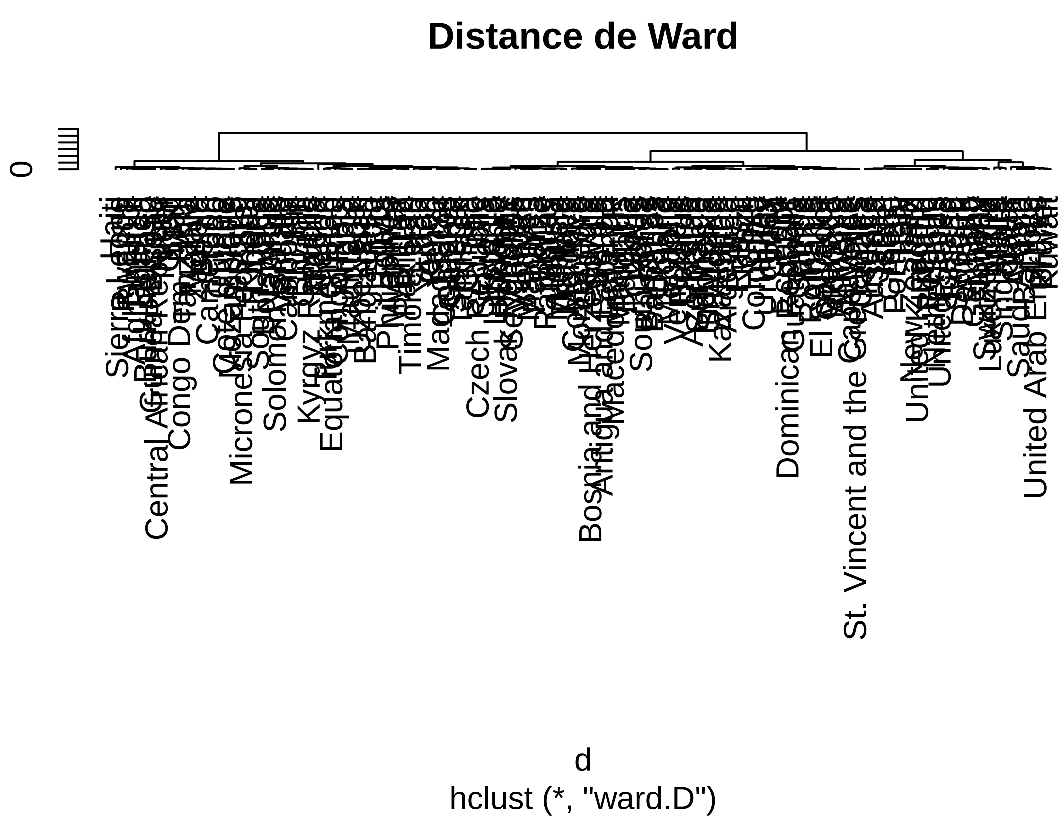
Utilisation des algorithmes de classification vus en cours . Reflexion sur les choix operer decider d'une classification finale . Nombre de groupes ?

2.1 CAH

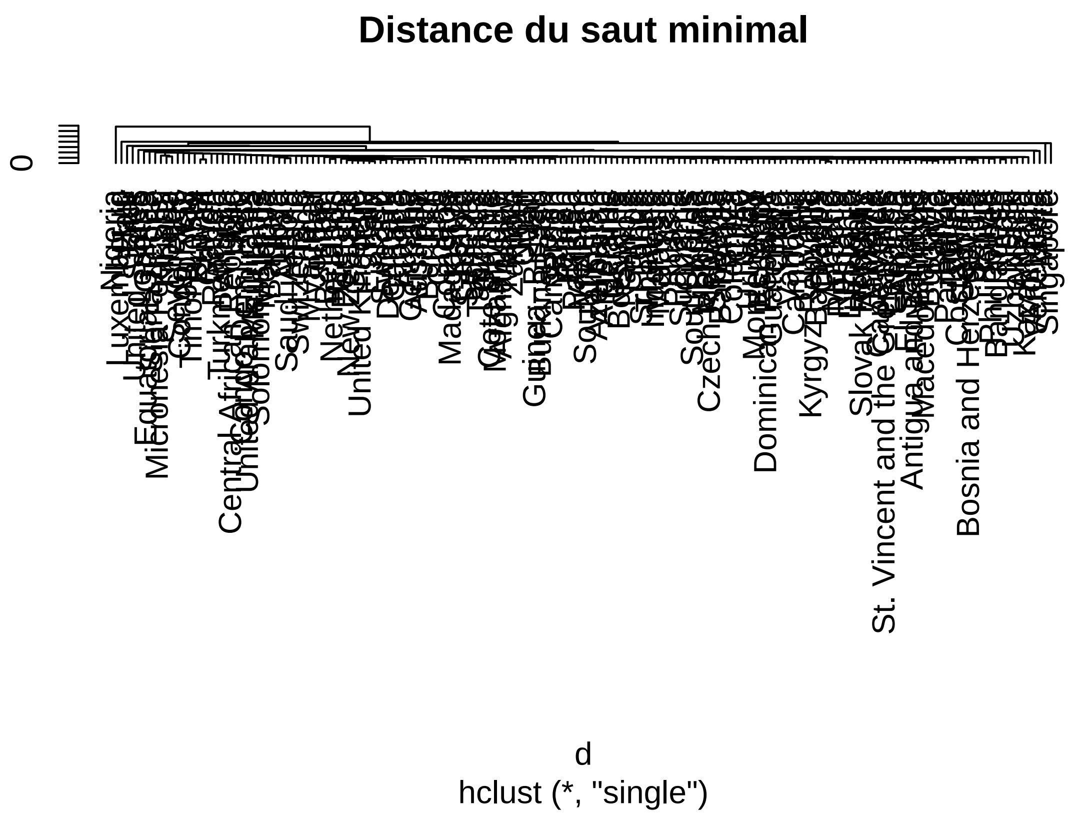
```
set.seed(123)
d <- dist(donnee)
#d <- dist(e19, method = "manhattan")
#d <- dist(e19, method = "minkowski")
cah.ward <- hclust(d, method = "ward.D")
cah.min <- hclust(d, method = "single")
cah.max <- hclust(d, method = "complete")
```

Dengrogrammes

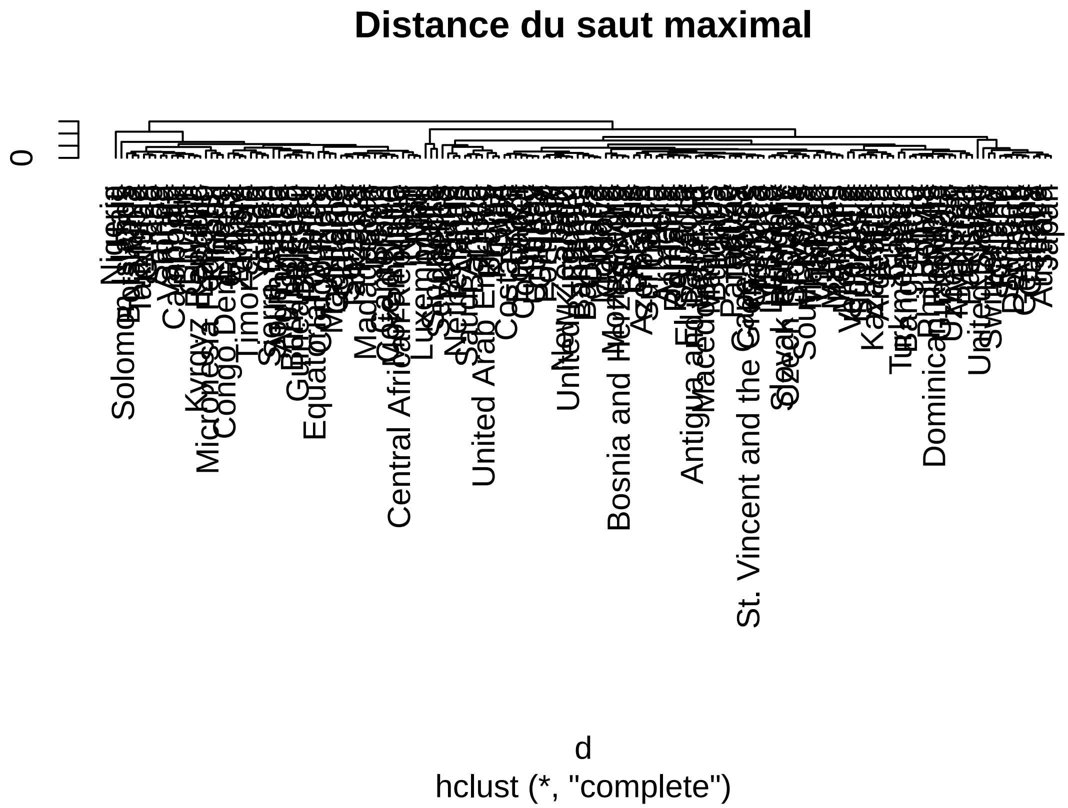
```
plot(cah.ward, hang = -1, main = "Distance de Ward", ylab = " ")
```




```
plot(cah.min, hang = -1, main = "Distance du saut minimal", ylab = " ")
```



```
plot(cah.max, hang = -1, main = "Distance du saut maximal", ylab = " ")
```

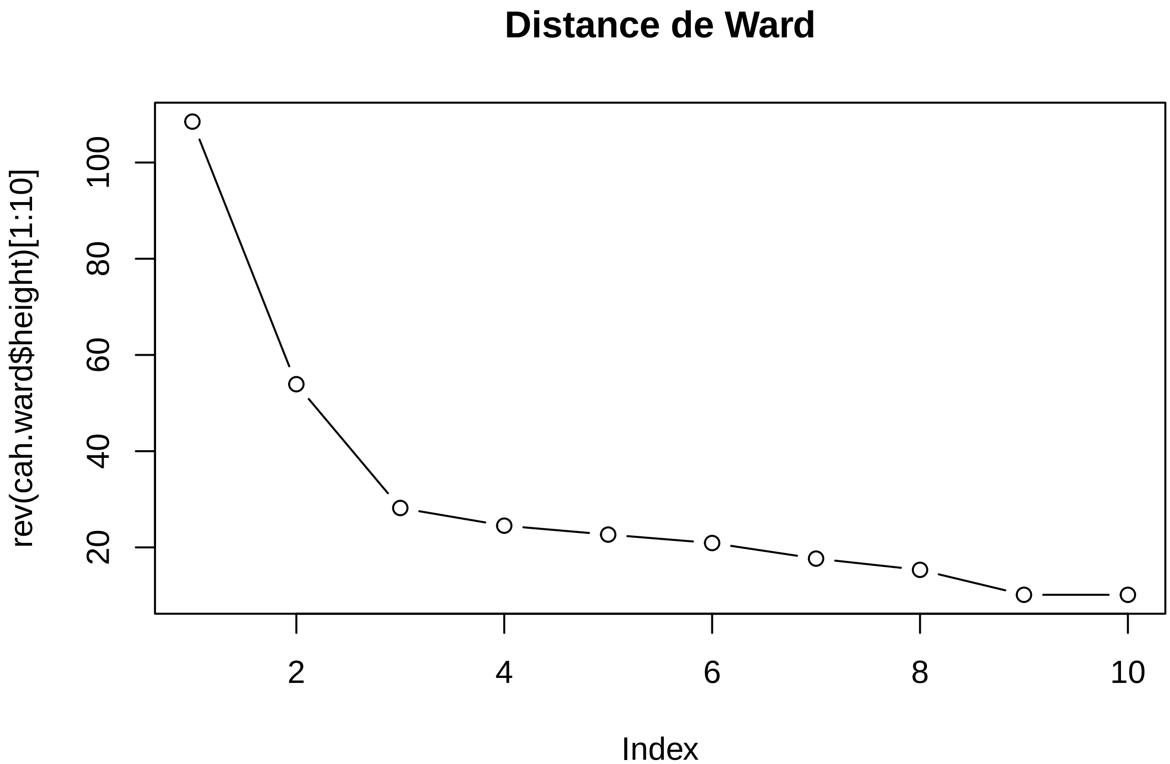


On s'apercoit raipdement que c'est le critère de Ward qui correspond le mieux à nos données. On voit déjà qu'on peut partitionner nos données en 3 ou 4 groupes

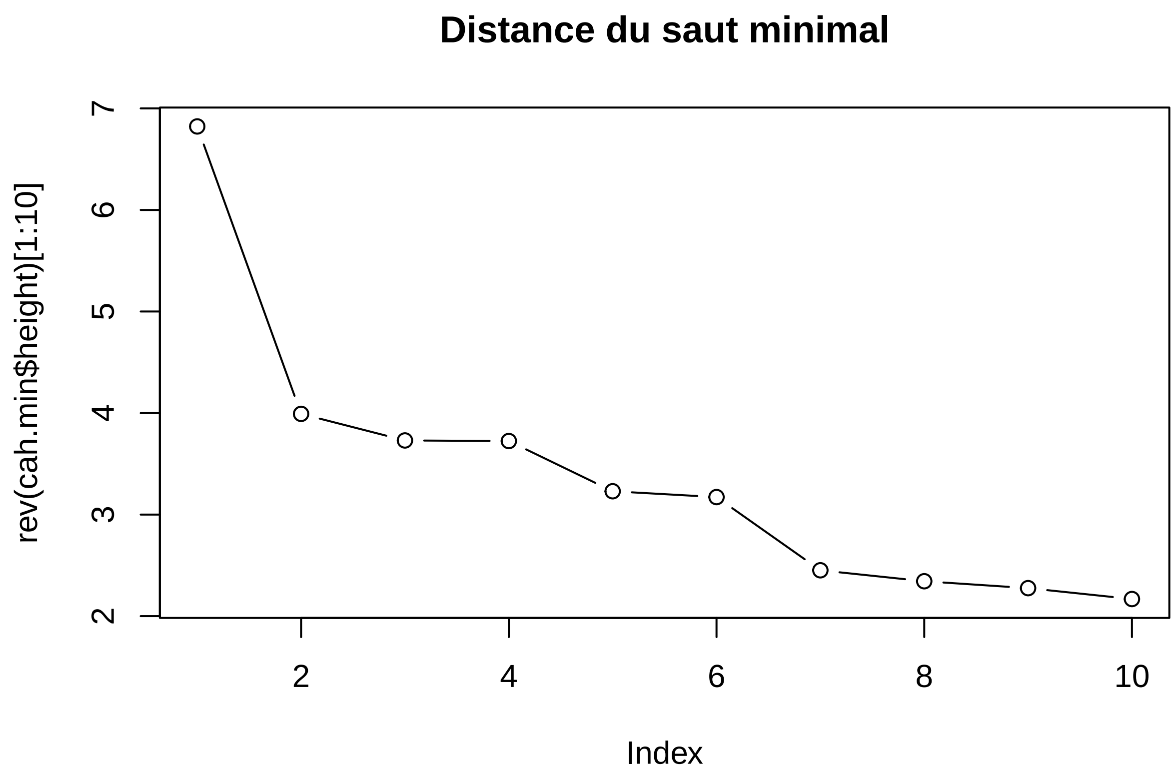
Fonction de perte

Pour rappel, on cherche à maximiser l'inertie inter-classe. En effet, nous avons pour objectif de créer des groupes d'individus se ressemblant fortement (inertie intra-classes faible) et tels que les groupes soient les plus distints possible (inertie inter-classes élevée). L'inertie inter-classe est logiquement maximale (égale à l'intertie totale) lorsqu'il y a autant de classes que d'individus. Nous cherchons dans le graphique ci-dessous un "coude" qui correspond à une rupture dans la courbe (moment où l'inertie inter augmente beaucoup).

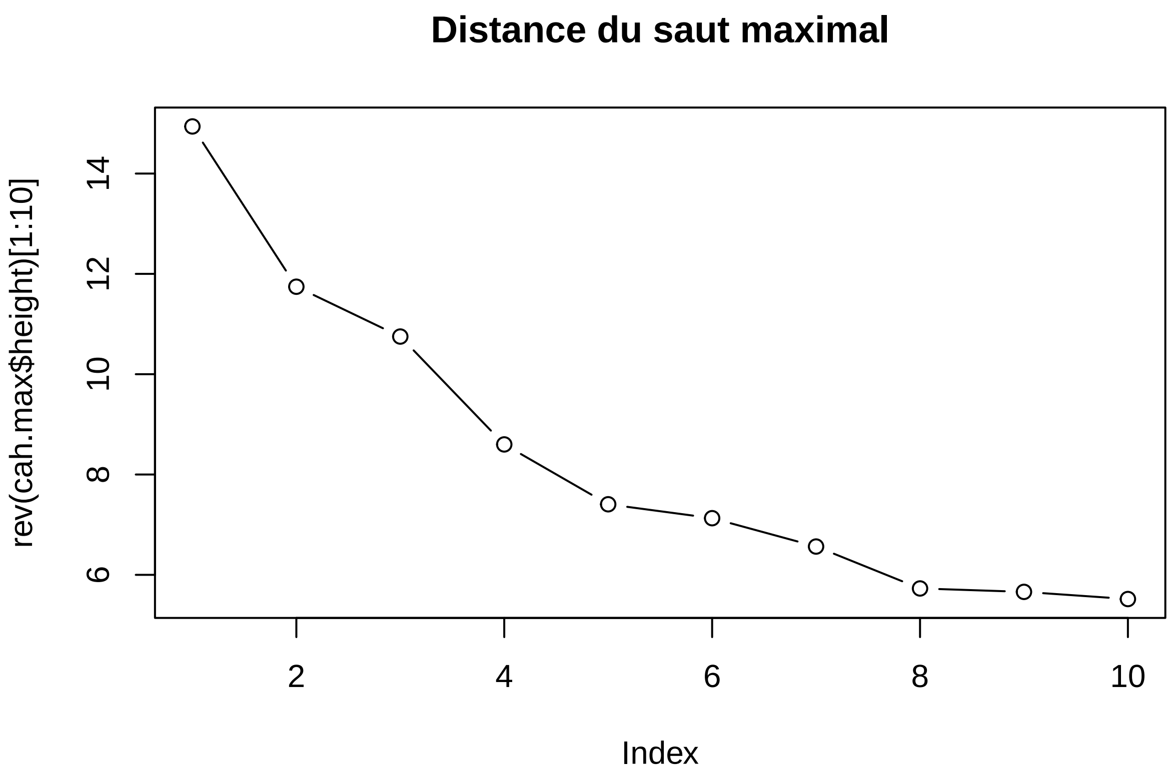
```
plot(rev(cah.ward$height)[1:10], type = "b", main = "Distance de Ward")
```




```
plot(rev(cah.min$height)[1:10], type = "b", main = "Distance du saut minimal")
```



