

# Les pays à aider

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

Margaux Bailleul  
Oriane Duclos

15 avril, 2023

## Contents

<b>1</b>	<b>Compréhension et pré-traitement des données</b>	<b>1</b>
1.1	Statistiques descriptives . . . . .	2
1.2	Pre-traitement . . . . .	2
<b>2</b>	<b>Classification des pays en utilisant les différents algorithmes abordés en cours</b>	<b>4</b>
2.1	CAH . . . . .	4
2.2	Algorithme des Kmeans . . . . .	20
2.3	Interprétation des groupes . . . . .	22
2.4	Visualisation des résultats obtenus (carte) . . . . .	26
<b>3</b>	<b>Traitement du groupe des pays les moins favorisés</b>	<b>29</b>
3.1	CAH sur les pays moins développés . . . . .	29
3.2	Avec les kmeans : . . . . .	38
3.3	Interprétation des groupes . . . . .	43
<b>4</b>	<b>Conclusion vis à vis des choix effectués</b>	<b>48</b>
<b>5</b>	<b>Suggestion d'une liste de pays à aider en priorité</b>	<b>48</b>
<b>6</b>	<b>Pour aller plus loin</b>	<b>51</b>
6.1	Améliorations . . . . .	51
6.2	Pistes . . . . .	51

## 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-traitement

**Donnees manquantes ? Outliers**

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

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



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

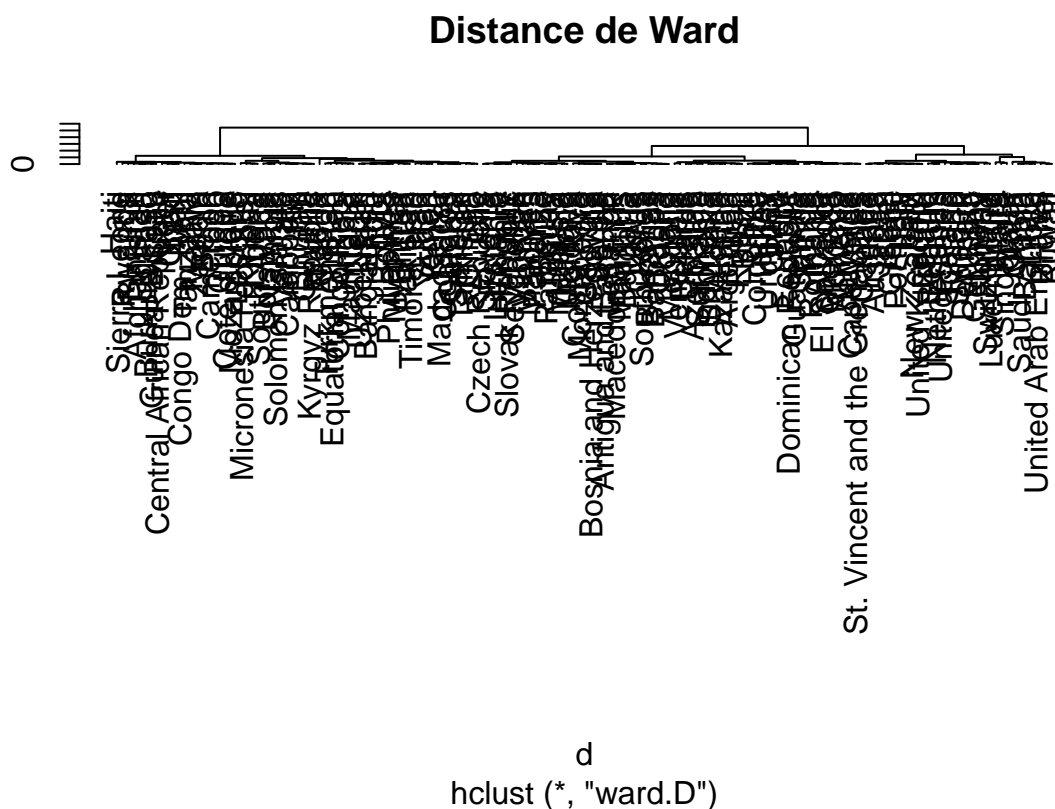
Utilisation des algorithmes de classification vus en cours . Reflexion sur les choix operer decider d'une classification finale . Nombre de groupes ?