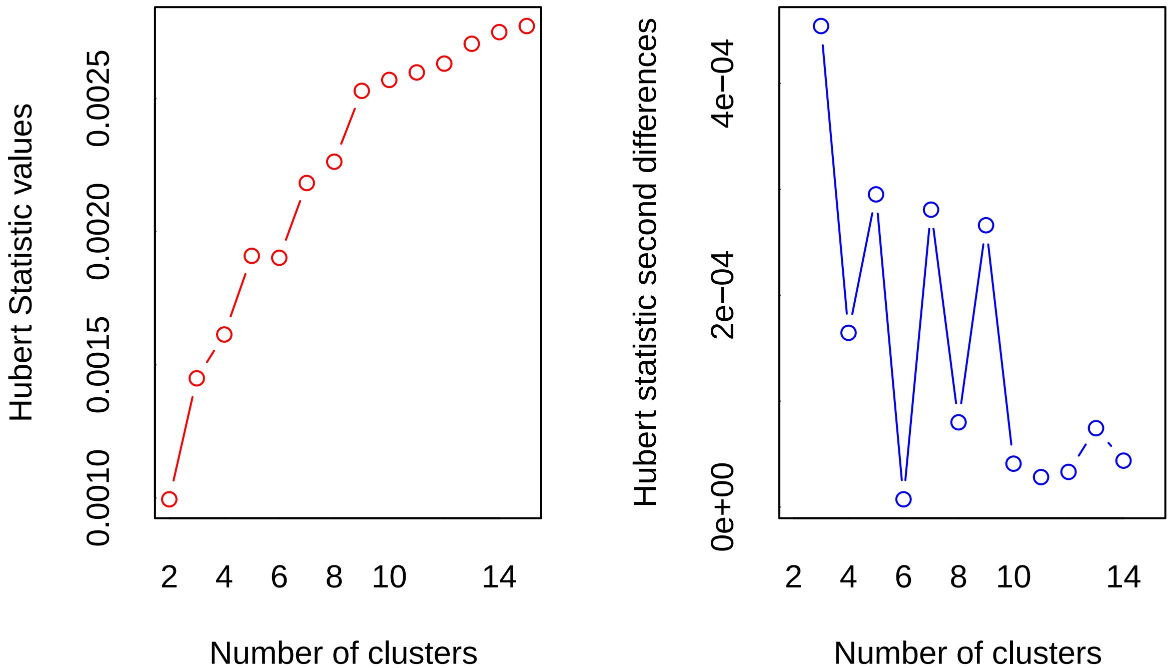

```
plot(rev(cah.max$height)[1:10], type = "b", main = "Distance du saut maximal")
```



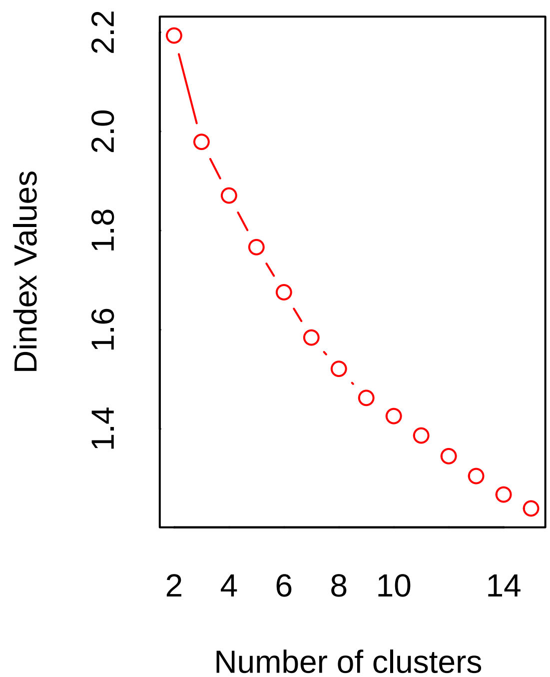
Avec le critère de Ward, la trace de la perte d'inertie nous incite à choisir des partitions en 3 groupes ("coude" très visible).

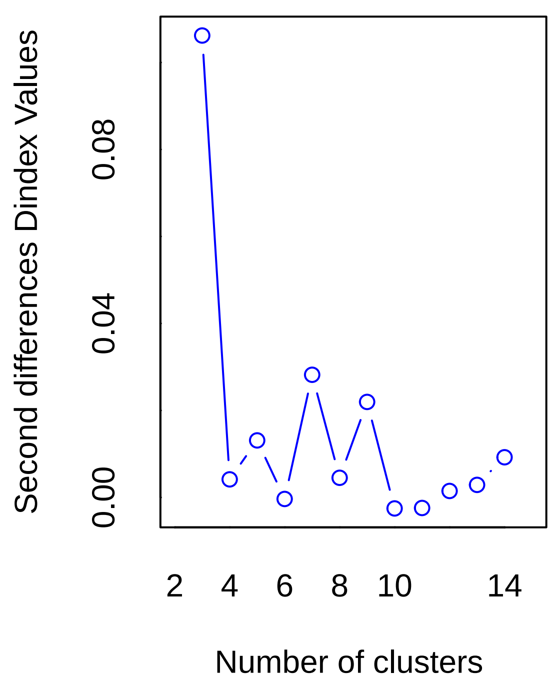
```
matrix <- as.matrix(donnee)
```

```
NbClust(matrix, min.nc = 2, max.nc = 15, method = "ward.D", index = "all")
```




```
## *** : The Hubert index is a graphical method of determining the number of clusters.
##                 In the plot of Hubert index, we seek a significant knee that corresponds to a
##                 significant increase of the value of the measure i.e the significant peak in Hubert
##                 index second differences plot.
##
```






```
## *** : The D index is a graphical method of determining the number of clusters.
##                 In the plot of D index, we seek a significant knee (the significant peak in Dindex
##                 second differences plot) that corresponds to a significant increase of the value of
##                 the measure.
##
## *******************************************************************
## * Among all indices:
## * 5 proposed 2 as the best number of clusters
## * 4 proposed 3 as the best number of clusters
## * 5 proposed 4 as the best number of clusters
## * 1 proposed 5 as the best number of clusters
## * 1 proposed 8 as the best number of clusters
## * 4 proposed 9 as the best number of clusters
## * 1 proposed 12 as the best number of clusters
## * 1 proposed 14 as the best number of clusters
## * 1 proposed 15 as the best number of clusters
##
##                    ***** Conclusion *****
##
## * According to the majority rule, the best number of clusters is  2
##
##
## *******************************************************************
```

```
## $All.index
##        KL      CH Hartigan     CCC    Scott      Marriot    TrCovW    TraceW
## 2  2.3386 68.6210  33.7214 -2.6434 225.4314 7.313743e+16 23244.901 1055.1703
## 3  1.8427 57.8307  20.9221 -2.4313 418.9626 5.164539e+16 17615.022  876.1166
```

```
## 4  1.5564 50.1387  14.8863 -2.6786  609.3518 2.936225e+16 13591.412  776.9927
## 5  1.1442 44.4853  12.5772 -3.1997  758.7814 1.875028e+16 12060.060  711.9705
## 6  0.2926 40.6143  28.1333 -3.4454  808.6017 2.003593e+16  9447.050  660.6776
## 7  2.0767 44.1722  16.2945  0.1436  962.9977 1.081897e+16  6363.185  562.4029
## 8  0.5419 43.7703  28.2797  1.4605 1070.1097 7.440776e+15  4995.833  510.4213
## 9  4.3721 48.3399   9.3875  5.1119 1220.3724 3.829616e+15  3394.298  433.3464
## 10 1.1997 46.2701   8.1650  5.2609 1293.2347 3.056237e+15  3031.433  409.0434
## 11 0.8340 44.3410   8.9717  5.3083 1376.7840 2.242316e+15  2823.262  388.8221
## 12 1.2044 43.1654   7.8186  5.6184 1447.0356 1.752186e+15  2505.380  367.6767
## 13 0.9742 41.9434   7.8612  5.7962 1506.8698 1.437148e+15  2361.741  350.0208
## 14 1.5395 41.0299   5.8597  6.0549 1560.7539 1.207096e+15  2068.108  333.0212
## 15 1.2204 39.7156   5.0920  6.0050 1614.6635 1.003397e+15  1975.666  320.7374
##    Friedman  Rubin Cindex     DB Silhouette   Duda Pseudot2   Beale Ratkowsky
## 2   16.5255 1.4159 0.2743 1.5019     0.2817 0.7340  36.2418  2.1548    0.3334
## 3   25.3844 1.7053 0.2347 1.5929     0.2289 0.6755  15.3735  2.7975    0.3307
## 4   36.3323 1.9228 0.2246 1.4508     0.2470 0.8298  12.9207  1.2123    0.3286
## 5   40.4147 2.0984 0.2063 1.7295     0.2079 0.7280  24.6545  2.2097    0.3070
## 6   42.7143 2.2613 0.2032 1.7717     0.1599 0.3414  17.3592 10.4241    0.2951
## 7   51.2007 2.6565 0.1987 1.5066     0.1827 0.7968  10.4568  1.4951    0.2928
## 8   54.2108 2.9270 0.1882 1.4706     0.2036 1.0665  -1.6830 -0.3609    0.2832
## 9   56.8841 3.4476 0.3108 1.2326     0.2160 0.7129  10.4715  2.3289    0.2800
## 10  59.8853 3.6524 0.2997 1.2020     0.2206 0.7251  12.1343  2.2081    0.2688
## 11  62.3662 3.8424 0.2914 1.2141     0.2056 0.4977  12.1126  5.5951    0.2587
## 12  64.6251 4.0634 0.2862 1.1860     0.2105 0.6908   9.4000  2.5657    0.2503
## 13  68.3495 4.2683 0.2798 1.2286     0.1915 0.7334  11.6328  2.1168    0.2424
## 14  70.8060 4.4862 0.2721 1.2700     0.1875 0.7291   7.4314  2.1250    0.2353
## 15  72.5606 4.6580 0.2654 1.3223     0.1767 0.5385  13.7138  4.8442    0.2286
##        Ball Ptbiserial    Frey McClain   Dunn Hubert SDindex Dindex   SDbw
## 2  527.5852     0.3422  0.2595  0.6490 0.0751 0.0010  2.7240 2.1934 1.0880
## 3  292.0389     0.4053 -0.1502  1.1448 0.0751 0.0014  2.8973 1.9790 0.9576
## 4  194.2482     0.4357  0.4909  1.1797 0.0757 0.0016  3.0800 1.8707 1.0002
## 5  142.3941     0.4312  5.5517  1.5461 0.0757 0.0019  3.1602 1.7666 0.9660
## 6  110.1129     0.3474 -0.1479  2.5747 0.0685 0.0019  3.1581 1.6756 0.7597
## 7   80.3433     0.3571  0.1256  2.5488 0.0685 0.0022  3.1016 1.5843 0.6454
## 8   63.8027     0.3659 -0.1291  2.8953 0.0717 0.0023  3.1233 1.5211 0.6410
## 9   48.1496     0.3835  0.1872  2.8069 0.1221 0.0025  2.9451 1.4625 0.4967
## 10  40.9043     0.3829  0.8481  2.9427 0.1221 0.0026  2.9247 1.4258 0.4672
## 11  35.3475     0.3608  0.0927  3.4443 0.1221 0.0026  3.1190 1.3866 0.4425
## 12  30.6397     0.3617  0.4867  3.4868 0.1221 0.0026  3.0365 1.3450 0.4064
## 13  26.9247     0.3521  1.0162  3.7714 0.1154 0.0027  2.9761 1.3048 0.3864
## 14  23.7872     0.3208  0.4286  4.6963 0.1154 0.0027  3.4028 1.2676 0.3676
## 15  21.3825     0.3095  1.4422  5.1586 0.1154 0.0028  3.4239 1.2396 0.3519
##
## $All.CriticalValues
##    CritValue_Duda CritValue_PseudoT2 Fvalue_Beale
## 2          0.7868            27.0994       0.0231
## 3          0.6825            14.8875       0.0037
## 4          0.7508            20.9124       0.2845
## 5          0.7548            21.4445       0.0200
## 6          0.4954             9.1671       0.0000
## 7          0.7098            16.7607       0.1478
## 8          0.6621            13.7821       1.0000
## 9          0.6573            13.5542       0.0158
## 10         0.6825            14.8875       0.0216
## 11         0.5447            10.0311       0.0000
## 12         0.6292            12.3746       0.0083
```

```
## 13         0.6825            14.8875       0.0282
## 14         0.6225            12.1297       0.0296
## 15         0.5901            11.1141       0.0000
##
## $Best.nc
##                      KL     CH Hartigan     CCC    Scott      Marriot   TrCovW
## Number_clusters 9.0000  2.000   9.0000 14.0000   3.0000 5.000000e+00    3.000
## Value_Index     4.3721 68.621  18.8923  6.0549 193.5312 1.189761e+16 5629.879
##                 TraceW Friedman   Rubin Cindex     DB Silhouette   Duda
## Number_clusters   3.00    4.000  9.0000 8.0000 12.000     2.0000 4.0000
## Value_Index      79.93   10.948 -0.3158 0.1882  1.186     0.2817 0.8298
##                 PseudoT2  Beale Ratkowsky     Ball PtBiserial Frey McClain
## Number_clusters   4.0000 4.0000    2.0000   3.0000     4.0000    1   2.000
## Value_Index      12.9207 1.2123    0.3334 235.5463     0.4357   NA   0.649
##                   Dunn Hubert SDindex Dindex    SDbw
## Number_clusters 9.0000      0   2.000      0 15.0000
## Value_Index     0.1221      0   2.724      0  0.3519
##
## $Best.partition
##                    Afghanistan                          Albania
##                              1                                2
##                        Algeria                           Angola
##                              2                                1
##            Antigua and Barbuda                        Argentina
##                              2                                2
##                        Armenia                        Australia
##                              2                                2
##                        Austria                       Azerbaijan
##                              2                                2
##                        Bahamas                          Bahrain
##                              2                                2
##                     Bangladesh                         Barbados
##                              1                                2
##                        Belarus                          Belgium
##                              2                                2
##                         Belize                            Benin
##                              2                                1
##                         Bhutan                          Bolivia
##                              1                                1
##         Bosnia and Herzegovina                         Botswana
##                              2                                1
##                         Brazil                           Brunei
##                              2                                2
##                       Bulgaria                     Burkina Faso
##                              2                                1
##                        Burundi                         Cambodia
##                              1                                1
##                       Cameroon                           Canada
##                              1                                2
##                     Cape Verde         Central African Republic
##                              2                                1
##                           Chad                            Chile
##                              1                                2
##                          China                         Colombia
##                              2                                2
##                        Comoros                   Congo Dem. Rep.
```

```
##                          1                           1
##                  Congo Rep.                 Costa Rica
##                          1                           2
##              Cote d'Ivoire                     Croatia
##                          1                           2
##                     Cyprus              Czech Republic
##                          2                           2
##                    Denmark          Dominican Republic
##                          2                           2
##                    Ecuador                       Egypt
##                          2                           1
##                El Salvador           Equatorial Guinea
##                          2                           1
##                    Eritrea                     Estonia
##                          1                           2
##                       Fiji                     Finland
##                          1                           2
##                     France                       Gabon
##                          2                           1
##                     Gambia                     Georgia
##                          1                           2
##                    Germany                       Ghana
##                          2                           1
##                     Greece                     Grenada
##                          2                           2
##                  Guatemala                      Guinea
##                          2                           1
##              Guinea-Bissau                      Guyana
##                          1                           1
##                      Haiti                     Hungary
##                          1                           2
##                    Iceland                       India
##                          2                           1
##                  Indonesia                        Iran
##                          2                           2
##                       Iraq                     Ireland
##                          1                           2
##                     Israel                       Italy
##                          2                           2
##                    Jamaica                       Japan
##                          2                           2
##                     Jordan                  Kazakhstan
##                          2                           2
##                      Kenya                    Kiribati
##                          1                           1
##                     Kuwait             Kyrgyz Republic
##                          2                           1
##                        Lao                      Latvia
##                          1                           2
##                    Lebanon                     Lesotho
##                          2                           1
##                    Liberia                       Libya
##                          1                           2
##                  Lithuania                  Luxembourg
##                          2                           2
##              Macedonia FYR                  Madagascar
```

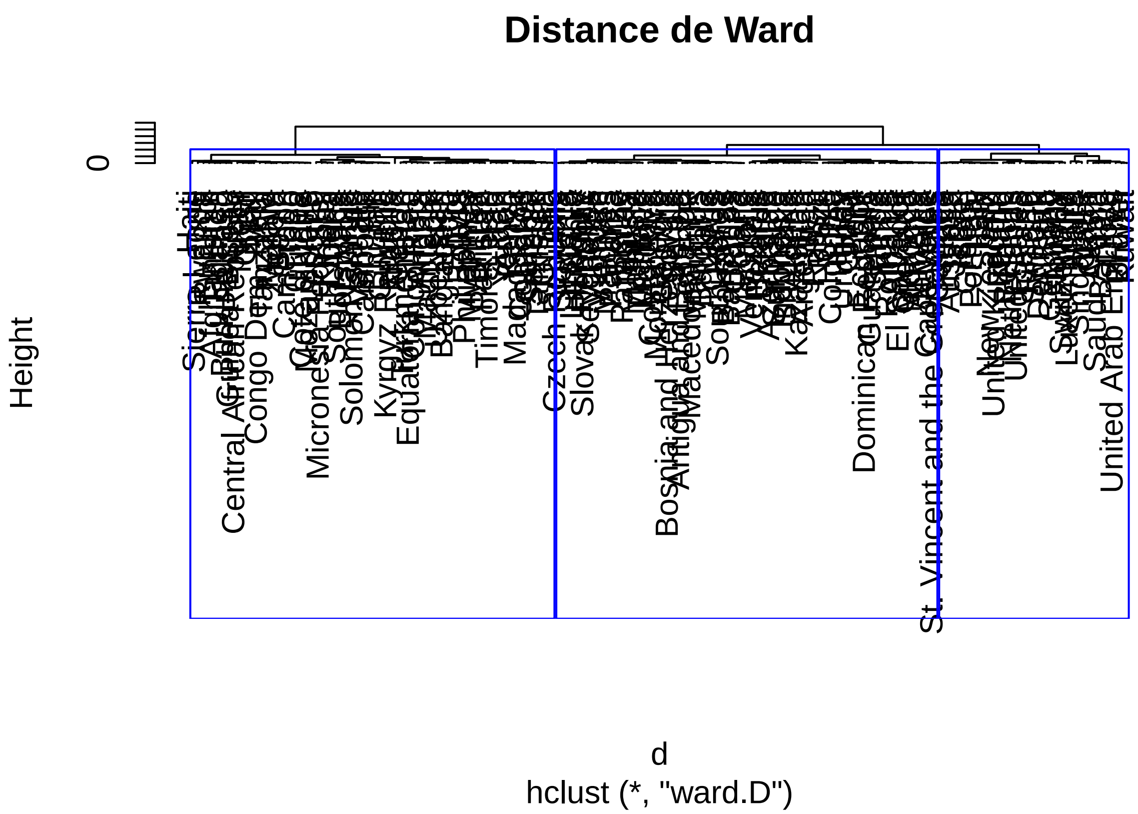
```
##                            2                                 1
##                       Malawi                          Malaysia
##                            1                                 2
##                     Maldives                              Mali
##                            2                                 1
##                        Malta                        Mauritania
##                            2                                 1
##                    Mauritius            Micronesia Fed. Sts.
##                            2                                 1
##                      Moldova                          Mongolia
##                            2                                 2
##                   Montenegro                           Morocco
##                            2                                 2
##                   Mozambique                           Myanmar
##                            1                                 1
##                      Namibia                             Nepal
##                            1                                 1
##                  Netherlands                       New Zealand
##                            2                                 2
##                        Niger                           Nigeria
##                            1                                 1
##                       Norway                              Oman
##                            2                                 2
##                     Pakistan                            Panama
##                            1                                 2
##                     Paraguay                              Peru
##                            2                                 2
##                  Philippines                            Poland
##                            1                                 2
##                     Portugal                             Qatar
##                            2                                 2
##                      Romania                            Russia
##                            2                                 2
##                       Rwanda                             Samoa
##                            1                                 2
##                 Saudi Arabia                           Senegal
##                            2                                 1
##                       Serbia                        Seychelles
##                            2                                 2
##                 Sierra Leone                         Singapore
##                            1                                 2
##              Slovak Republic                          Slovenia
##                            2                                 2
##              Solomon Islands                      South Africa
##                            1                                 1
##                  South Korea                             Spain
##                            2                                 2
##                    Sri Lanka St. Vincent and the Grenadines
##                            2                                 2
##                        Sudan                          Suriname
##                            1                                 2
##                       Sweden                       Switzerland
##                            2                                 2
##                   Tajikistan                          Tanzania
##                            1                                 1
##                     Thailand                       Timor-Leste
```

```
##                            2                            1
##                         Togo                        Tonga
##                            1                            2
##                      Tunisia                       Turkey
##                            2                            2
##                 Turkmenistan                       Uganda
##                            1                            1
##                      Ukraine         United Arab Emirates
##                            2                            2
##               United Kingdom                United States
##                            2                            2
##                      Uruguay                   Uzbekistan
##                            2                            1
##                      Vanuatu                    Venezuela
##                            1                            2
##                      Vietnam                        Yemen
##                            2                            1
##                       Zambia
##                            1
```

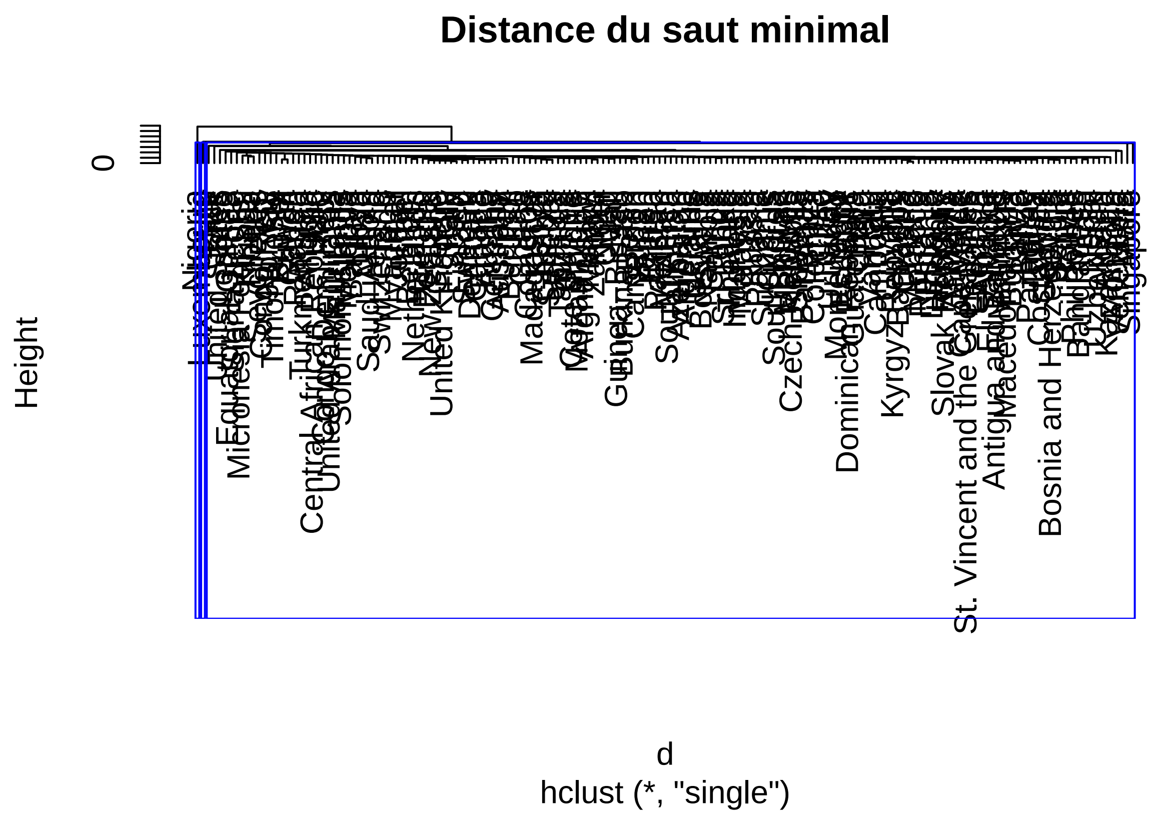
On nous dit que les meilleurs clusters sont 2 ou 4 avec 5 chacun ou 3 avec 4. Au vu de l'interprétation graphique faite précédemment, nous allons rester sur 3 clusters, qui nous semble le plus pertinent.

Cutree

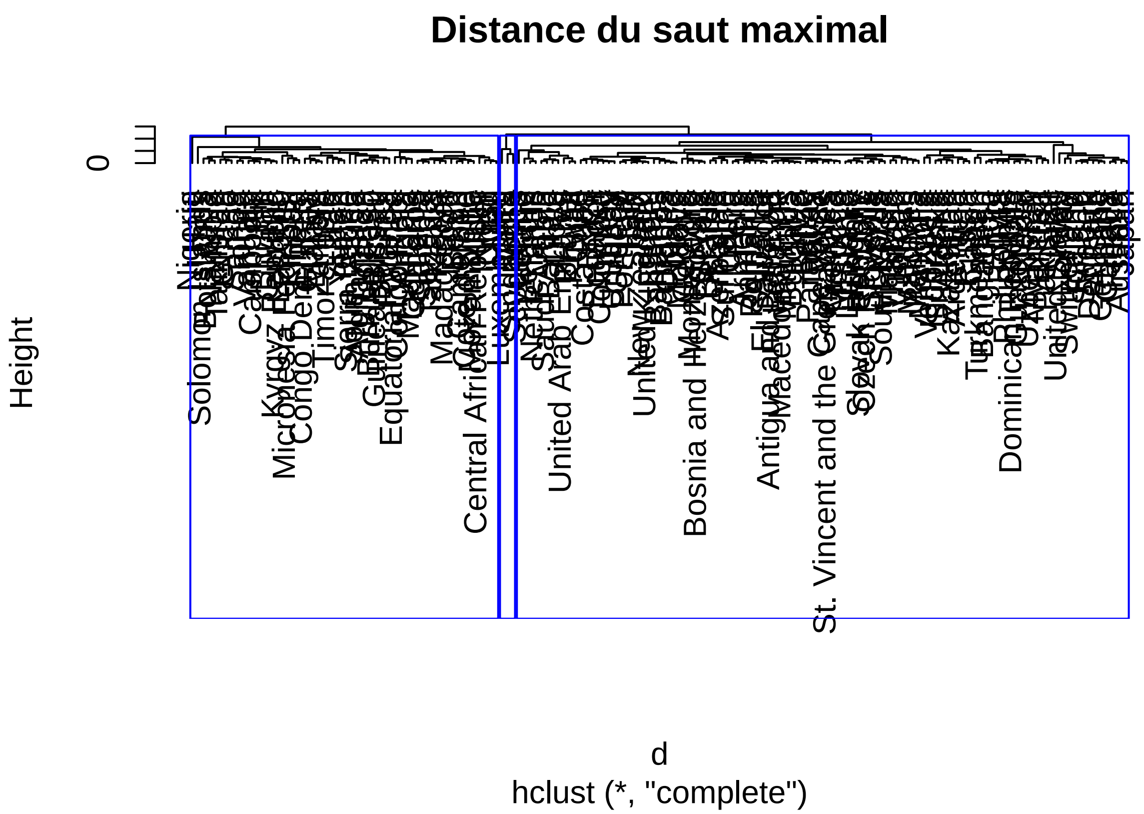
```r
nbc <- 3
gpe.ward <- cutree(cah.ward, k = nbc) # Classe affectée pour chaque individu
gpe.min <- cutree(cah.min, k = nbc)
gpe.max <- cutree(cah.max, k = nbc)
plot(cah.ward, hang = -1, main = "Distance de Ward")
rect.hclust(cah.ward, nbc, border = "blue")
```



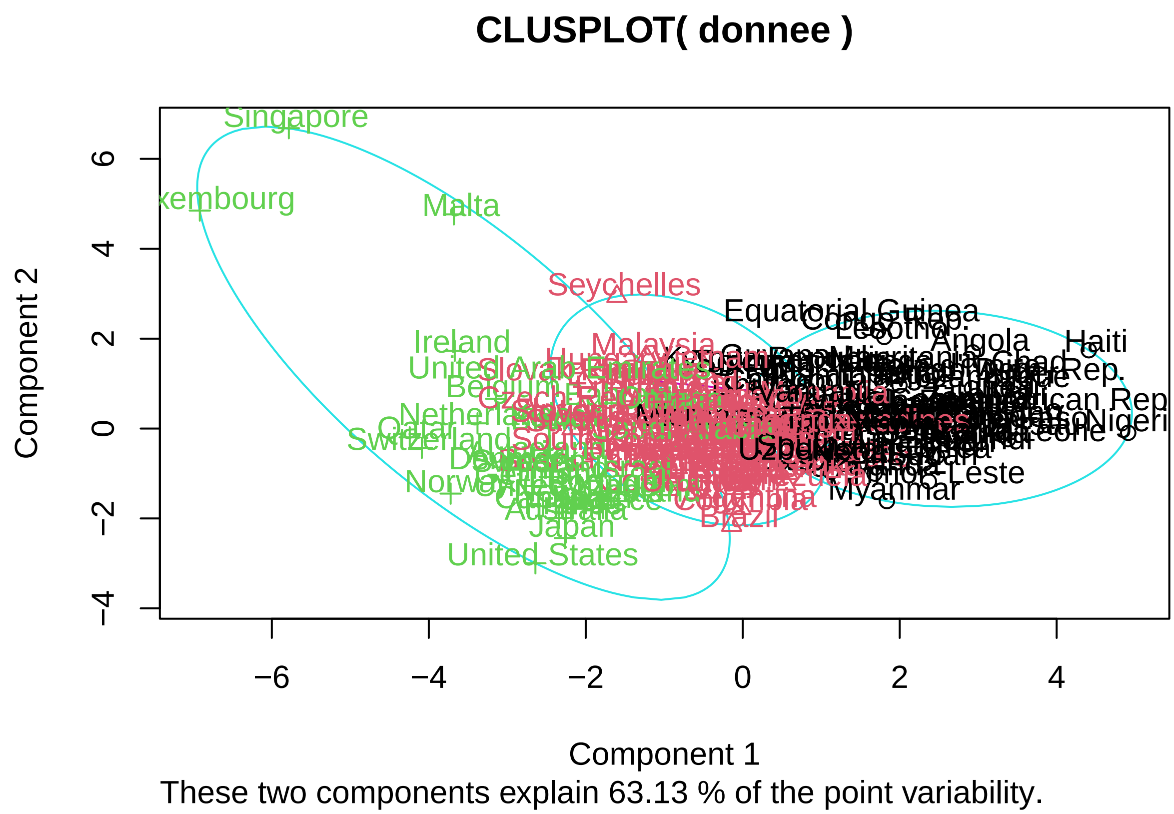

```
plot(cah.min, hang = -1, main = "Distance du saut minimal")
rect.hclust(cah.min, nbc, border = "blue")
```




```r
plot(cah.max, hang = -1, main = "Distance du saut maximal")
rect.hclust(cah.max, nbc, border = "blue")
```




```
clusplot(donnee, gpe.ward, labels = nbc, col.p = as.numeric(gpe.ward))
```

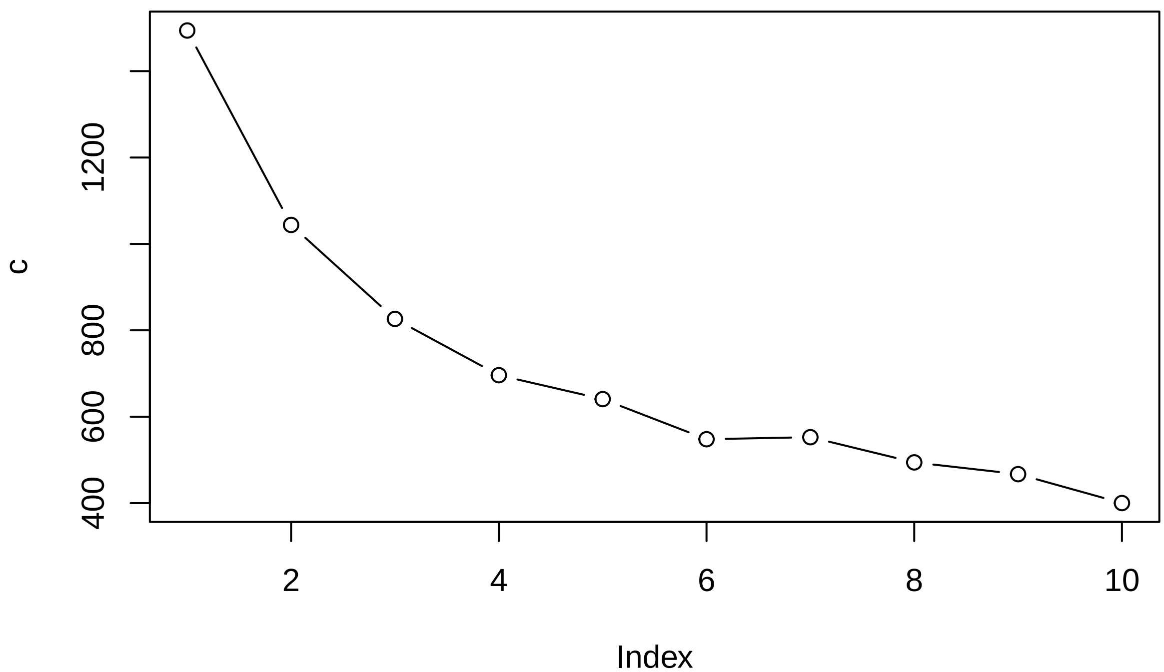


Les 3 groupes sont reconnaissables mais mélangés à certains endroits, particulièrement entre .

Ce graphe correspond à la représentation des groupes sur les deux premiers axes principaux d'une ACP. De plus, des ellipses de contour autour des groupes sont tracées. On observe ici en colorant les points avec leur vraie classe que les groupes vert et rouge et rouge et noir sont difficiles à retrouver.

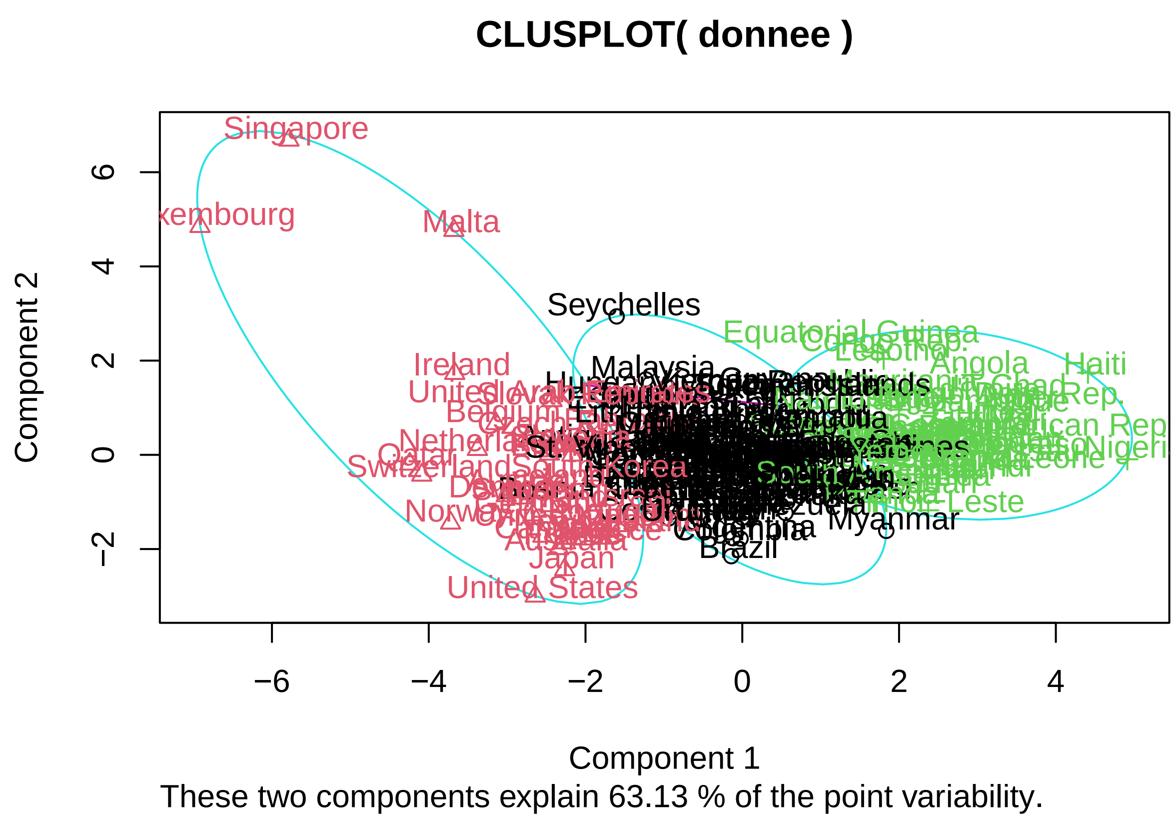
2.2 Algorithme des Kmeans

Tout d'abord nous allons utiliser l'algorithme des k-means pour avoir une première idée de notre classification finale. Si on ne sait pas a priori combien de groupes comporte le jeu de donnees, on peut appliquer l'algorithme pour plusieurs choix de K possibles et tracer la courbe d'évolution de l'inertie . On lance l'algorithme des kmeans et on observe l'évolution de la variance intra-groupes en fonction du nombre de groupes. On rajoute également l'option « nstart =50 » pour stabiliser les résultats.