### 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")
```

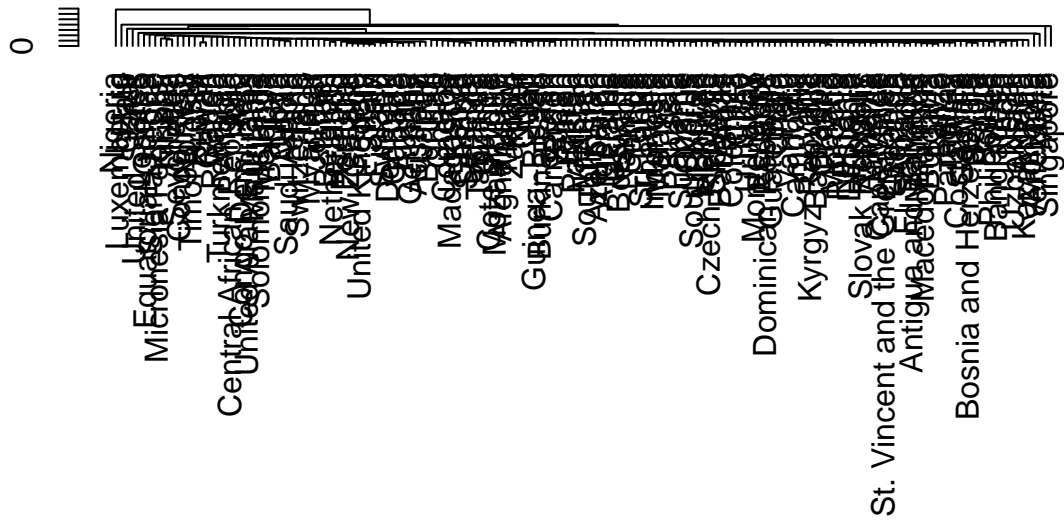
#### Dendrogrammes

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



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

## Distance du saut minimal



d  
hclust (\*, "single")

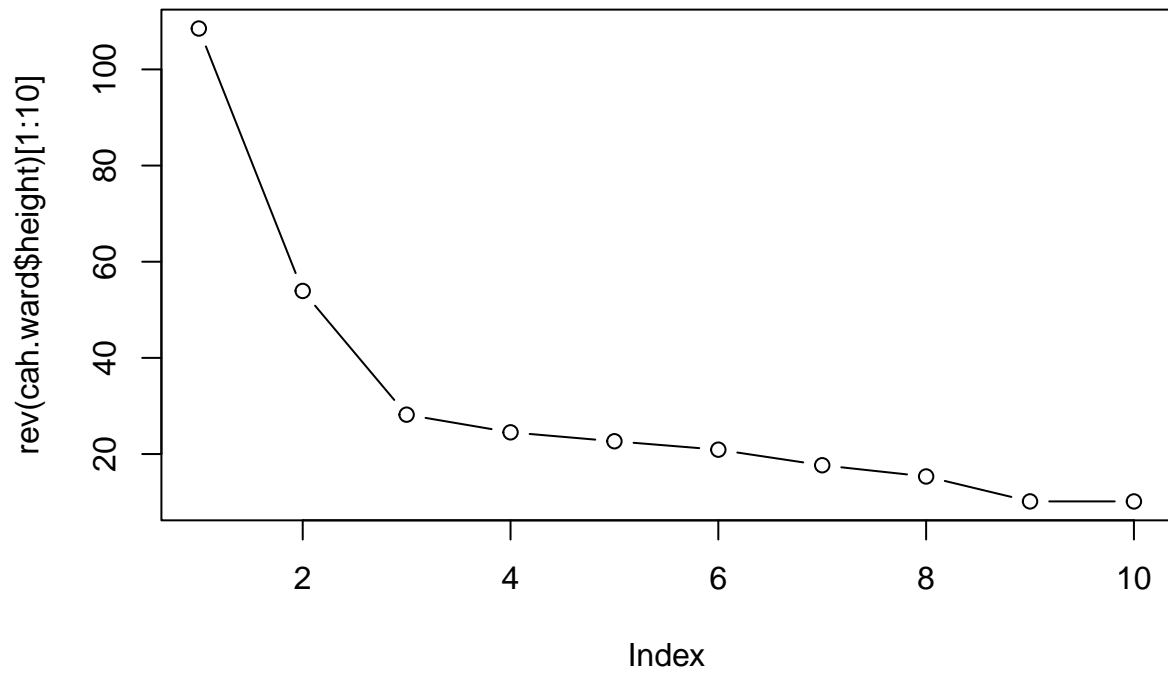
```
plot(cah.max, hang = -1, main = "Distance du saut maximal", ylab = " ")
```

A dendrogram illustrating hierarchical clustering of 48 countries. The x-axis is labeled 'd' and 'hclust (\*, "complete")'. The y-axis lists the countries: Solomon Islands, Nigeria, Cape Verde, Kyrgyz Republic, Congo, Democratic Republic of the Congo, Timor, Sao Tome and Principe, Equatorial Guinea, Madagascar, Central African Republic, Luxembourg, Slovenia, Saudi Arabia, United Arab Emirates, Costa Rica, Cuba, United Kingdom, New Zealand, Bosnia and Herzegovina, Azerbaijan, Antigua and Barbuda, Macedonia, St. Vincent and