A la vue de ce graphique, on aurait tendance à choisir K= 3,4 ou 5 groupes en appliquant la méthode dite « du coude ». Ayant, grâce à la CAH, choisi de garder K=3, nous allons conserver ce nombre pour les k-means. Ce graphique nous conforome tout de même dans notre idée.

```
K=3
cl = kmeans(donnee,K,nstart=50)
gpe = cl$cluster
clusplot(donnee,gpe,labels=3,col.p=gpe)
```



La représentation en clusplot nous permet de voir qu'il y a 3 groupes qui se séparent plutôt bien sur les composantes 1, 2 et 3. (on le voit au travers des différents couleur sur le graphique).

Representation des groupes sur le premier plan factoriel

2.3 Interprétation des groupes

Nous allons maintenant chercher à interpréter les groupes obtenus à l'aide de la fonction catdes.

```
gpe = cutree(cah.ward,k=3)
donnee$gpecah = as.factor(gpe)
interpcah = catdes(donnee,num.var = 10)
interpcah
```

```
##
## Link between the cluster variable and the quantitative variables
## ================================================================
##                   Eta2      P-value
## pib_h       0.72363077 1.592773e-46
## esper_vie   0.71468093 2.173330e-45
## revenu      0.69791718 2.346035e-43
## enfant_mort 0.65580744 1.041649e-38
## fert        0.62232782 2.105862e-35
## exports     0.13621101 6.101387e-06
## sant.       0.10399187 1.229080e-04
## inflation   0.05970019 6.424517e-03
##
## Description of each cluster by quantitative variables
```

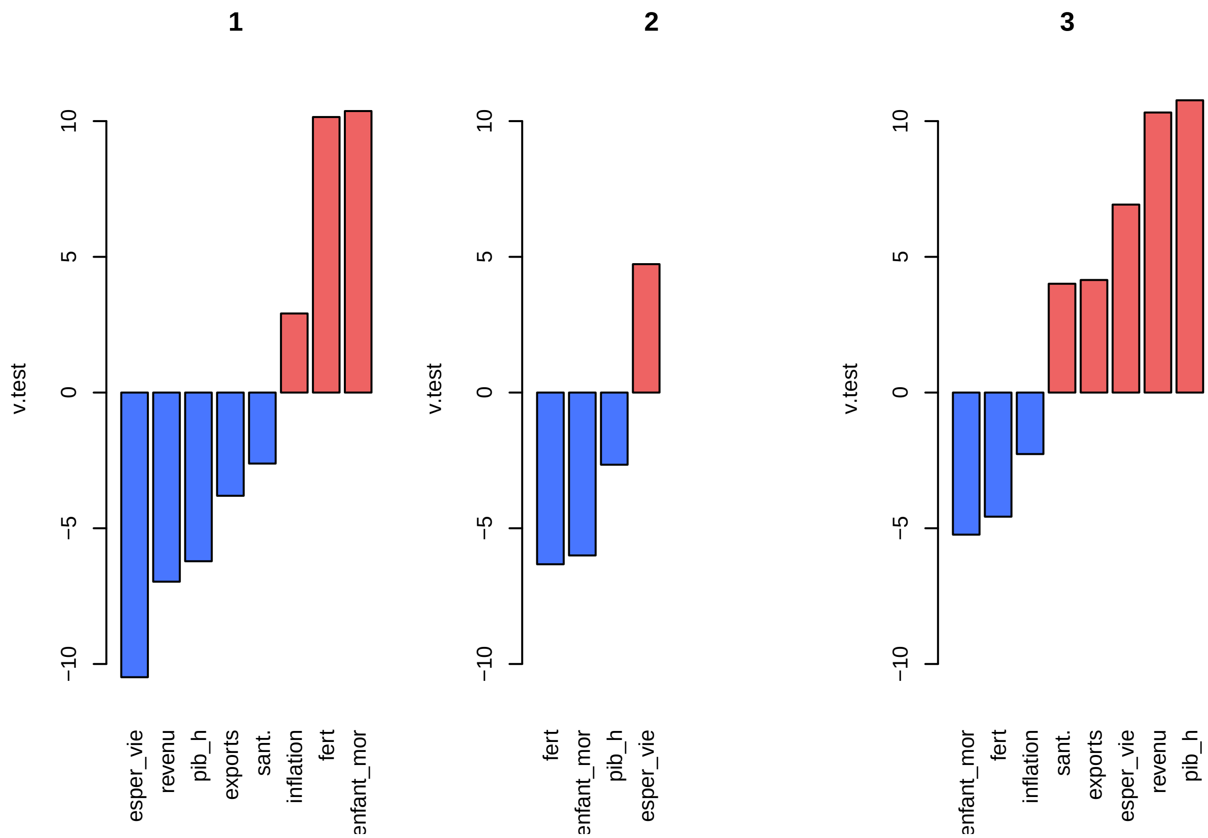
```
## ====================================================
## $`1`
##                 v.test Mean in category  Overall mean sd in category Overall sd
## enfant_mort  10.370649        1.0052894  1.555642e-16      0.9111885  0.9970015
## fert         10.150674        0.9839659  1.728491e-17      0.8579969  0.9970015
## inflation     2.913863        0.2824583  1.329608e-17      1.2650602  0.9970015
## sant.        -2.615632       -0.2535490 -1.403069e-15      0.9651035  0.9970015
## exports      -3.802046       -0.3685552 -3.478588e-16      0.6775757  0.9970015
## pib_h        -6.214645       -0.6024230  2.393295e-17      0.1393288  0.9970015
## revenu       -6.968102       -0.6754601 -7.445807e-17      0.2556201  0.9970015
## esper_vie   -10.486756       -1.0165444  3.616535e-16      0.7596372  0.9970015
##                  p.value
## enfant_mort 3.372265e-25
## fert        3.290824e-24
## inflation   3.569862e-03
## sant.       8.906240e-03
## exports     1.435063e-04
## pib_h       5.144073e-10
## revenu      3.212442e-12
## esper_vie   9.938179e-26
##
## $`2`
##                v.test Mean in category Overall mean sd in category Overall sd
## esper_vie    4.730693        0.4417023 3.616535e-16      0.3438267  0.9970015
## pib_h       -2.657982       -0.2481744 2.393295e-17      0.3297308  0.9970015
## enfant_mort -6.001733       -0.5603786 1.555642e-16      0.2069384  0.9970015
## fert        -6.325848       -0.5906411 1.728491e-17      0.4173776  0.9970015
##                  p.value
## esper_vie   2.237542e-06
## pib_h       7.861014e-03
## enfant_mort 1.952226e-09
## fert        2.518459e-10
##
## $`3`
##                v.test Mean in category  Overall mean sd in category Overall sd
## pib_h       10.768111        1.6480397  2.393295e-17     1.04631502  0.9970015
## revenu      10.318192        1.5791804 -7.445807e-17     1.05150950  0.9970015
## esper_vie    6.925852        1.0599890  3.616535e-16     0.23111362  0.9970015
## exports      4.147405        0.6347527 -3.478588e-16     1.54724683  0.9970015
## sant.        4.009263        0.6136103 -1.403069e-15     1.27746390  0.9970015
## inflation   -2.266208       -0.3468390  1.329608e-17     0.50958288  0.9970015
## fert        -4.572607       -0.6998292  1.728491e-17     0.29691512  0.9970015
## enfant_mort -5.234428       -0.8011195  1.555642e-16     0.08690297  0.9970015
##                  p.value
## pib_h       4.868867e-27
## revenu      5.831062e-25
## esper_vie   4.333583e-12
## exports     3.362651e-05
## sant.       6.090858e-05
## inflation   2.343864e-02
## fert        4.816923e-06
## enfant_mort 1.654969e-07
```

```
head(donnee)
```

```
##                     enfant_mort    exports      sant.    imports     revenu
```

```
## Afghanistan           1.2876597 -1.13486665  0.27825140 -0.08220771 -0.80582187
## Albania              -0.5373329 -0.47822017 -0.09672528  0.07062429 -0.37424335
## Algeria              -0.2720146 -0.09882442 -0.96317624 -0.63983800 -0.22018227
## Angola                2.0017872  0.77305618 -1.44372888 -0.16481961 -0.58328920
## Antigua and Barbuda  -0.6935483  0.16018613 -0.28603389  0.49607554  0.10142673
## Argentina            -0.5894047 -0.81019144  0.46756001 -1.27594958  0.08067776
##                      inflation  esper_vie        fert       pib_h gpecah
## Afghanistan          0.1568645 -1.6142372  1.89717646 -0.67714308      1
## Albania             -0.3114109  0.6459238 -0.85739418 -0.48416709      2
## Algeria              0.7869076  0.6684130 -0.03828924 -0.46398018      2
## Angola               1.3828944 -1.1756985  2.12176975 -0.51472026      1
## Antigua and Barbuda -0.5999442  0.7021467 -0.54032130 -0.04169175      2
## Argentina            1.2409928  0.5897009 -0.38178486 -0.14535428      2
```

```
plot.catdes(interpcah,barplot=T)
```



Les 3 groupes sont donc caractérisés ainsi :

- Le premier groupe a une très faible espérance de vie, un faible revenu, un faible pib, et un fort taux de fertilité et de mortalité infantile.
- Le second groupe se démarque déjà très largement du premier. En effet, il a un faible taux de mort infantile et une haute espérance de vie. Il a cependant un pib par habitant plutôt faible, mais toujours moins que le premier groupe.
- Le troisième groupe se démarque également du deuxième groupe : il a un très fort pib par habitant, de forts revenus.

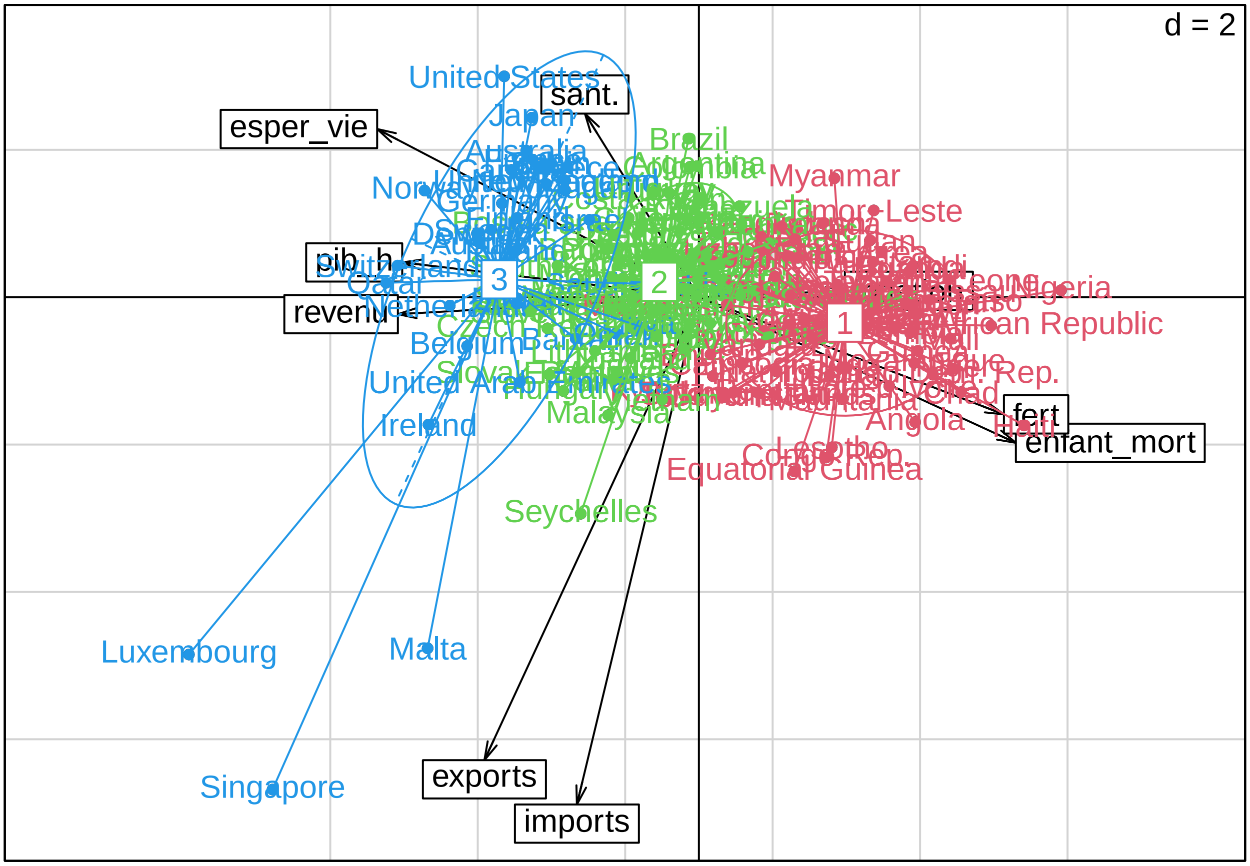
```
CCpca = dudi.pca(donnee[1:9],scannf=FALSE,nf=2)
cumsum(CCpca$eig)/sum(CCpca$eig) # 63% de variabilité expliquée sur les deux premiers axes
```

```
## [1] 0.4595174 0.6313337 0.7613762 0.8719079 0.9453100 0.9701523 0.9827566
## [8] 0.9925694 1.0000000
```

```
scatter(CCpca,posieig = "none",clab.row=0,pch=NA)
```

```
## NULL
```

```
text(CCpca$li[,1], CCpca$li[,2],labels = row.names(donnee),col=gpe+1,xpd=TRUE)
s.class(CCpca$li, factor(gpe), col = 2:4, add.plot = TRUE,clabel = 1)
```



Suite à l'analyse de nos différentes méthodes, nous nous rendons compte que 3 gros groupes se sont formés. Nous décidons de nous concentrer sur le groupe des pays les moins développés.