the Grenadines, Czech Republic, South Africa, Vietnam, Kazakhstan, Turkmenistan, Dominican Republic, Grenada, Uganda, Belarus, and Australia. The dendrogram shows a complex pattern of clustering, with many countries forming small groups that then merge into larger clusters. The scale on the x-axis ranges from 0 to approximately 100.

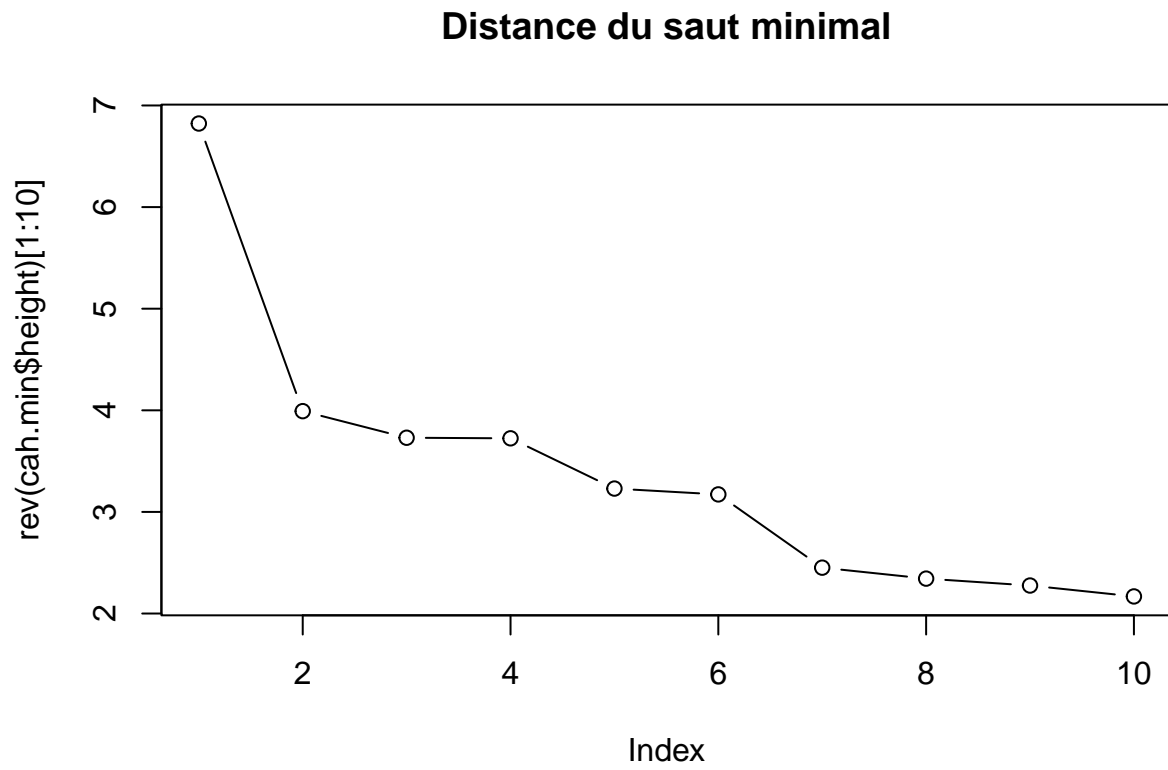
## Fonction de perte

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

## Distance de Ward



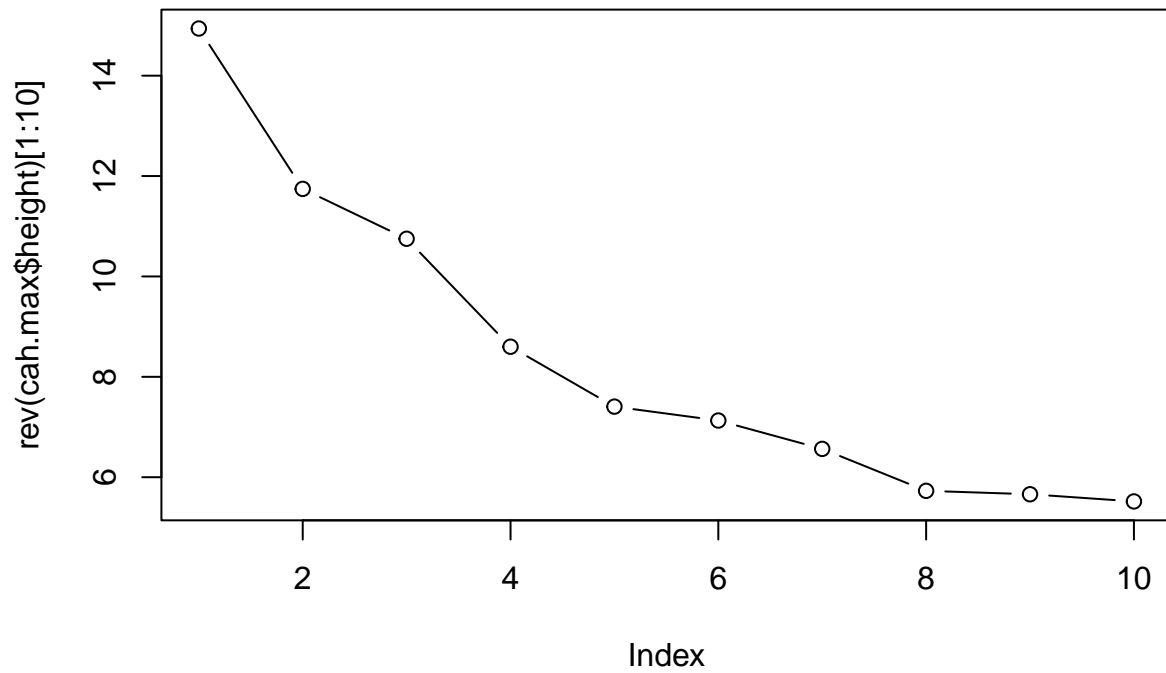
```
plot(rev(cah.min$height)[1:10], type = "b", main = "Distance du saut minimal")
```



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



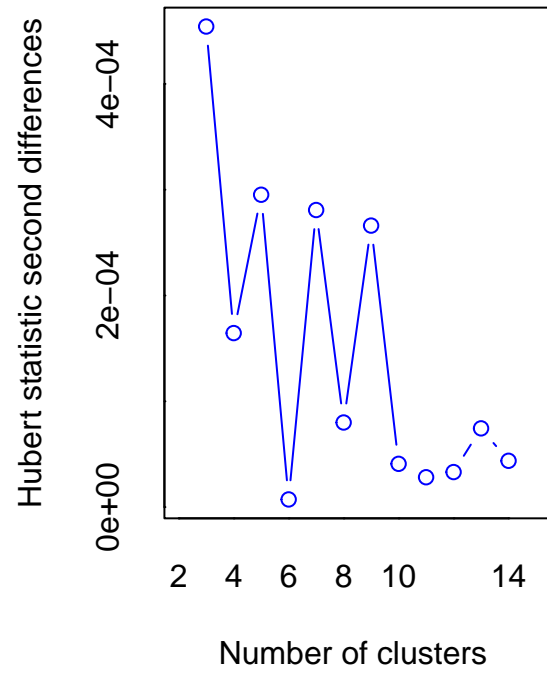
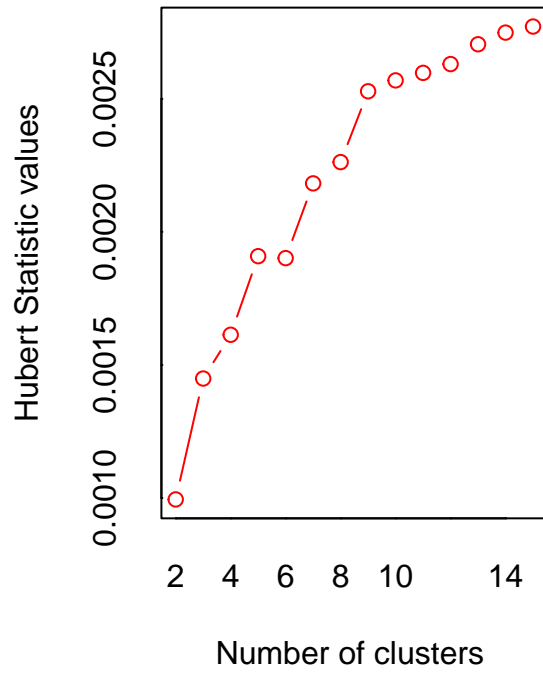
## Distance du saut maximal



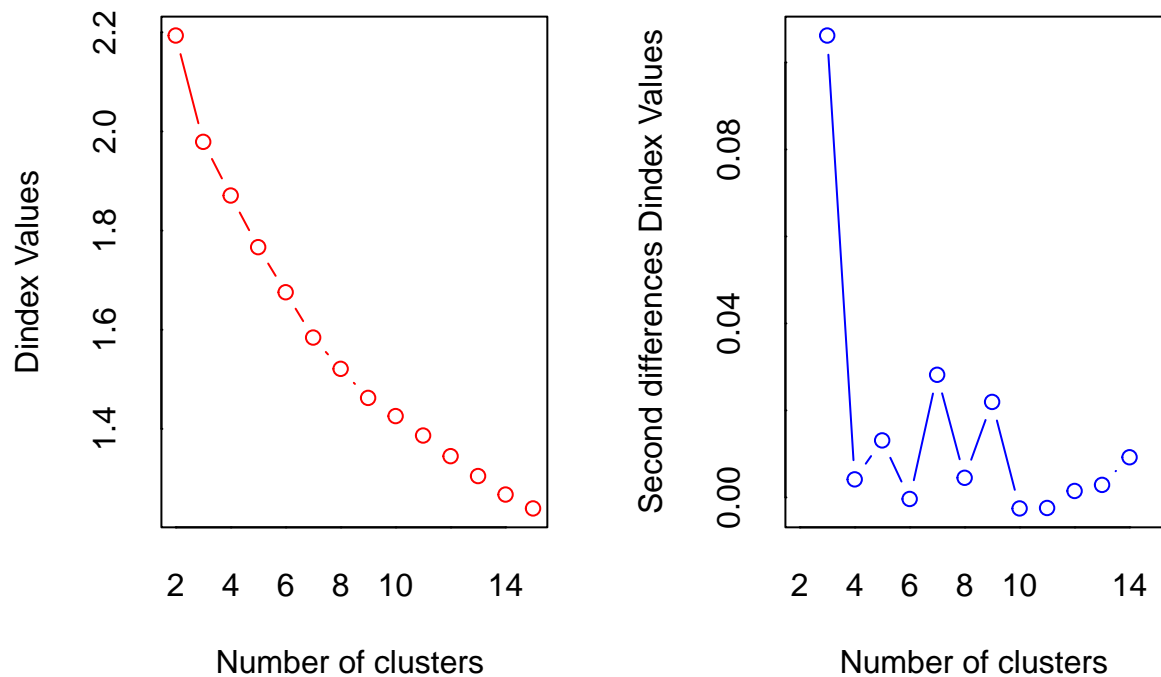
Avec le critère de Ward, la trace de la perte d'inertie nous incite à choisir des partitions en 3 groupes ("coude" très visible).

```
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	

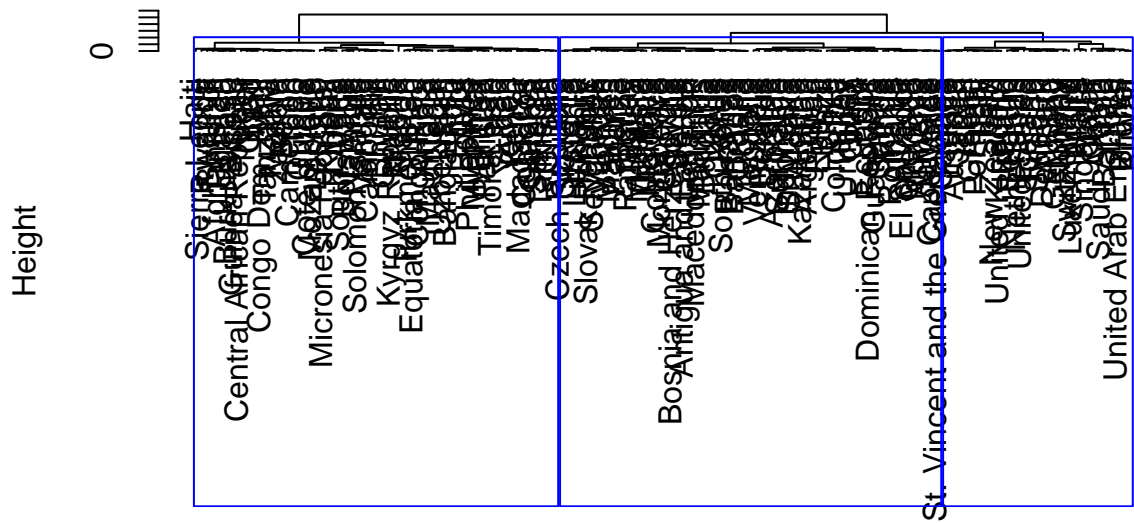
On nous dit que les meilleurs clusters sont 2 ou 4 avec 5 chacun ou 3 avec 4. Au vu de l'interprétation graphique faite précédemment, nous allons rester sur 3 clusters, qui nous semble le plus pertinent.