2.4 Visualisation des résultats obtenus (carte)

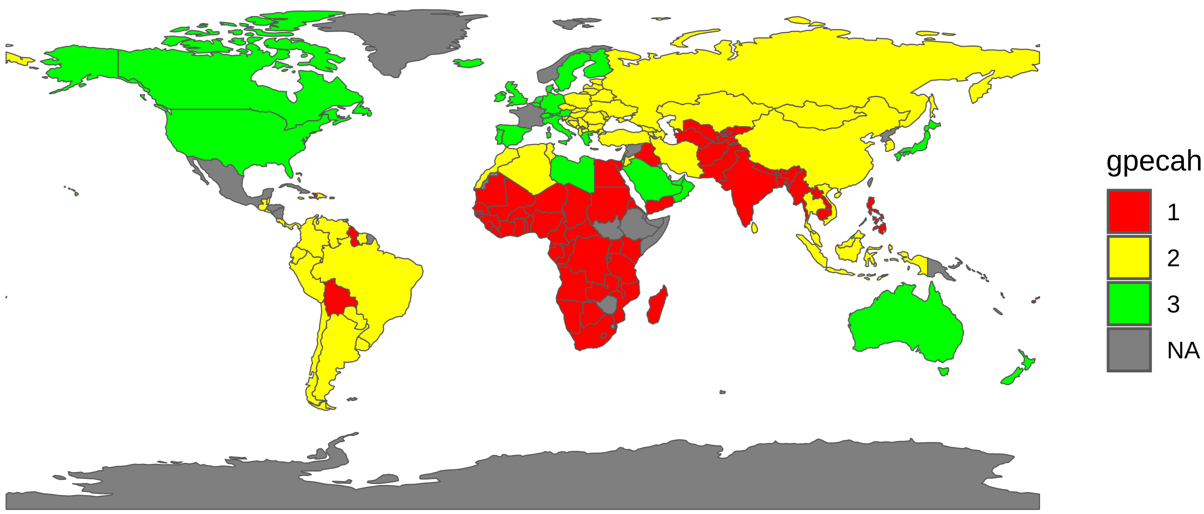
```
##   iso3c       lat       lon
## 1   AFG  33.85640  66.08669
## 2   AGO -12.29155  17.50291
## 3   ALB  41.14135  20.03243
## 4   ARE  23.86863  54.20671
## 5   ARG -35.22017 -65.14954
## 6   ARM  40.21661  45.00029
```

```
## Simple feature collection with 6 features and 94 fields
## Geometry type: MULTIPOLYGON
## Dimension:     XY
## Bounding box:  xmin: -180 ymin: -18.28799 xmax: 180 ymax: 83.23324
## Geodetic CRS:  +proj=longlat +datum=WGS84 +no_defs +ellps=WGS84 +towgs84=0,0,0
##        featurecla scalerank labelrank                  sovereignt sov_a3
## 0 Admin-0 country         1         6                        Fiji    FJI
## 1 Admin-0 country         1         3 United Republic of Tanzania    TZA
## 2 Admin-0 country         1         7              Western Sahara    SAH
## 3 Admin-0 country         1         2                      Canada    CAN
## 4 Admin-0 country         1         2    United States of America    US1
## 5 Admin-0 country         1         3                  Kazakhstan    KAZ
##   adm0_dif level              type                       admin adm0_a3 geou_dif
## 0        0     2 Sovereign country                        Fiji     FJI        0
## 1        0     2 Sovereign country United Republic of Tanzania     TZA        0
```

```
## 2        0     2     Indeterminate              Western Sahara     SAH        0
## 3        0     2 Sovereign country                      Canada     CAN        0
## 4        1     2           Country    United States of America     USA        0
## 5        0     2 Sovereign country                  Kazakhstan     KAZ        0
##                    geounit gu_a3 su_dif        subunit su_a3 brk_diff
## 0                     Fiji   FJI      0           Fiji   FJI        0
## 1                 Tanzania   TZA      0       Tanzania   TZA        0
## 2           Western Sahara   SAH      0 Western Sahara   SAH        1
## 3                   Canada   CAN      0         Canada   CAN        0
## 4 United States of America   USA      0  United States   USA        0
## 5               Kazakhstan   KAZ      0     Kazakhstan   KAZ        0
##                       name      name_long brk_a3      brk_name brk_group
## 0                     Fiji           Fiji    FJI          Fiji      <NA>
## 1                 Tanzania       Tanzania    TZA      Tanzania      <NA>
## 2                W. Sahara Western Sahara    B28     W. Sahara      <NA>
## 3                   Canada         Canada    CAN        Canada      <NA>
## 4 United States of America  United States    USA United States      <NA>
## 5               Kazakhstan     Kazakhstan    KAZ    Kazakhstan      <NA>
##    abbrev postal                        formal_en formal_fr     name_ciawf
## 0    Fiji     FJ                 Republic of Fiji      <NA>           Fiji
## 1   Tanz.     TZ      United Republic of Tanzania      <NA>       Tanzania
## 2 W. Sah.     WS Sahrawi Arab Democratic Republic      <NA> Western Sahara
## 3    Can.     CA                           Canada      <NA>         Canada
## 4  U.S.A.     US         United States of America      <NA>  United States
## 5    Kaz.     KZ           Republic of Kazakhstan      <NA>     Kazakhstan
##     note_adm0                          note_brk                name_sort name_alt
## 0        <NA>                              <NA>                     Fiji     <NA>
## 1        <NA>                              <NA>                 Tanzania     <NA>
## 2 Self admin. Self admin.; Claimed by Morocco           Western Sahara     <NA>
## 3        <NA>                              <NA>                   Canada     <NA>
## 4        <NA>                              <NA> United States of America     <NA>
## 5        <NA>                              <NA>               Kazakhstan     <NA>
##   mapcolor7 mapcolor8 mapcolor9 mapcolor13   pop_est pop_rank gdp_md_est
## 0         5         1         2          2    920938       11  8.374e+03
## 1         3         6         2          2  53950935       16  1.506e+05
## 2         4         7         4          4    603253       11  9.065e+02
## 3         6         6         2          2  35623680       15  1.674e+06
## 4         4         5         1          1 326625791       17  1.856e+07
## 5         6         1         6          1  18556698       14  4.607e+05
##   pop_year lastcensus gdp_year                   economy              income_grp
## 0     2017       2007     2016      6. Developing region 4. Lower middle income
## 1     2017       2002     2016 7. Least developed region           5. Low income
## 2     2017         NA     2007 7. Least developed region           5. Low income
## 3     2017       2011     2016   1. Developed region: G7    1. High income: OECD
## 4     2017       2010     2016   1. Developed region: G7    1. High income: OECD
## 5     2017       2009     2016      6. Developing region 3. Upper middle income
##   wikipedia fips_10_ iso_a2 iso_a3 iso_a3_eh iso_n3 un_a3 wb_a2 wb_a3   woe_id
## 0        NA       FJ     FJ    FJI       FJI    242   242    FJ   FJI 23424813
## 1        NA       TZ     TZ    TZA       TZA    834   834    TZ   TZA 23424973
## 2        NA       WI     EH    ESH       ESH    732   732  <NA>  <NA> 23424990
## 3        NA       CA     CA    CAN       CAN    124   124    CA   CAN 23424775
## 4         0       US     US    USA       USA    840   840    US   USA 23424977
## 5        NA       KZ     KZ    KAZ       KAZ    398   398    KZ   KAZ      -90
##   woe_id_eh                                   woe_note adm0_a3_is adm0_a3_us
## 0  23424813                 Exact WOE match as country        FJI        FJI
## 1  23424973                 Exact WOE match as country        TZA        TZA
```

```
## 2  23424990                 Exact WOE match as country        MAR        SAH
## 3  23424775                 Exact WOE match as country        CAN        CAN
## 4  23424977                 Exact WOE match as country        USA        USA
## 5  23424871 Includes Baykonur Cosmodrome as an admin-1        KAZ        KAZ
##   adm0_a3_un adm0_a3_wb     continent region_un       subregion
## 0         NA         NA       Oceania   Oceania       Melanesia
## 1         NA         NA        Africa    Africa  Eastern Africa
## 2         NA         NA        Africa    Africa Northern Africa
## 3         NA         NA North America  Americas Northern America
## 4         NA         NA North America  Americas Northern America
## 5         NA         NA          Asia      Asia    Central Asia
##                   region_wb name_len long_len abbrev_len tiny homepart
## 0       East Asia & Pacific        4        4          4   NA        1
## 1        Sub-Saharan Africa        8        8          5   NA        1
## 2 Middle East & North Africa       9       14          7   NA        1
## 3             North America        6        6          4   NA        1
## 4             North America       24       13          6   NA        1
## 5     Europe & Central Asia       10       10          4   NA        1
##   min_zoom min_label max_label      ne_id wikidataid name_ar name_bn
## 0      0.0       3.0       8.0 1159320625       Q712    <NA>    <NA>
## 1      0.0       3.0       8.0 1159321337       Q924    <NA>    <NA>
## 2      4.7       6.0      11.0 1159321223      Q6250    <NA>    <NA>
## 3      0.0       1.7       5.7 1159320467        Q16    <NA>    <NA>
## 4      0.0       1.7       5.7 1159321369        Q30    <NA>    <NA>
## 5      0.0       3.0       7.0 1159320967       Q232    <NA>    <NA>
##             name_de                  name_en           name_es
## 0           Fidschi                     Fiji              Fiyi
## 1          Tansania                 Tanzania          Tanzania
## 2        Westsahara           Western Sahara Sahara Occidental
## 3            Kanada                   Canada            Canadá
## 4 Vereinigte Staaten United States of America    Estados Unidos
## 5        Kasachstan               Kazakhstan        Kazajistán
##            name_fr name_el name_hi                  name_hu         name_id
## 0            Fidji    <NA>    <NA>          Fidzsi-szigetek            Fiji
## 1          Tanzanie    <NA>    <NA>                 Tanzánia        Tanzania
## 2 Sahara occidental    <NA>    <NA>           Nyugat-Szahara    Sahara Barat
## 3           Canada    <NA>    <NA>                   Kanada          Kanada
## 4        États-Unis    <NA>    <NA> Amerikai Egyesült Államok Amerika Serikat
## 5        Kazakhstan    <NA>    <NA>               Kazahsztán      Kazakhstan
##                name_it name_ja name_ko                    name_nl
## 0                 Figi    <NA>    <NA>                       Fiji
## 1             Tanzania    <NA>    <NA>                   Tanzania
## 2    Sahara Occidentale    <NA>    <NA>            Westelijke Sahara
## 3               Canada    <NA>    <NA>                     Canada
## 4 Stati Uniti d'America    <NA>    <NA> Verenigde Staten van Amerika
## 5           Kazakistan    <NA>    <NA>                 Kazachstan
##            name_pl         name_pt name_ru    name_sv
## 0            Fidzi            Fiji    <NA>       Fiji
## 1          Tanzania        Tanzânia    <NA>   Tanzania
## 2  Sahara Zachodnia Saara Ocidental    <NA> Västsahara
## 3            Kanada          Canadá    <NA>     Kanada
## 4 Stany Zjednoczone  Estados Unidos    <NA>        USA
## 5        Kazachstan     Cazaquistão    <NA>  Kazakstan
##                      name_tr    name_vi name_zh                       geometry
## 0                       Fiji       Fiji    <NA> MULTIPOLYGON (((180 -16.067...
## 1                   Tanzanya   Tanzania    <NA> MULTIPOLYGON (((33.90371 -0...
```

```
## 2                  Bati Sahra Tây Sahara    <NA> MULTIPOLYGON (((-8.66559 27...
## 3                      Kanada     Canada    <NA> MULTIPOLYGON (((-122.84 49,...
## 4 Amerika Birlesik Devletleri       <NA>    <NA> MULTIPOLYGON (((-122.84 49,...
## 5                  Kazakistan Kazakhstan    <NA> MULTIPOLYGON (((87.35997 49...
```



Voici une représentation cartographique de nos 3 groupes. Pour le choix des couleurs (roueg étant les pays les plus dans le besoin et vert les pays le moins dans le besoin), nous nous sommes basées sur la représentation de la CAH faite plus haut ainsi que sur le rendu du catdes. En effet, nous apercevons que dans le groupe 1 (les pays qui ont un fort taux de mortalité infantile et une faible espérance de vie) se trouvent des pays comme l'Angola ou le Nigeria. Nous avons alors reliés la couleur rouge au groupe de ces pays. On observe bien que les pays dans le besoin (les individus se trouvant dans le groupe 1 de notre cah) se situent principalement en afrique et en asie.

3 Traitement du groupe des pays les moins favorisés

Caractérisation de la partition obtenue Représentation informative des résultats. Graphiques adaptés, représentations factorielles si adaptées Optionnel : Représentation spatiale des résultats sur la carte de Rennes Faire une ACP

Nous allons maintenant uniquement nous pencher sur les pays les moins développés (ceux appartenant au premier groupe).

3.1 CAH sur les pays moins développés

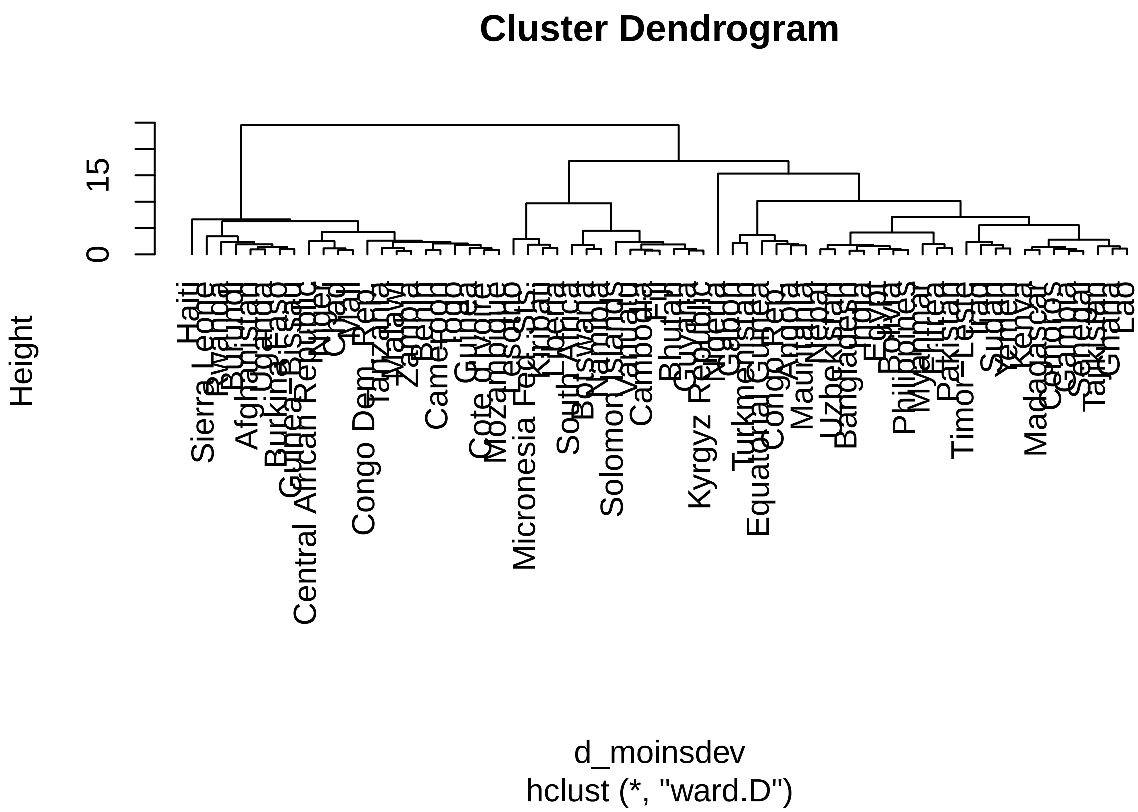
On decide de realiser une deuxième CAH sur le groupe 1, qui sont les pays moins développés :

```
donnee_groupe <- donnee
donnee_groupe$gpecah <- as.factor(gpe.ward)
donnee_moinsdev <- donnee_groupe[donnee_groupe$gpecah ==1,]
donnee_moinsdev <-donnee_moinsdev[1:9]
```

On enlève la dernière colonne qui ne nous sert plus à rien.

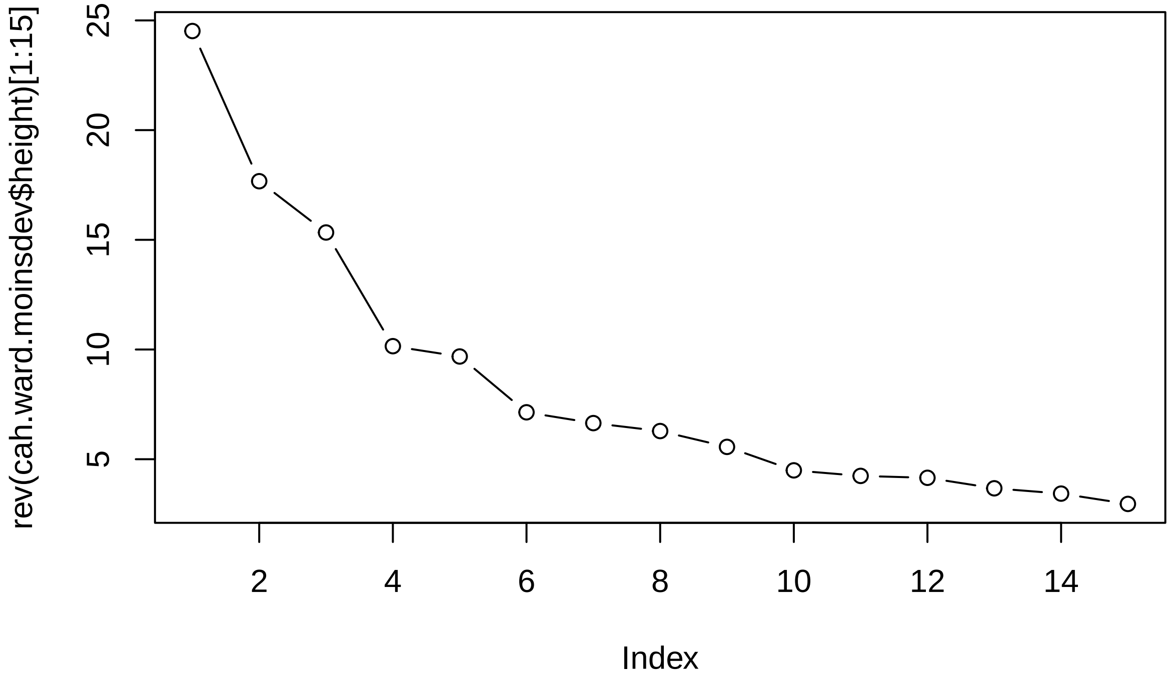
On decide d'appliquer une CAH sur ces données avec la distance euclidienne et la stratégie d'aggrégation de ward (au vue du travail effectué plus haut c'est ce qui nous semble le plus pertinent)

```
d_moinsdev = dist(donnee_moinsdev)
cah.ward.moinsdev = hclust(d_moinsdev,method="ward.D")

plot(cah.ward.moinsdev,hang=-1)
```



De la même façon que la seconde partie, on observe la présence d'une structure "naturelle" en un nombre de groupe modéré. Regardons la courbe de perte d'inertie (on se contente des 15 premières valeurs pour ne pas "noyer" l'information importante)

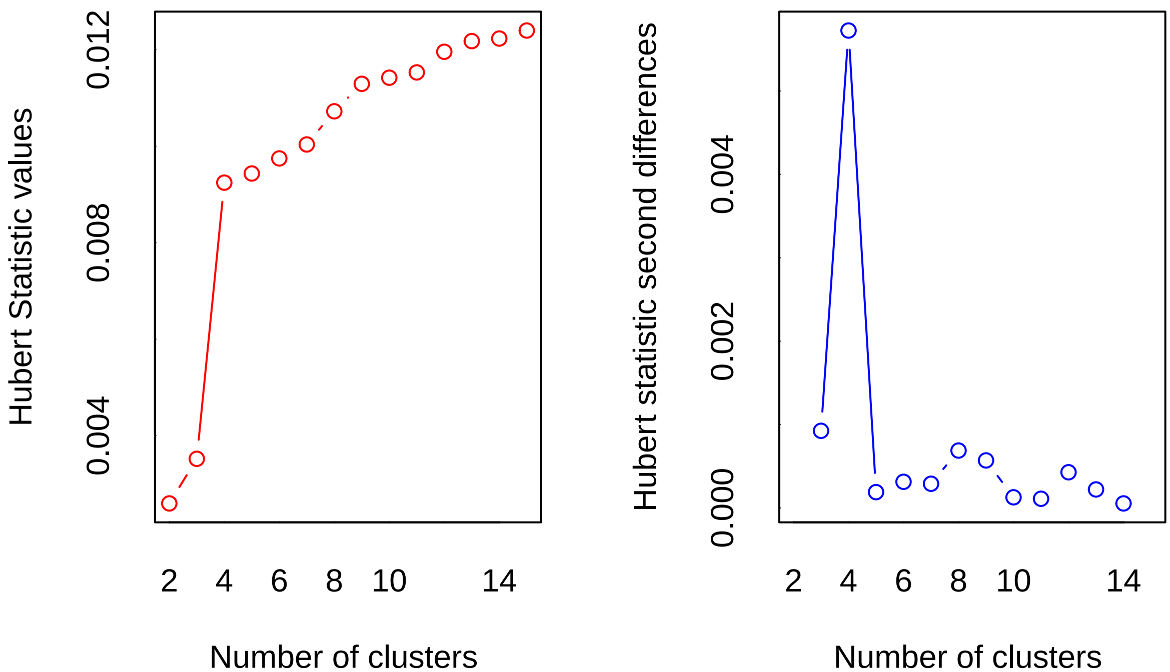
```
plot(rev(cah.ward.moinsdev$height)[1:15],type="b")
```