### Cutree

```
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")
```

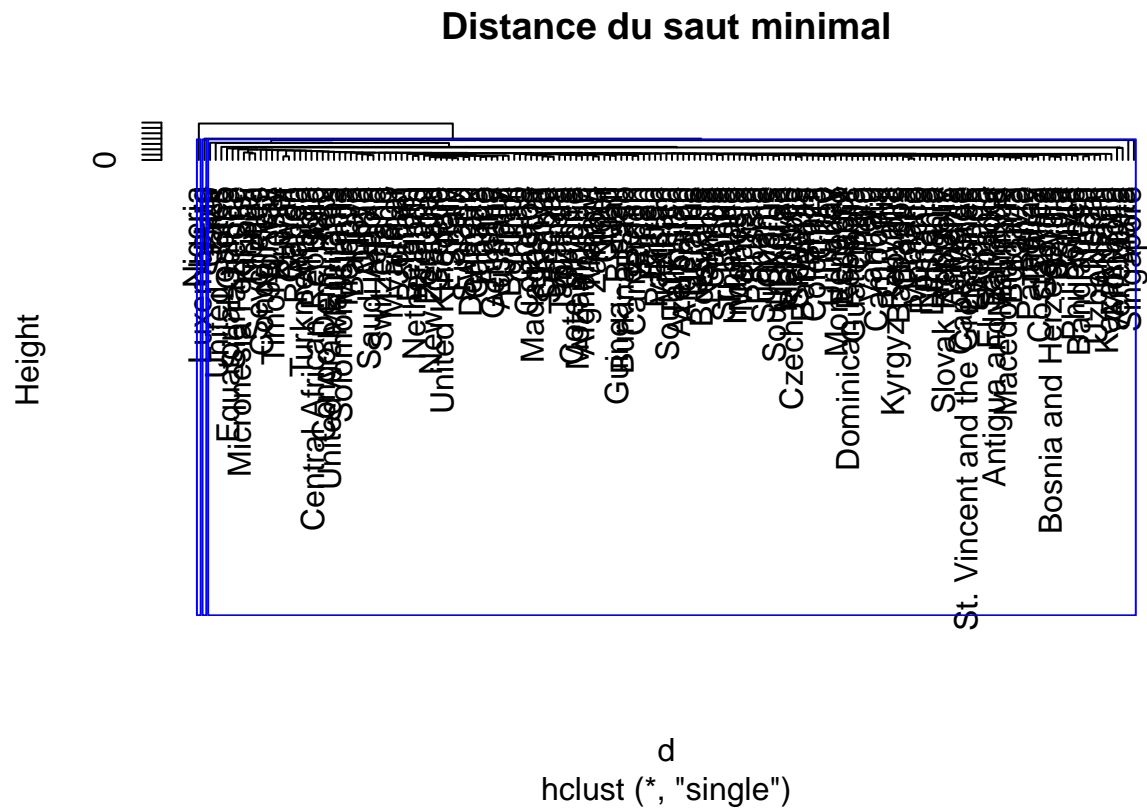


## Distance de Ward



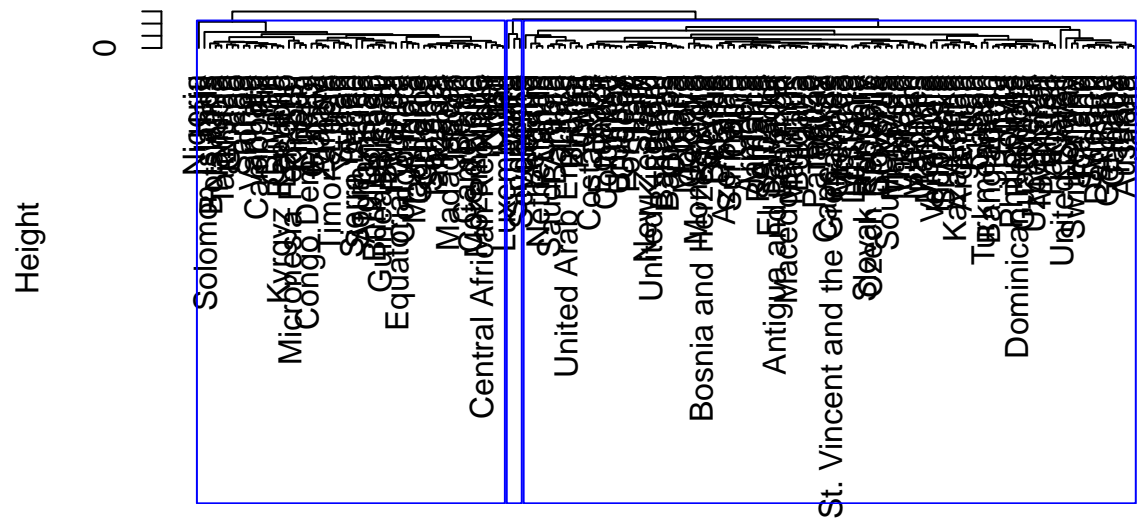
```
hclust (*, "ward.D")
```

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



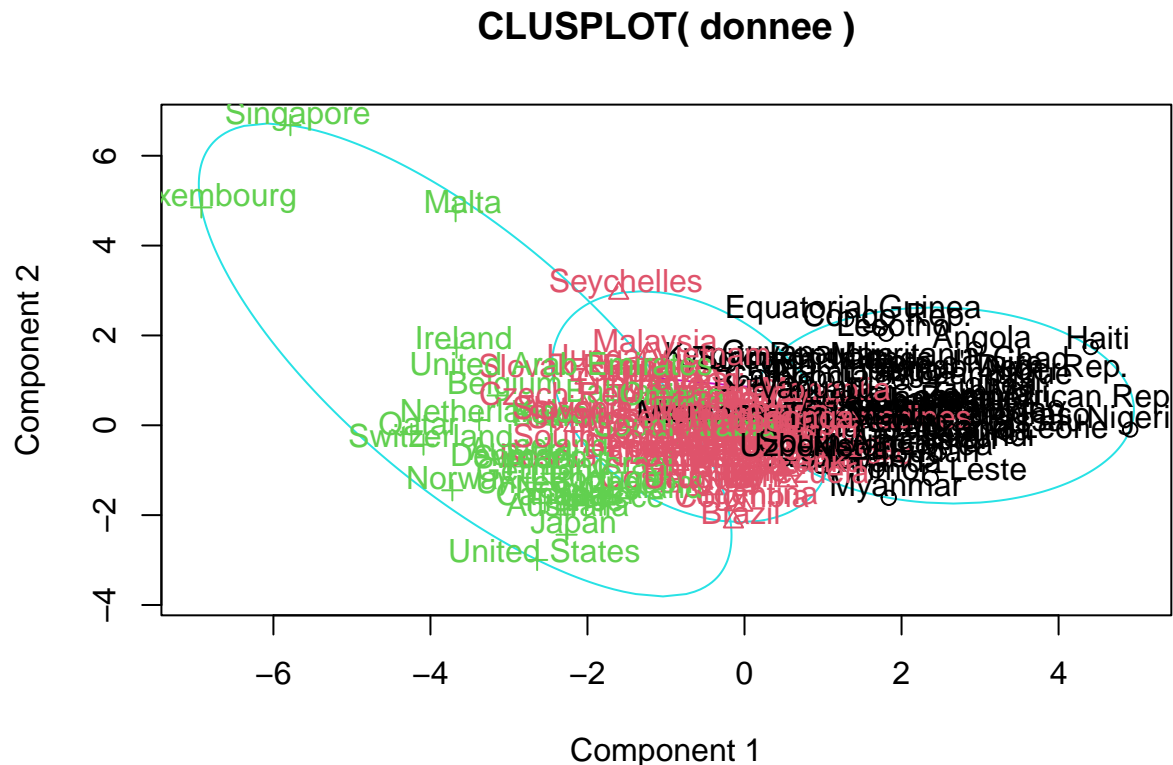
```
plot(cah.max, hang = -1, main = "Distance du saut maximal")
rect.hclust(cah.max, nbc, border = "blue")
```

## Distance du saut maximal



d  
hclust (\*, "complete")

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



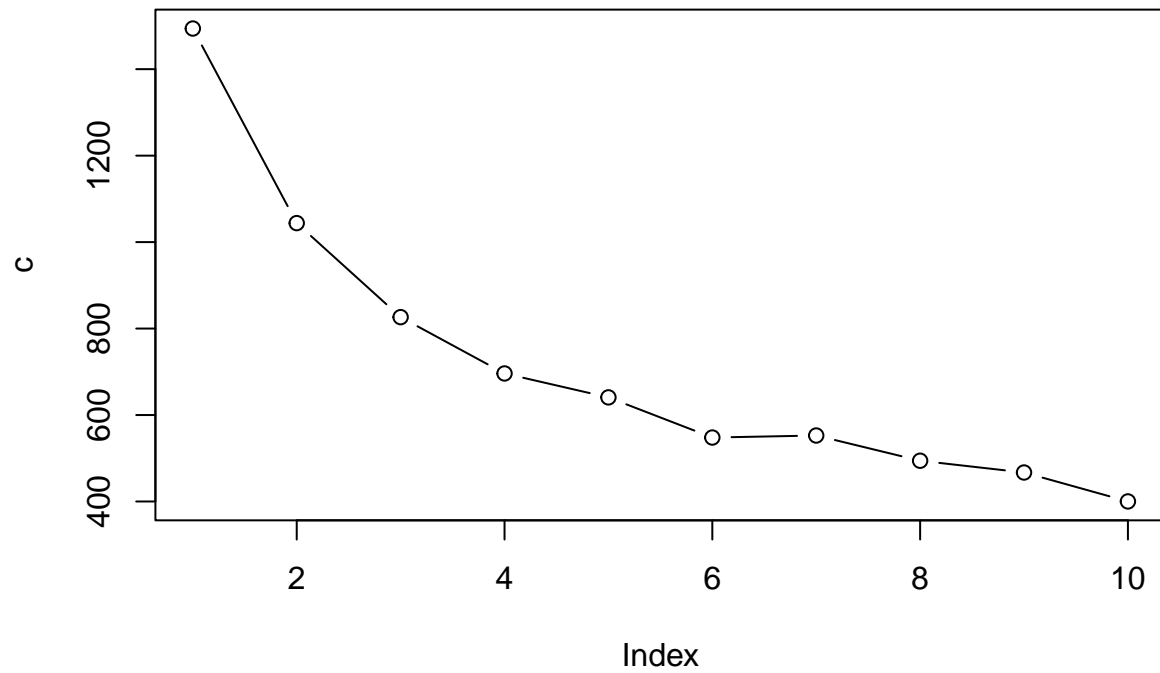
These two components explain 63.13 % of the point variability.