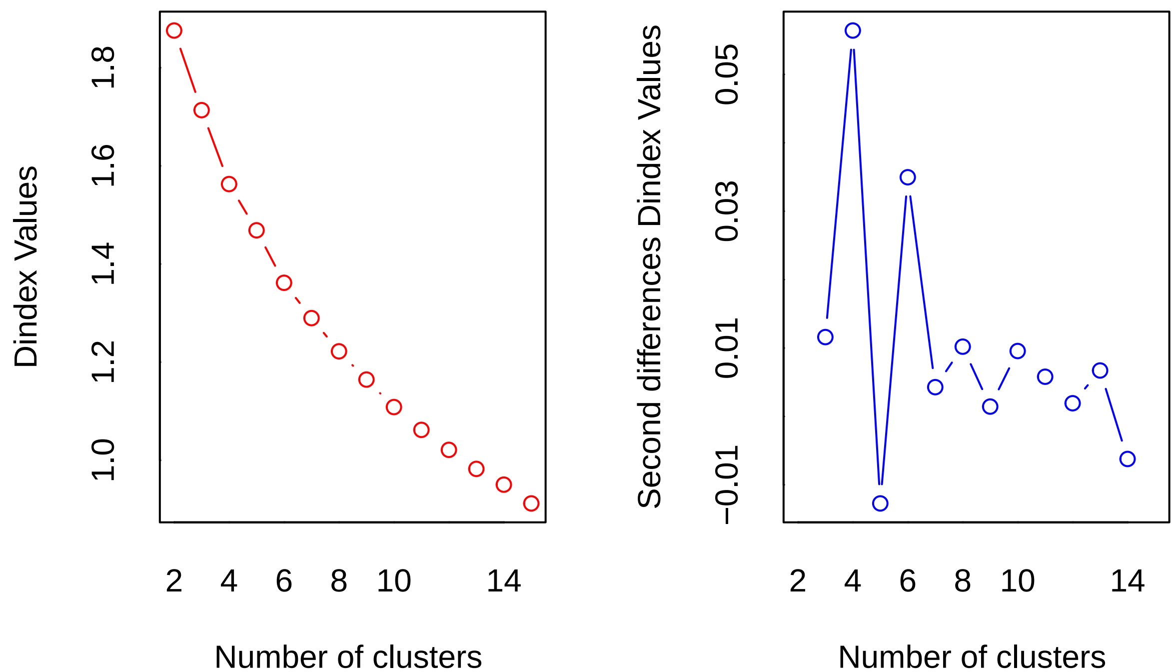
Le tracé de la perte d'inertie nous incite à choisir une partition en 4 groupes (lecture de gauche à droite : juste avant le coude ou changement de pente s'opérant au passage de 4 à 6 groupes)

On peut aussi s'aider de critères automatiques calculés dans le package `NbClust`

```
NbClust(donnee_moinsdev,min.nc = 2,max.nc = 15,method="ward.D",index="all")
```




```
## *** : The Hubert index is a graphical method of determining the number of clusters.
##                 In the plot of Hubert index, we seek a significant knee that corresponds to a
##                 significant increase of the value of the measure i.e the significant peak in Hubert
##                 index second differences plot.
##
```




```
## *** : The D index is a graphical method of determining the number of clusters.
##                 In the plot of D index, we seek a significant knee (the significant peak in Dindex
##                 second differences plot) that corresponds to a significant increase of the value of
##                 the measure.
##
## *******************************************************************
## * Among all indices:
## * 4 proposed 2 as the best number of clusters
## * 2 proposed 3 as the best number of clusters
## * 8 proposed 4 as the best number of clusters
## * 3 proposed 5 as the best number of clusters
## * 1 proposed 6 as the best number of clusters
## * 5 proposed 15 as the best number of clusters
##
##                    ***** Conclusion *****
##
## * According to the majority rule, the best number of clusters is  4
##
##
## *******************************************************************

## $All.index
##        KL      CH Hartigan    CCC    Scott     Marriot    TrCovW   TraceW
## 2  0.3883 12.9207  12.3551 2.5877 363.0264 13911997237 2553.4315 317.0411
## 3  0.3814 13.6842  25.4204 1.9072 440.1236  9559850713 1654.2922 265.0596
## 4  3.7956 20.9925   9.0571 5.4259 555.6019  2875846038  702.5026 187.9847
## 5  0.9972 20.0128   8.9011 6.0732 626.1356  1518160273  563.6929 163.6817
## 6  1.8912 19.8295   5.5642 6.7570 674.7096  1035465881  397.5363 142.5362
```

```
## 7  0.5562 18.6881   8.6302 6.8218  713.6353   774370946  351.8538 130.2524
## 8  1.3731 19.2962   6.8707 7.8378  773.6406   401800021  256.0183 113.3816
## 9  1.3054 19.4312   5.6523 8.4255  821.4176   243834537  187.1099 101.1850
## 10 1.3948 19.2928   4.3904 8.7362  867.9183   147203472  152.6398  91.9083
## 11 1.1455 18.8397   3.9477 8.7416  907.4463    96961404  129.8641  85.1141
## 12 0.9719 18.3910   4.0353 8.6853  935.3844    75077386  106.0332  79.3156
## 13 0.8223 18.1296   4.8131 8.7214  965.4181    55509159   88.7523  73.7040
## 14 1.1920 18.2955   4.2511 9.0531  991.5743    43049889   73.2914  67.4599
## 15 1.2670 18.3416   3.5485 9.2532 1036.6613    24697458   64.3842  62.2694
##    Friedman   Rubin Cindex     DB Silhouette   Duda Pseudot2   Beale Ratkowsky
## 2  474.1703  2.0505 0.2210 1.9433     0.1817 0.7968  10.4568  1.4951    0.2700
## 3  531.4995  2.4526 0.2011 1.8086     0.1960 1.0665  -1.6830 -0.3609    0.2980
## 4  544.3378  3.4582 0.3426 1.2290     0.2243 0.7129  10.4715  2.3289    0.2933
## 5  608.6435  3.9717 0.3089 1.1433     0.2397 0.4977  12.1126  5.5951    0.3139
## 6  619.1856  4.5609 0.2926 1.0923     0.2419 0.7291   7.4314  2.1250    0.3023
## 7  635.0339  4.9910 0.2841 1.2445     0.2118 1.3568  -5.2600 -1.5041    0.2869
## 8  646.2607  5.7337 0.3852 1.1287     0.2372 0.7251   7.2019  2.1624    0.2780
## 9  688.6921  6.4248 0.3854 1.1520     0.2286 0.5549   8.0228  4.3797    0.2673
## 10 707.5520  7.0733 0.3755 1.0662     0.2215 0.5265   7.1948  4.8005    0.2574
## 11 716.4159  7.6379 0.3635 1.0335     0.2291 0.7197   4.6729  2.1585    0.2521
## 12 724.0598  8.1963 0.3411 1.0730     0.2248 0.5408   6.7938  4.5329    0.2434
## 13 744.4823  8.8203 0.3242 1.0469     0.2356 0.5837   2.8526  3.4259    0.2362
## 14 756.5697  9.6367 0.3447 1.0386     0.2420 8.1930  -4.3897 -4.3934    0.2295
## 15 772.6338 10.4400 0.3486 0.9885     0.2570 3.1208  -1.3591 -2.7205    0.2230
##        Ball Ptbiserial    Frey McClain   Dunn Hubert SDindex Dindex   SDbw
## 2  158.5206     0.1661 -0.0183  0.7077 0.0987 0.0026  2.7495 1.8758 1.2264
## 3   88.3532     0.2527 -0.4439  1.4106 0.1033 0.0035  2.5346 1.7136 0.9173
## 4   46.9962     0.3661  0.2515  1.3011 0.1918 0.0092  2.0181 1.5629 0.3983
## 5   32.7363     0.3812  0.0828  1.6504 0.1918 0.0094  1.9970 1.4687 0.3693
## 6   23.7560     0.3932  2.1401  1.7577 0.1918 0.0097  2.0985 1.3617 0.3098
## 7   18.6075     0.3464 -0.1014  2.4649 0.1918 0.0100  2.5808 1.2898 0.2891
## 8   14.1727     0.3759  0.4820  2.4516 0.2717 0.0107  2.2849 1.2220 0.2419
## 9   11.2428     0.3489  0.2747  3.3008 0.2527 0.0113  2.3459 1.1645 0.2353
## 10   9.1908     0.3421  0.4000  3.6580 0.2597 0.0114  2.3922 1.1085 0.2164
## 11   7.7376     0.3339  0.4312  3.9643 0.2597 0.0115  2.4080 1.0620 0.1994
## 12   6.6096     0.3146  0.2876  4.7289 0.2597 0.0120  2.6006 1.0212 0.1949
## 13   5.6695     0.3051  0.0423  5.2169 0.2597 0.0122  2.6006 0.9825 0.1866
## 14   4.8186     0.3079  0.0437  5.3009 0.2867 0.0122  2.6004 0.9504 0.1820
## 15   4.1513     0.3099  0.0593  5.3619 0.3011 0.0124  2.5316 0.9121 0.1601
##
## $All.CriticalValues
##    CritValue_Duda CritValue_PseudoT2 Fvalue_Beale
## 2          0.7098            16.7607       0.1478
## 3          0.6621            13.7821       1.0000
## 4          0.6573            13.5542       0.0158
## 5          0.5447            10.0311       0.0000
## 6          0.6225            12.1297       0.0296
## 7          0.6225            12.1297       1.0000
## 8          0.6153            11.8814       0.0269
## 9          0.5139             9.4601       0.0001
## 10         0.4742             8.8696       0.0001
## 11         0.5447            10.0311       0.0305
## 12         0.4742             8.8696       0.0001
## 13         0.3418             7.7024       0.0039
## 14         0.3854             7.9739       1.0000
## 15         0.2098             7.5336       1.0000
```

```
##
## $Best.nc
##                     KL      CH Hartigan     CCC    Scott    Marriot   TrCovW
## Number_clusters 4.0000  4.0000   4.0000 15.0000   4.0000          4   4.0000
## Value_Index     3.7956 20.9925  16.3633  9.2532 115.4783 5326318910 951.7895
##                  TraceW Friedman   Rubin Cindex      DB Silhouette   Duda
## Number_clusters  4.0000   5.0000  4.0000 3.0000 15.0000     15.000 2.0000
## Value_Index     52.7719  64.3057 -0.4921 0.2011  0.9885      0.257 0.7968
##                 PseudoT2  Beale Ratkowsky    Ball PtBiserial Frey McClain
## Number_clusters   2.0000 2.0000    5.0000  3.0000     6.0000    1  2.0000
## Value_Index      10.4568 1.4951    0.3139 70.1674     0.3932   NA  0.7077
##                    Dunn Hubert SDindex Dindex    SDbw
## Number_clusters 15.0000      0   5.000      0 15.0000
## Value_Index      0.3011      0   1.997      0  0.1601
##
## $Best.partition
##             Afghanistan                   Angola               Bangladesh
##                       1                        2                        2
##                   Benin                   Bhutan                  Bolivia
##                       1                        3                        2
##                Botswana             Burkina Faso                  Burundi
##                       3                        1                        1
##                Cambodia                 Cameroon Central African Republic
##                       3                        1                        1
##                    Chad                  Comoros          Congo Dem. Rep.
##                       1                        2                        1
##              Congo Rep.            Cote d'Ivoire                    Egypt
##                       2                        1                        2
##       Equatorial Guinea                  Eritrea                     Fiji
##                       2                        2                        3
##                   Gabon                   Gambia                    Ghana
##                       2                        2                        2
##                  Guinea            Guinea-Bissau                   Guyana
##                       1                        1                        3
##                   Haiti                    India                     Iraq
##                       1                        2                        2
##                   Kenya                 Kiribati          Kyrgyz Republic
##                       2                        3                        3
##                     Lao                  Lesotho                  Liberia
##                       2                        3                        3
##              Madagascar                   Malawi                     Mali
##                       2                        1                        1
##              Mauritania    Micronesia Fed. Sts.               Mozambique
##                       2                        3                        1
##                 Myanmar                  Namibia                    Nepal
##                       2                        3                        2
##                   Niger                  Nigeria                 Pakistan
##                       1                        4                        2
##             Philippines                   Rwanda                  Senegal
##                       2                        1                        2
##            Sierra Leone          Solomon Islands             South Africa
##                       1                        3                        3
##                   Sudan               Tajikistan                 Tanzania
##                       2                        2                        1
##             Timor-Leste                     Togo             Turkmenistan
##                       2                        1                        2
```

```
##                  Uganda           Uzbekistan               Vanuatu
##                       1                    2                     3
##                   Yemen               Zambia
##                       2                    1
```

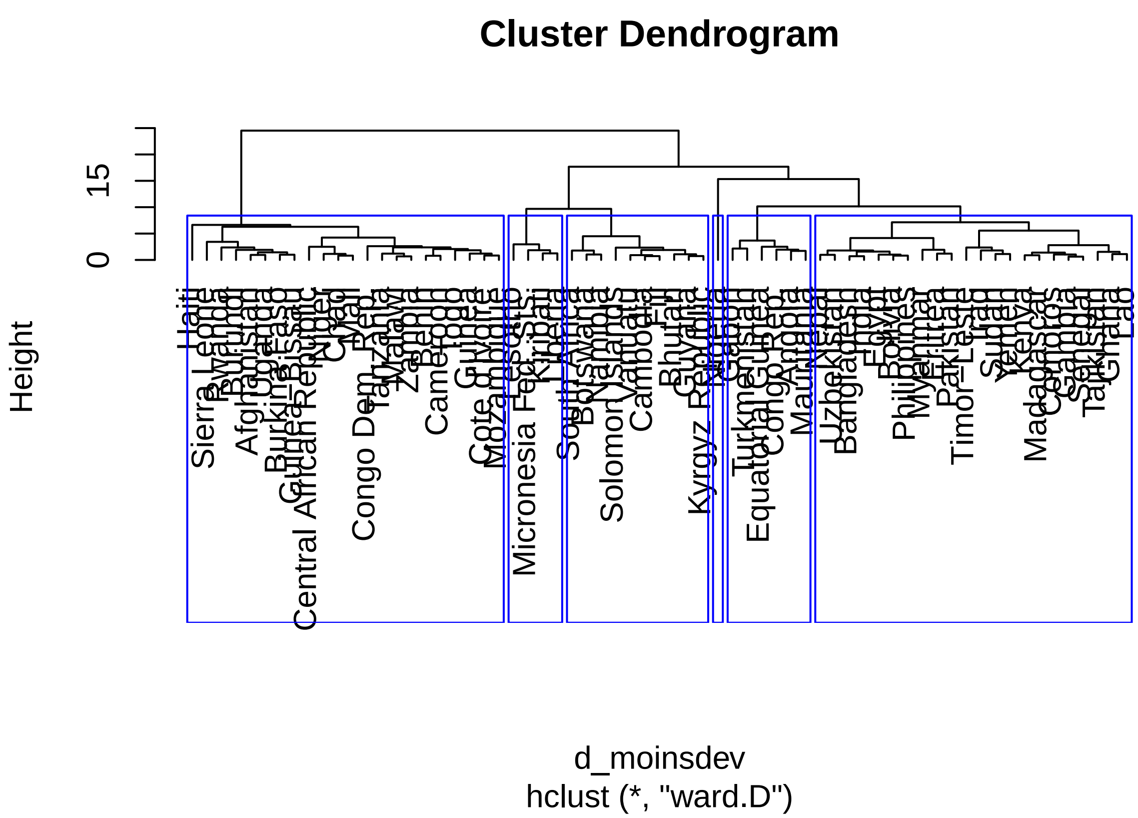
C'est aussi une partition en 6 groupes qui obtient un vote majoritaire, nous confortant dans notre premier choix. Néanmoins, on peut déjà observé la variabilité des réponses apportées par les différents critères. Cela souligne l'importance de garder une inspection visuelle de la courbe d'inertie/dendrogramme.

- Partition en 6 groupes

```
K=6
gpe.ward.moinsdev = cutree(cah.ward.moinsdev,k=K)
```

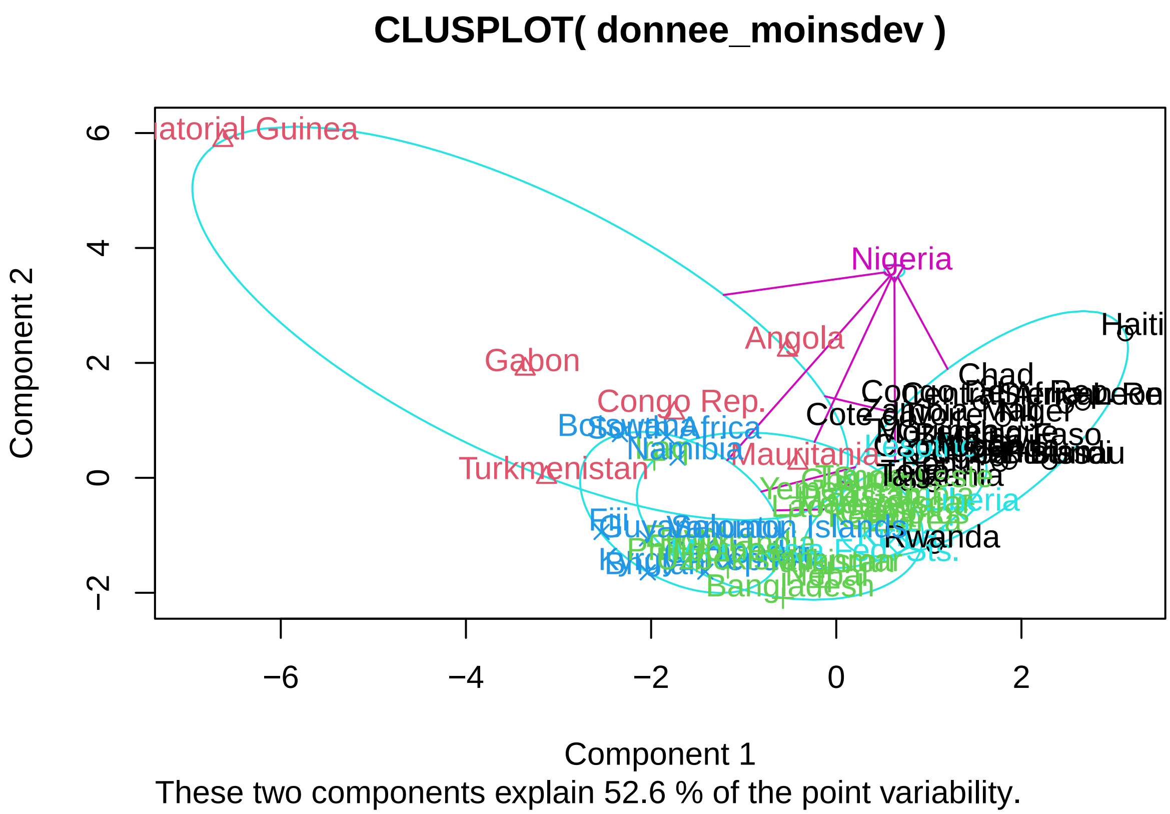
- Representation du dendogramme avec les différents groupes obtenus

```
plot(cah.ward.moinsdev,hang=-1)
rect.hclust(cah.ward.moinsdev, K, border ="blue")
```