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.

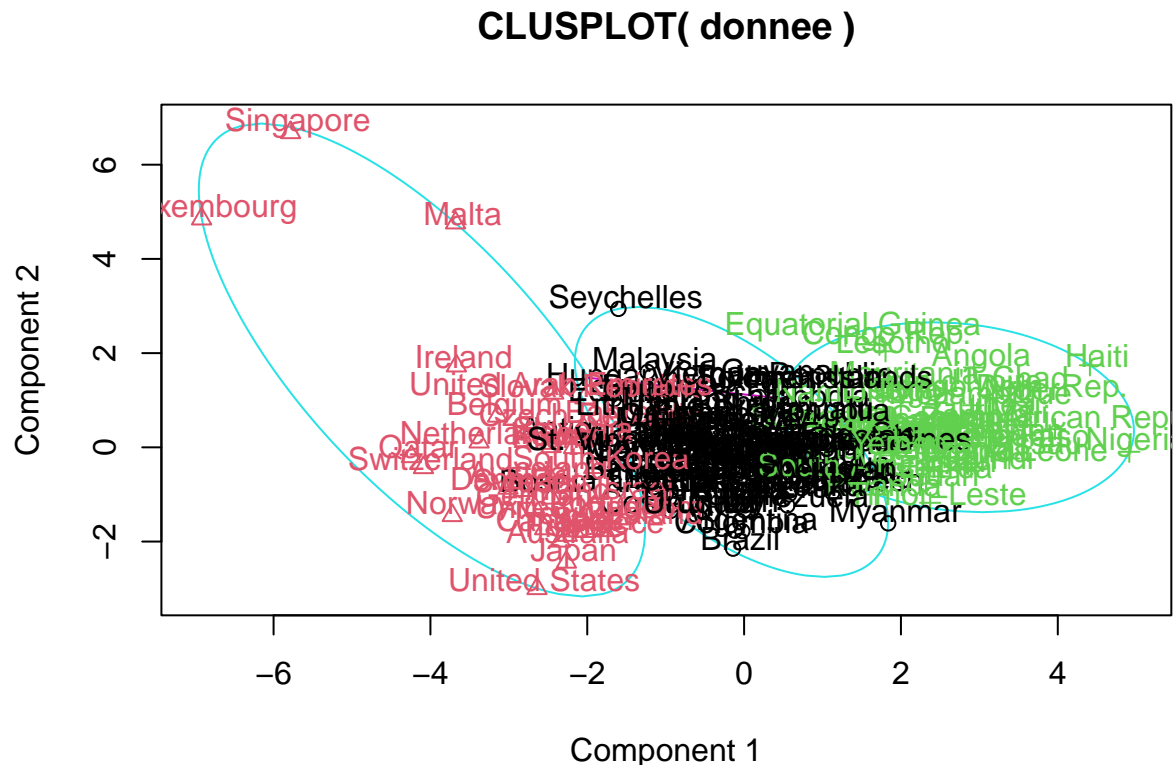
## 2.2 Algorithme des Kmeans

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 données, 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 conforte 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)
```



These two components explain 63.13 % of the point variability.

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).

Représentation 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 -3.093417e-17      0.9111885 0.9970015
## fert        10.150674      0.9839659  1.932087e-17      0.8579969 0.9970015
## inflation   2.913863      0.2824583 -1.996490e-17      1.2650602 0.9970015
## sant.       -2.615632     -0.2535490 -1.047794e-16      0.9651035 0.9970015
## exports     -3.802046     -0.3685552 -4.103608e-17      0.6775757 0.9970015
## pib_h       -6.214645     -0.6024230  3.620846e-17      0.1393288 0.9970015
## revenu      -6.968102     -0.6754601 -8.768144e-17      0.2556201 0.9970015
## esper_vie   -10.486756    -1.0165444  3.564649e-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  3.564649e-16      0.3438267 0.9970015
## pib_h       -2.657982     -0.2481744  3.620846e-17      0.3297308 0.9970015
## enfant_mort -6.001733     -0.5603786 -3.093417e-17      0.2069384 0.9970015
## fert        -6.325848     -0.5906411  1.932087e-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  3.620846e-17      1.04631502 0.9970015
## revenu      10.318192      1.5791804 -8.768144e-17      1.05150950 0.9970015
## esper_vie    6.925852      1.0599890  3.564649e-16      0.23111362 0.9970015
## exports     4.147405      0.6347527 -4.103608e-17      1.54724683 0.9970015
## sant.       4.009263      0.6136103 -1.047794e-16      1.27746390 0.9970015
## inflation   -2.266208     -0.3468390 -1.996490e-17      0.50958288 0.9970015
## fert        -4.572607     -0.6998292  1.932087e-17      0.29691512 0.9970015
## enfant_mort -5.234428     -0.8011195 -3.093417e-17      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
```

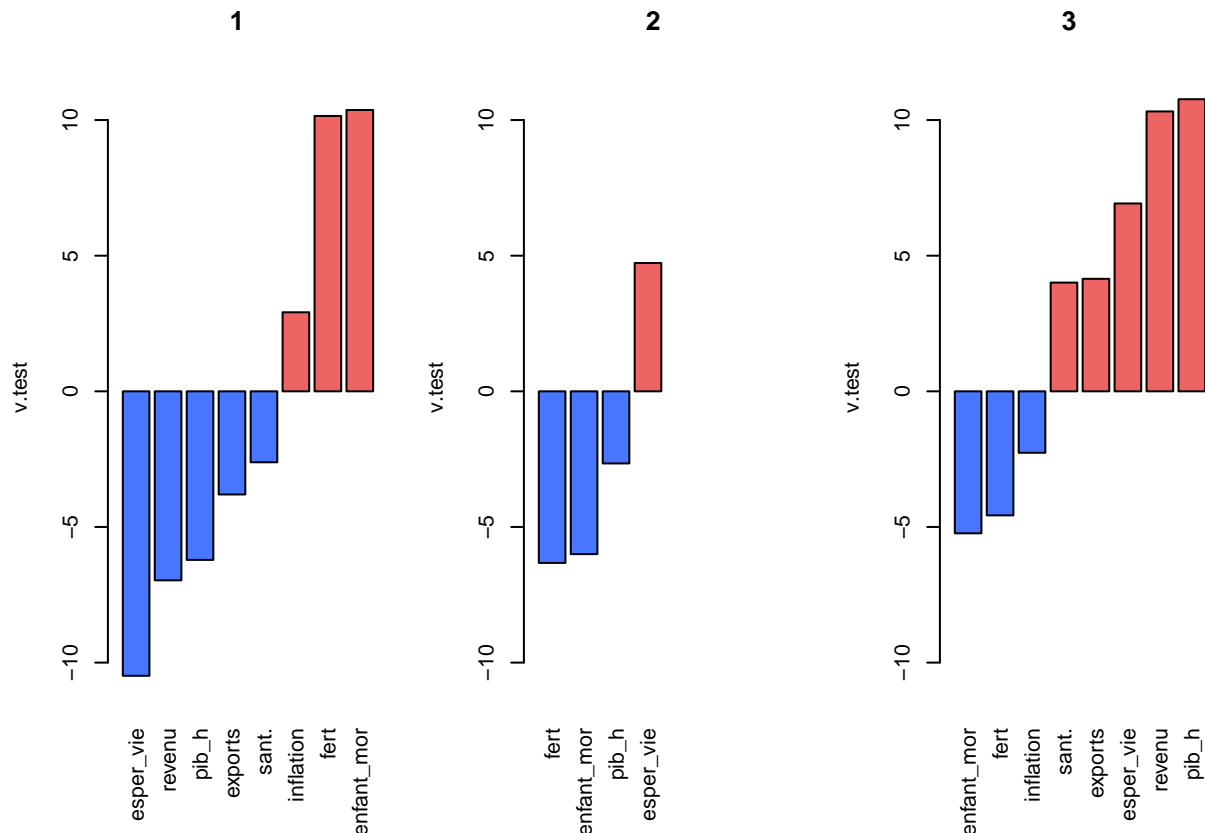
```
head(donnee)
```

```
##          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.

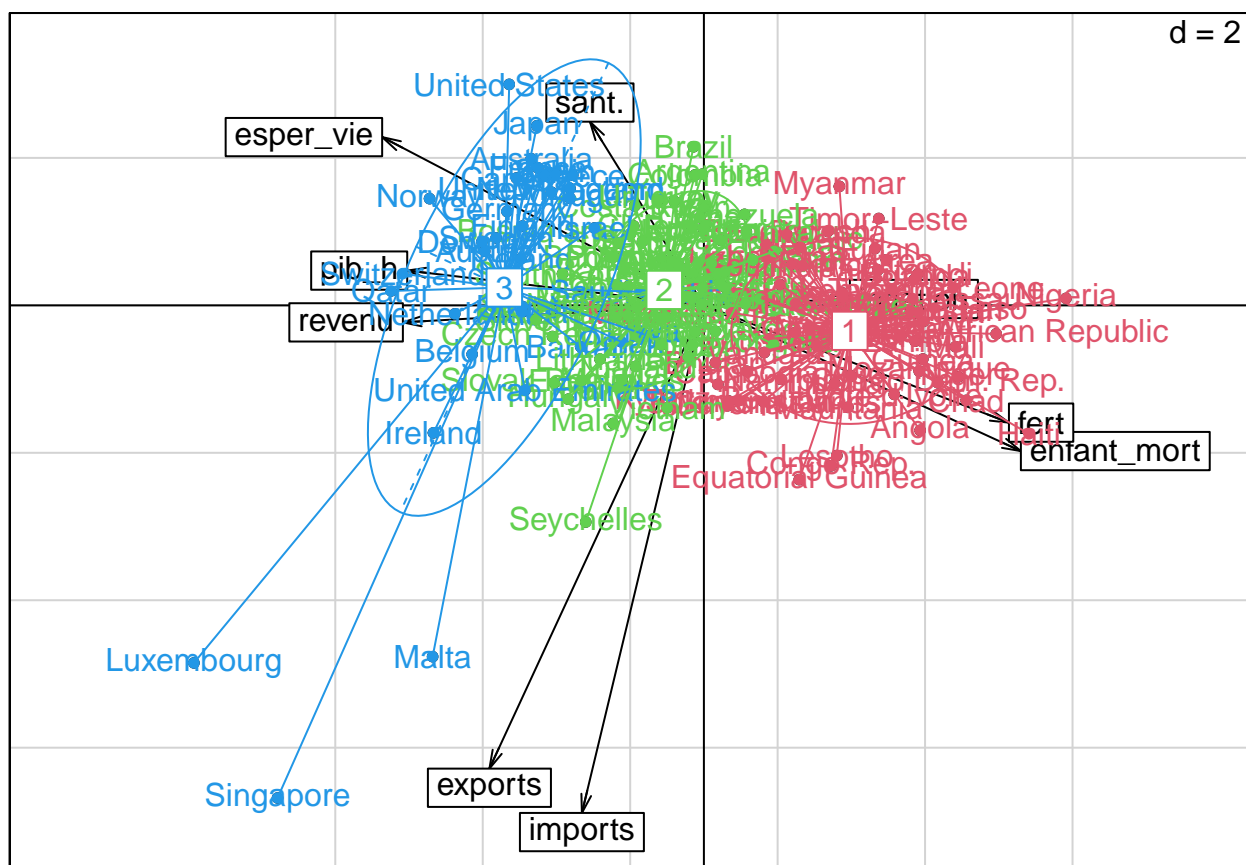
```
CCpca = dudi.pca(donnee[1:9],scannf=FALSE,nf=2)
cumsum(CCpca$eig)/sum(CCpca$eig) # 63% de variabilité expliquée sur les deux premiers axes