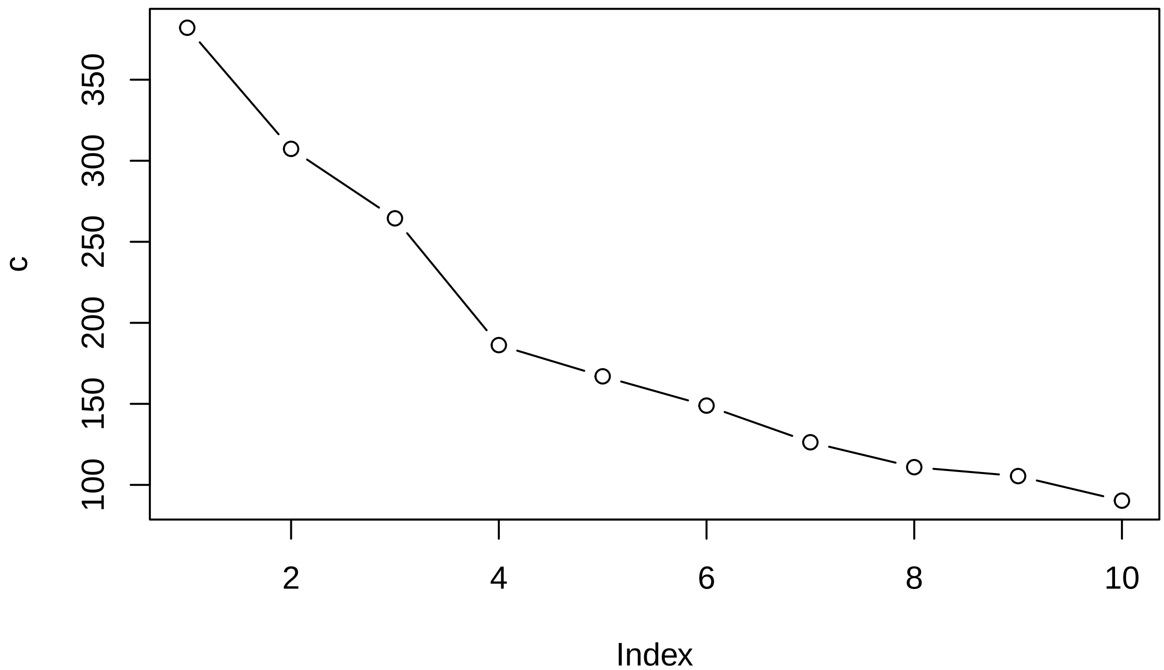


- Clusplot

```
clusplot(donnee_moinsdev, gpe.ward.moinsdev, labels = nbc, col.p = as.numeric(gpe.ward.moinsdev))
```

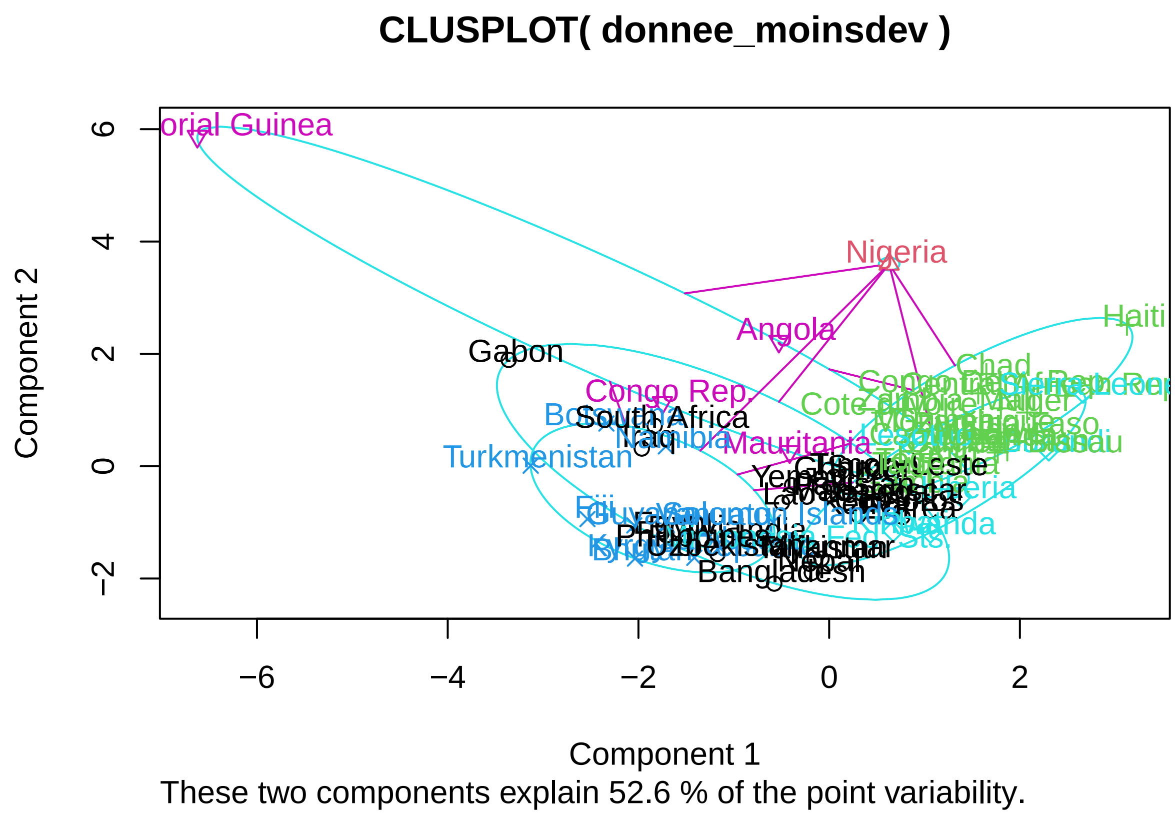

CLUSPLOT(donnee_moinsdev)
Component 2
Component 1
These two components explain 52.6 % of the point variability.
Nigeria
Haiti
Angola
Gabon
Chad
Congo Rep.
Botswana
South Africa
Namibia
Mauritania
Turkmenistan
Rwanda
Bangladesh
Nepal
Fiji
Guyana
Vanuatu
Solomon Islands

3.2 Avec les kmeans :



A la vue de ce graphique, on aurait tendance à choisir K= 5 ou 6 groupes en appliquant la méthode dite « du coude ». Ayant, grâce à la CAH, choisi de garder K=3, nous allons conserver ce nombre pour les k-means. Ce graphique nous conforome tout de même dans notre idée.

```
K=6
cl = kmeans(donnee_moinsdev,K,nstart=50)
gpe = cl$cluster
clusplot(donnee_moinsdev,gpe,labels=3,col.p=gpe)
```




```
donnee_moinsdev

##                          enfant_mort       exports       sant.     imports
## Afghanistan               1.28765971 -1.1348666486  0.27825140 -0.08220771
## Angola                    2.00178723  0.7730561847 -1.44372888 -0.16481961
## Bangladesh                0.27597905 -0.9159844880 -1.19981201 -1.03637509
## Benin                     1.80341848 -0.6314376792 -0.98866010 -0.40026351
## Bhutan                    0.10984521  0.0507450547 -0.58819957  0.98348572
## Bolivia                   0.20654998  0.0033205866 -0.71925938 -0.52005075
## Botswana                  0.35284694  0.0908734508  0.54037102  0.18215035
## Burkina Faso              1.92739895 -0.7992473357 -0.02755482 -0.71418870
## Burundi                   1.37196643 -1.1742654376  1.74175261 -0.31765161
## Cambodia                  0.15199858  0.4739172319 -0.41345315  0.52085911
## Cameroon                  1.72903019 -0.6898062554 -0.61368342 -0.82158417
## Central African Republic  2.74567007 -1.0692020005 -1.03234670 -0.84223714
## Chad                      2.77046617 -0.1571929979 -0.83211643 -0.14003604
## Comoros                   1.23806752 -0.8977443080 -0.83939753  0.19867273
## Congo Dem. Rep.           1.92739895 -0.0003274495  0.39838956  0.11193024
## Congo Rep.                0.63552242  1.6048083951 -1.58571034  0.32259057
## Cote d'Ivoire             1.80341848  0.3462359715 -0.55179406 -0.14829723
## Egypt                    -0.22738167 -0.7226385795 -0.78478928 -0.83810654
## Equatorial Guinea         1.80341848  1.6303446471 -0.85031919  0.49607554
## Eritrea                   0.41979640 -1.3249293248 -1.51289933 -0.97441617
## Fiji                     -0.35136215  0.6088945643 -0.71197827  0.70260528
## Gabon                     0.63056320  0.6052465282 -1.20709311 -1.15616234
## Gambia                    1.04217837 -0.6314376792 -0.40981260 -0.17308080
## Ghana                     0.90332024 -0.4234996266 -0.58091846 -0.04090177
## Guinea                    1.75382629 -0.3943153386 -0.68649442 -0.15242782
```

```
## Guinea-Bissau            1.87780676 -0.9561128841  0.61318202 -0.48287540
## Guyana                  -0.01661487  0.3754202596 -0.52266966  1.33045567
## Haiti                    4.20863965 -0.9415207401  0.03433453  0.73565004
## India                    0.50906234 -0.6752141114 -1.00686285 -0.81745357
## Iraq                    -0.03397213 -0.0623440616  0.58041707 -0.52831194
## Kenya                    0.59336906 -0.7445267956 -0.75202433 -0.54896492
## Kiribati                 0.60576711 -1.0144814603  1.63253610  1.36350043
## Kyrgyz Republic         -0.21498363  0.3827163316 -0.23142564  1.43785114
## Lao                      1.00746384 -0.2082655020 -0.85395974  0.09953845
## Lesotho                  1.52322261 -0.0623440616  1.55972509  2.23505591
## Liberia                  1.26534322 -0.8028953717  1.81456361  1.88808596
## Madagascar               0.59336906 -0.5876612471 -1.10879825 -0.16068901
## Malawi                   1.29509854 -0.6679180393 -0.08216308 -0.49526718
## Mali                     2.44811694 -0.6679180393 -0.66829167 -0.48700600
## Mauritania               1.46619159  0.3498840075 -0.87580304  0.59107922
## Micronesia Fed. Sts.     0.04289576 -0.6423817873  2.68829568  1.40893697
## Mozambique               1.55545753 -0.3505389064 -0.58455902 -0.02850998
## Myanmar                  0.64792047 -1.4956938904 -1.76409730 -1.93412267
## Namibia                  0.43963327  0.2440909632 -0.01299262  0.57042625
## Nepal                    0.21646842 -1.1501883999 -0.56999681 -0.43330826
## Niger                    2.10097161 -0.6898062554 -0.60276177  0.09127726
## Nigeria                  2.27454427 -0.5767171391 -0.63552672 -1.21812126
## Pakistan                 1.33477229 -1.0071853883 -1.68036465 -1.13550936
## Philippines             -0.15795261 -0.2301537181 -1.16704706 -0.42504707
## Rwanda                   0.62808359 -1.0619059284  1.34129208 -0.69766632
## Senegal                  0.70743109 -0.5913092831 -0.42073425 -0.27221507
## Sierra Leone             3.01842711 -0.8868002000  2.28783515 -0.51178956
## Solomon Islands         -0.25217777  0.2988115034  0.63138478  1.41719816
## South Africa             0.38260226 -0.4563319507  0.77336624 -0.80506179
## Sudan                    0.95291243 -0.7810071557 -0.18045794 -1.22638245
## Tajikistan               0.35036733 -0.9561128841 -0.30423664  0.48368376
## Tanzania                 0.83389118 -0.8174875158 -0.29331499 -0.73484168
## Timor-Leste              0.60328750 -1.4194134574  0.83889614 -0.78853941
## Togo                     1.29013932 -0.0331597736  0.30373525  0.42998603
## Turkmenistan             0.58840984  1.2837812262 -1.57114814 -0.09873009
## Uganda                   1.05953564 -0.8758560919  0.79885009 -0.75549465
## Uzbekistan              -0.04884979 -0.3432428344 -0.36612600 -0.75962525
## Vanuatu                 -0.22490206  0.2003145311 -0.56999681  0.23997867
## Yemen                    0.44707210 -0.4052594466 -0.59548067 -0.51592016
## Zambia                   1.11160744 -0.1498969259 -0.33700160 -0.66049097
##                              revenu   inflation    esper_vie        fert
## Afghanistan             -0.80582187  0.15686445 -1.614237166  1.89717646
## Angola                  -0.58328920  1.38289444 -1.175698472  2.12176975
## Bangladesh              -0.76276777 -0.06071803 -0.017506535 -0.40820760
## Benin                   -0.79492867 -0.65244778 -0.984540579  1.59331495
## Bhutan                  -0.55631554 -0.16950927  0.173651358 -0.37517917
## Bolivia                 -0.60870668  0.09442774  0.117428448  0.16648699
## Botswana                -0.19943330  0.10767189 -1.513035929 -0.04489492
## Burkina Faso            -0.81515891 -0.09193639 -1.423079274  1.93020489
## Burundi                 -0.84970594  0.42742354 -1.445568438  2.18782660
## Cambodia                -0.75861797 -0.44101437 -0.501023557 -0.04489492
## Cameroon                -0.75135583 -0.55548168 -1.490546765  1.42817283
## Central African Republic -0.84327376 -0.54602157 -2.592515793  1.49422968
## Chad                    -0.78922270 -0.13166884 -1.580503421  2.40581421
## Comoros                 -0.81619636 -0.37006356 -0.523512721  1.19036817
## Congo Dem. Rep.         -0.85774616  1.23153271 -1.468057602  2.37278578
```

```
## Congo Rep.              -0.62011861  1.22207261 -1.141964726  1.32248187
## Cote d'Ivoire           -0.74979966 -0.22626992 -1.602992585  1.53386379
## Egypt                   -0.37787442  0.21930116 -0.006261953  0.15988131
## Equatorial Guinea        0.85876404  1.61939714 -1.085741816  1.49422968
## Eritrea                 -0.81567763  0.36120278 -0.995785161  1.09788858
## Fiji                    -0.50807419 -0.33600717 -0.590980212 -0.18361431
## Gabon                   -0.09050122  0.83420818 -0.860850178  0.74778727
## Gambia                  -0.80322825 -0.32938510 -0.568491048  1.82451393
## Ghana                   -0.73060687  0.83420818 -0.939562252  0.87329529
## Guinea                  -0.82760829  0.78690764 -1.411834692  1.58010358
## Guinea-Bissau           -0.81723381 -0.45520453 -1.681704658  1.38853872
## Guyana                  -0.58640154 -0.19410555 -0.568491048 -0.19682568
## Haiti                   -0.81152784 -0.22059386 -4.324181408  0.25236090
## India                   -0.66057910  0.11334795 -0.489778975 -0.22985410
## Iraq                    -0.23055675  0.83420818 -0.377333156  1.06486015
## Kenya                   -0.76069287 -0.53845348 -0.872094760  0.93935214
## Kiribati                -0.79959718 -0.59237610 -1.108230980  0.58925083
## Kyrgyz Republic         -0.74461242  0.20984106 -0.231153591  0.10043014
## Lao                     -0.68288424  0.13416019 -0.759648941  0.13345857
## Lesotho                 -0.76588011 -0.34357526 -2.704961612  0.23254384
## Liberia                 -0.85302577 -0.21870183 -1.096986398  1.36872166
## Madagascar              -0.81723381  0.09537375 -1.096986398  1.09128289
## Malawi                  -0.83590788  0.40850332 -1.962819206  1.56028653
## Mali                    -0.79233504 -0.32276302 -1.243165963  2.37939147
## Mauritania              -0.71712004  1.05179066 -0.264887337  1.34229892
## Micronesia Fed. Sts.    -0.71608259 -0.37668564 -0.579735630  0.33823480
## Mozambique              -0.84171759 -0.01341749 -1.805395059  1.72542865
## Myanmar                 -0.69637107 -0.07017814 -0.422311484 -0.35536212
## Namibia                 -0.45049580 -0.39938990 -1.344367201  0.43071439
## Nepal                   -0.78611035  0.69230656 -0.253642755 -0.22324842
## Niger                   -0.84711232 -0.49493699 -1.321878037  3.00032586
## Nigeria                 -0.62219351  9.10234253 -1.130720144  1.91038783
## Pakistan                -0.66732252  0.29498203 -0.590980212  0.59585652
## Philippines             -0.59885092 -0.33695318 -0.174930682  0.14006425
## Rwanda                  -0.81930870 -0.48926092 -0.669692286  1.03183173
## Senegal                 -0.77625459 -0.56115774 -0.737159777  1.39514440
## Sierra Leone            -0.82605212  0.89096883 -1.749172149  1.48762399
## Solomon Islands         -0.79700356 -0.09193639 -0.995785161  0.85347823
## South Africa            -0.26686744 -0.13545288 -1.827884223 -0.23645979
## Sudan                   -0.71452642  1.11801142 -0.478534393  1.27624207
## Tajikistan              -0.77988566  0.44634375 -0.107463190  0.37126323
## Tanzania                -0.78092311  0.13889025 -1.265655127  1.63955475
## Timor-Leste             -0.79337249  1.77075887  0.061205539  2.16800955
## Togo                    -0.82657084 -0.62454047 -1.333122619  1.26963639
## Turkmenistan            -0.37372463 -0.51764125 -0.298621083 -0.07792335
## Uganda                  -0.80945294  0.26660170 -1.546769675  2.11516407
## Uzbekistan              -0.66939741  0.82474807 -0.197419845 -0.40160191
## Vanuatu                 -0.73631283 -0.48831491 -0.849605596  0.36465754
## Yemen                   -0.65694803  1.49641574 -0.343599410  1.13752269
## Zambia                  -0.71919493  0.58824537 -2.086509607  1.61973769
##                              pib_h
## Afghanistan             -0.6771431
## Angola                  -0.5147203
## Bangladesh              -0.6659584
## Benin                   -0.6659584
## Bhutan                  -0.5883752
```

```
## Bolivia                   -0.5992871
## Botswana                  -0.3608632
## Burkina Faso              -0.6759428
## Burundi                   -0.6947112
## Cambodia                  -0.6644308
## Cameroon                  -0.6358417
## Central African Republic -0.6829809
## Chad                      -0.6583747
## Comoros                   -0.6653583
## Congo Dem. Rep.           -0.6890916
## Congo Rep.                -0.5578220
## Cote d'Ivoire             -0.6407521
## Egypt                     -0.5654603
## Equatorial Guinea          0.2256485
## Eritrea                   -0.6810168
## Fiji                      -0.5081732
## Gabon                     -0.2299211
## Gambia                    -0.6766521
## Ghana                     -0.6358417
## Guinea                    -0.6719600
## Guinea-Bissau             -0.6774704
## Guyana                    -0.5414543
## Haiti                     -0.6711961
## India                     -0.6336594
## Iraq                      -0.4617978
## Kenya                     -0.6545556
## Kiribati                  -0.6260211
## Kyrgyz Republic           -0.6593022
## Lao                       -0.6451168
## Lesotho                   -0.6434800
## Liberia                   -0.6894735
## Madagascar                -0.6847814
## Malawi                    -0.6822717
## Mali                      -0.6686864
## Mauritania                -0.6418433
## Micronesia Fed. Sts.      -0.5512749
## Mozambique                -0.6844540
## Myanmar                   -0.6534098
## Namibia                   -0.4241519
## Nepal                     -0.6750153
## Niger                     -0.6883277
## Nigeria                   -0.5801913
## Pakistan                  -0.6505727
## Philippines               -0.5911032
## Rwanda                    -0.6765975
## Senegal                   -0.6527551
## Sierra Leone              -0.6855452
## Solomon Islands           -0.6369329
## South Africa              -0.3101232
## Sudan                     -0.6265667
## Tajikistan                -0.6670496
## Tanzania                  -0.6690138
## Timor-Leste               -0.5109011
## Togo                      -0.6806894
## Turkmenistan              -0.4650714
## Uganda                    -0.6748516
```

```
## Uzbekistan              -0.6320226
## Vanuatu                 -0.5452734
## Yemen                   -0.6358417
## Zambia                  -0.6276579
```

3.3 Interprétation des groupes

Nous allons maintenant chercher à interpréter les groupes obtenus à l'aide de la fonction catdes.

```
gpe = cutree(cah.ward.moinsdev,k=6)
gpe
```

```
##              Afghanistan                   Angola               Bangladesh
##                        1                        2                        3
##                    Benin                   Bhutan                  Bolivia
##                        1                        4                        3
##                 Botswana             Burkina Faso                  Burundi
##                        4                        1                        1
##                 Cambodia                 Cameroon Central African Republic
##                        4                        1                        1
##                     Chad                  Comoros          Congo Dem. Rep.
##                        1                        3                        1
##               Congo Rep.            Cote d'Ivoire                    Egypt
##                        2                        1                        3
##        Equatorial Guinea                  Eritrea                     Fiji
##                        2                        3                        4
##                    Gabon                   Gambia                    Ghana
##                        2                        3                        3
##                   Guinea            Guinea-Bissau                   Guyana
##                        1                        1                        4
##                    Haiti                    India                     Iraq
##                        1                        3                        3
##                    Kenya                 Kiribati          Kyrgyz Republic
##                        3                        5                        4
##                      Lao                  Lesotho                  Liberia
##                        3                        5                        5
##               Madagascar                   Malawi                     Mali
##                        3                        1                        1
##               Mauritania    Micronesia Fed. Sts.               Mozambique
##                        2                        5                        1
##                  Myanmar                  Namibia                    Nepal
##                        3                        4                        3
##                    Niger                  Nigeria                 Pakistan
##                        1                        6                        3
##              Philippines                   Rwanda                  Senegal
##                        3                        1                        3
##             Sierra Leone          Solomon Islands             South Africa
##                        1                        4                        4
##                    Sudan               Tajikistan                 Tanzania
##                        3                        3                        1
##              Timor-Leste                     Togo             Turkmenistan
##                        3                        1                        2
##                   Uganda               Uzbekistan                  Vanuatu
##                        1                        3                        4
##                    Yemen                   Zambia
##                        3                        1
```

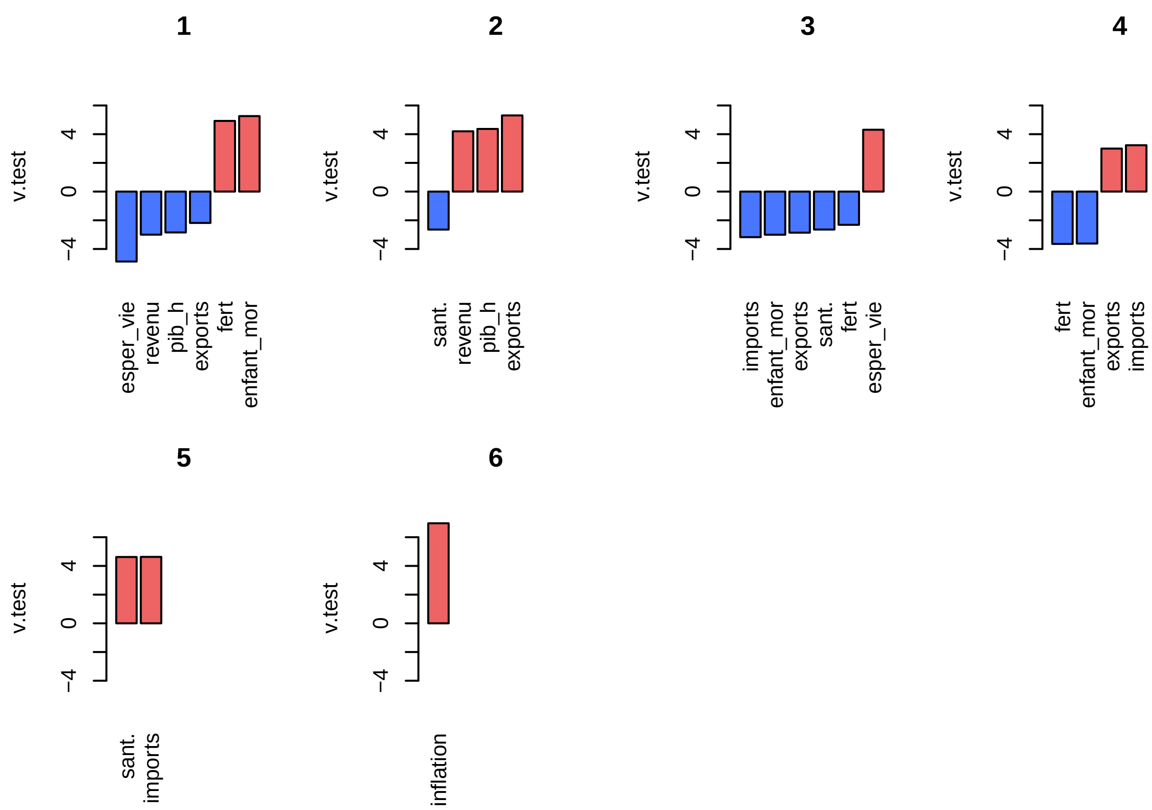
```
donnee_moinsdev$gpecah = as.factor(gpe)
interpcah_moinsdev = catdes(donnee_moinsdev,num.var = 10)
interpcah_moinsdev

##
## Link between the cluster variable and the quantitative variables
## ================================================================
##                  Eta2      P-value
## inflation   0.8277805 2.843357e-21
## exports     0.6632833 8.049063e-13
## imports     0.6101392 5.390651e-11
## enfant_mort 0.5882342 2.567210e-10
## sant.       0.5186260 2.154148e-08
## fert        0.5140868 2.806410e-08
## esper_vie   0.4686508 3.443915e-07
## pib_h       0.4190328 4.103777e-06
## revenu      0.3879273 1.718424e-05
##
## Description of each cluster by quantitative variables
## =====================================================
## $`1`
##                v.test Mean in category Overall mean sd in category Overall sd
## enfant_mort  5.261392        1.8430922    1.0052894     0.79735402  0.9111885
## fert         4.925025        1.7224261    0.9839659     0.55035786  0.8579969
## exports     -2.186203       -0.6274248   -0.3685552     0.40605966  0.6775757
## pib_h       -2.849173       -0.6717963   -0.6024230     0.01693266  0.1393288
## revenu      -3.003598       -0.8096345   -0.6754601     0.03448857  0.2556201
## esper_vie   -4.875814       -1.6638156   -1.0165444     0.69122515  0.7596372
##                  p.value
## enfant_mort 1.429687e-07
## fert        8.434950e-07
## exports     2.880075e-02
## pib_h       4.383308e-03
## revenu      2.668077e-03
## esper_vie   1.083606e-06
##
## $`2`
##            v.test Mean in category Overall mean sd in category Overall sd
## exports  5.307884        1.0411868   -0.3685552      0.4938734  0.6775757
## pib_h    4.366455       -0.3639549   -0.6024230      0.2925059  0.1393288
## revenu   4.202999       -0.2543316   -0.6754601      0.5379379  0.2556201
## sant.   -2.648928       -1.2556338   -0.2535490      0.3040798  0.9651035
##              p.value
## exports 1.109051e-07
## pib_h   1.262793e-05
## revenu  2.634019e-05
## sant.   8.074750e-03
##
## $`3`
##                v.test Mean in category Overall mean sd in category Overall sd
## esper_vie    4.310725       -0.4442895   -1.0165444      0.3459917  0.7596372
## fert        -2.316082        0.6366917    0.9839659      0.7296534  0.8579969
## sant.       -2.646476       -0.6998983   -0.2535490      0.6137348  0.9651035
## exports     -2.864561       -0.7077496   -0.3685552      0.4090737  0.6775757
## enfant_mort -3.007297        0.5264196    1.0052894      0.4282767  0.9111885
## imports     -3.175471       -0.5612330   -0.1108258      0.5264829  0.8116414
##                  p.value
```

```
## esper_vie   1.627198e-05
## fert        2.055378e-02
## sant.       8.133517e-03
## exports     4.175879e-03
## enfant_mort 2.635821e-03
## imports     1.495932e-03
##
## $`4`
##                v.test Mean in category Overall mean sd in category Overall sd
## imports      3.231242       0.65799486   -0.1108258      0.6567251  0.8116414
## exports      2.998008       0.22694519   -0.3685552      0.2785296  0.6775757
## enfant_mort -3.622402       0.03768858    1.0052894      0.2773539  0.9111885
## fert        -3.646689       0.06674115    0.9839659      0.3585549  0.8579969
##                  p.value
## imports     0.0012325344
## exports     0.0027175010
## enfant_mort 0.0002918801
## fert        0.0002656413
##
## $`5`
##           v.test Mean in category Overall mean sd in category Overall sd
## imports 4.630851         1.723895   -0.1108258      0.3596272  0.8116414
## sant.   4.621737         1.923780   -0.2535490      0.4510464  0.9651035
##              p.value
## imports 3.641654e-06
## sant.   3.805401e-06
##
## $`6`
##             v.test Mean in category Overall mean sd in category Overall sd
## inflation 6.971909         9.102343    0.2824583              0    1.26506
##                p.value
## inflation 3.126695e-12
```

```
head(donnee_moinsdev)
```

```
##             enfant_mort      exports      sant.     imports     revenu
## Afghanistan   1.2876597 -1.134866649  0.2782514 -0.08220771 -0.8058219
## Angola        2.0017872  0.773056185 -1.4437289 -0.16481961 -0.5832892
## Bangladesh    0.2759790 -0.915984488 -1.1998120 -1.03637509 -0.7627678
## Benin         1.8034185 -0.631437679 -0.9886601 -0.40026351 -0.7949287
## Bhutan        0.1098452  0.050745055 -0.5881996  0.98348572 -0.5563155
## Bolivia       0.2065500  0.003320587 -0.7192594 -0.52005075 -0.6087067
##               inflation   esper_vie       fert      pib_h gpecah
## Afghanistan  0.15686445 -1.61423717  1.8971765 -0.6771431      1
## Angola       1.38289444 -1.17569847  2.1217698 -0.5147203      2
## Bangladesh  -0.06071803 -0.01750653 -0.4082076 -0.6659584      3
## Benin       -0.65244778 -0.98454058  1.5933150 -0.6659584      1
## Bhutan      -0.16950927  0.17365136 -0.3751792 -0.5883752      4
## Bolivia      0.09442774  0.11742845  0.1664870 -0.5992871      3
```

```
plot.catdes(interpcah_moinsdev,barplot=T)
```




```
CCpca_moinsdev = dudi.pca(donnee_moinsdev[1:9],scannf=FALSE,nf=2)
```

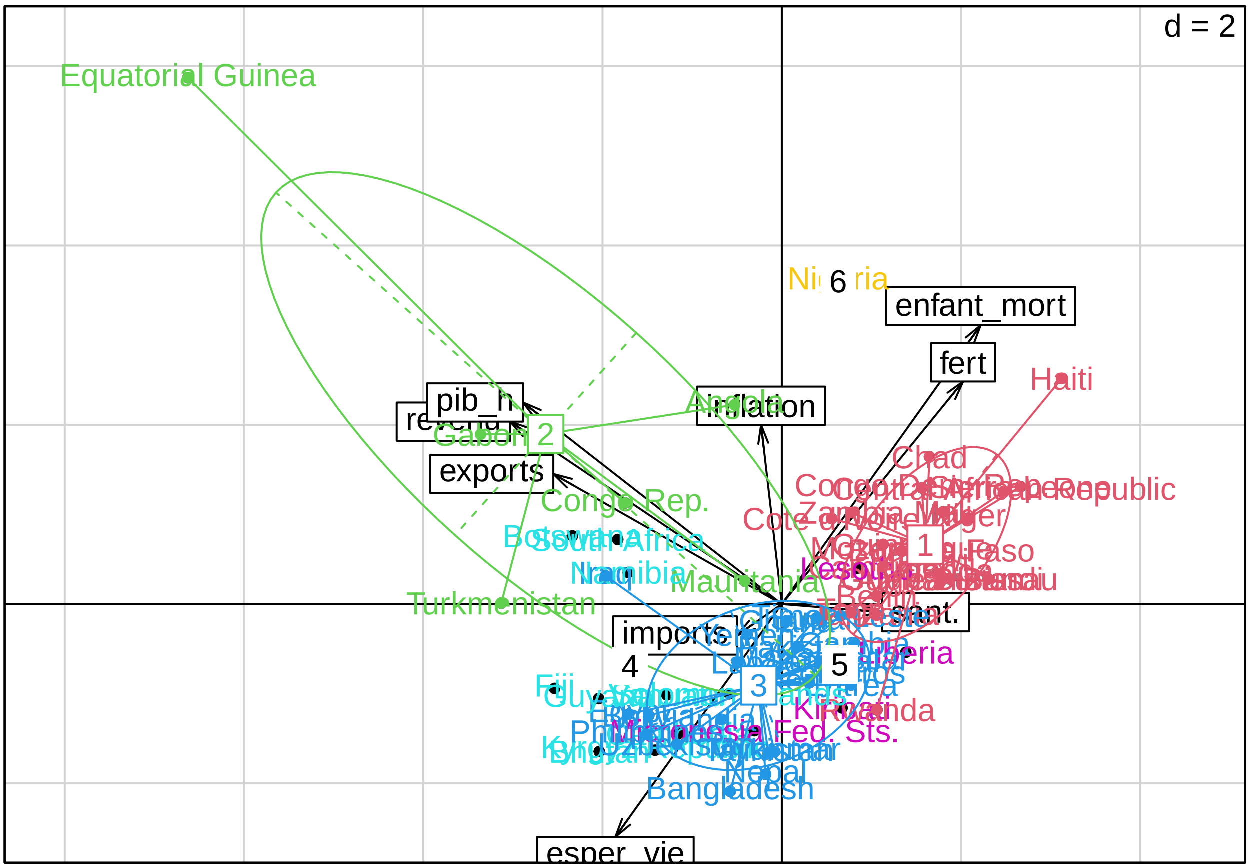
```
cumsum(CCpca_moinsdev$eig)/sum(CCpca_moinsdev$eig) # 52% de variabilité expliquée sur les deux premiers
```

```
## [1] 0.3176225 0.5259903 0.7065002 0.8096545 0.8955336 0.9556743 0.9804839
## [8] 0.9966107 1.0000000
```

```
scatter(CCpca_moinsdev,posieig = "none",clab.row=0,pch=NA)
```

```
## NULL
```

```
text(CCpca_moinsdev$li[,1], CCpca_moinsdev$li[,2],labels =row.names(donnee_moinsdev),col=gpe+1,xpd=TRUE)
s.class(CCpca_moinsdev$li, factor(gpe), col = 2:4, add.plot = TRUE,clabel = 1)
```



Tableaux repartisant les pays à aider en 6 groupes :

```
tab <- table(donnee_moinsdev$gpecah)

# Ajouter les marges au tableau
tab <- addmargins(tab)

# Formater les nombres dans le tableau
tab <- format(tab, scientific = FALSE, digits = 1)

# Afficher le tableau
tab
```

```
##
##     1     2     3     4     5     6   Sum
## "22" " 6" "22" "10" " 4" " 1" "65"
```

Notons que le groupe 1 est le groupe à aider en priorité

4 Conclusion vis à vis des choix effectués

Quels points peuvent être critiqués dans votre choix Quelles pistes pourraient être exploréess pour aller plus loin et/ou mieux explorer ces données ?

Nous avons fait un premier gros choix suite à l'obtention de nos premiers résultats. En effet, nous n'avons sélectionné que le groupe dont les pays étaient en sous-devéloppement. Ce choix peut être critiqué. Cependant, ayant déjà un grand nombre de pays dans ce groupe et n'ayant "que" 10 millions de dollars à partager, nous avons décidé de ne prioriser que ce groupe.

Nous avons enusite retraité ce groupe de pays défavorisés afin de pouvoir observer les pays qui étaient le plus en difficulté. Là encore, nous avons du faire un choix : donner une grosse somme d'argent aux pays dans le besoin puis une somme d'argent plus faible aux pays qui en ont moins besoin, mais une aide sera là quand même.

5 Suggestion d'une liste de pays à aider en priorité

```
## [1] "Il y a 22 pays à aider en priorité"
```

```
## Afghanistan Benin Burkina Faso Burundi Cameroon Central African Republic Chad Congo Dem. Rep. Cote d'
```

En voici la liste :

```
# Afficher les valeurs de la colonne "x" sous forme de liste à puce
cat(paste(x_values, sep = "\n"))
```

```
## Afghanistan Benin Burkina Faso Burundi Cameroon Central African Republic Chad Congo Dem. Rep. Cote d'
```

6 Pour aller plus loin

6.1 Améliorations

6.2 Pistes