## [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)

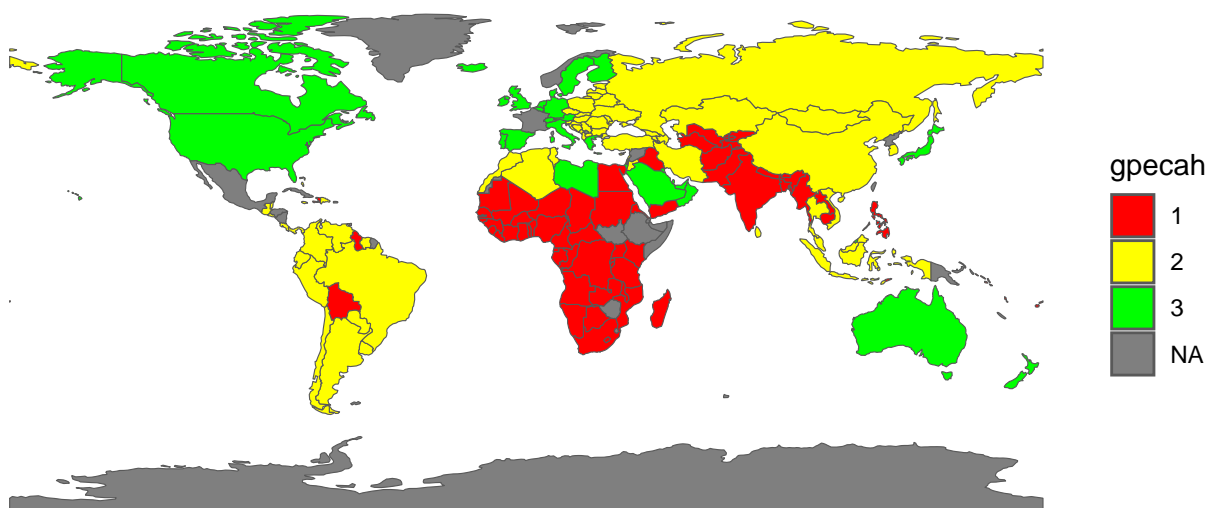
```
## iso3c lat lon
## 1 AFG 33.85640 66.08669
## 2 AGO -12.29155 17.50291
## 3 ALB 41.14135 20.03243
## 4 ARE 23.86863 54.20671
## 5 ARG -35.22017 -65.14954
## 6 ARM 40.21661 45.00029
```

```
## 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
## CRS: +proj=longlat +datum=WGS84 +no_defs +ellps=WGS84 +towgs84=0,0,0
## featurecla scalerank labelrank sovereignty 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>	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 (rouge 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

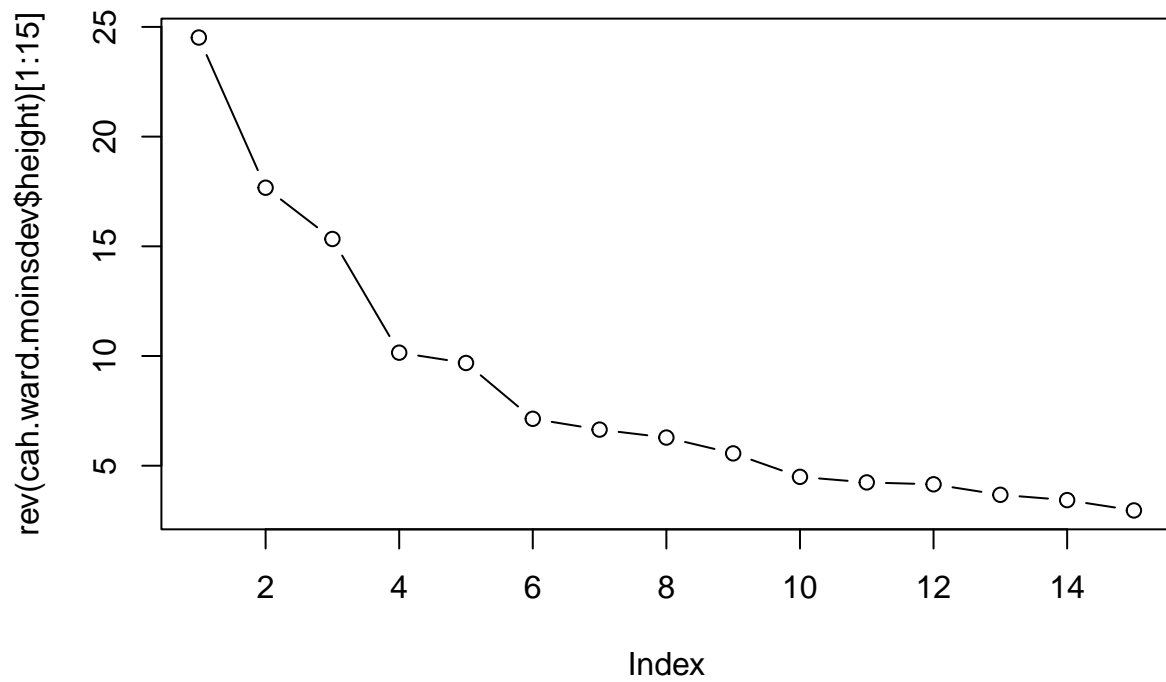
Caractérisation de la partition obtenue Représentation informative des résultats. Graphiques adaptés, représentations factorielles si adaptées Optionnel : Représentation spatiale des résultats sur la carte de Rennes Faire une ACP

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 décide de réaliser une deuxième CAH sur le groupe 1, qui sont les pays moins développés :

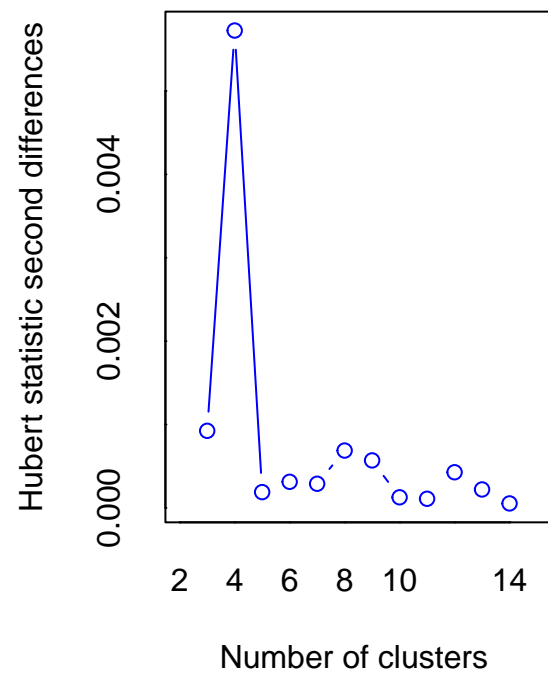
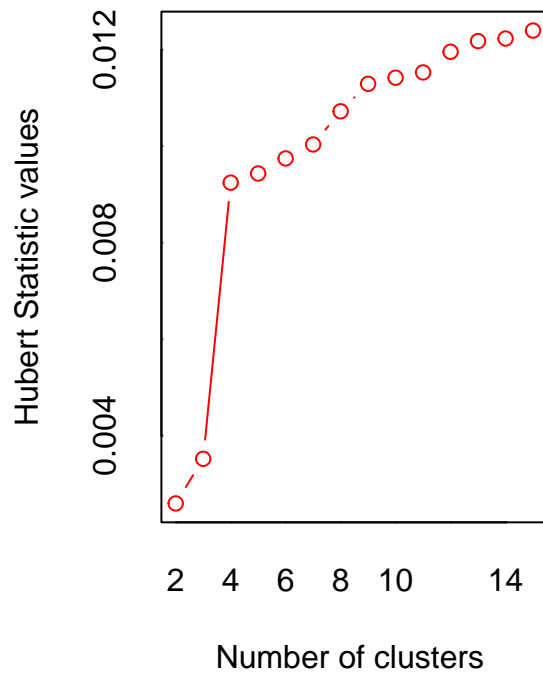




Le tracé de la perte d'inertie nous incite à choisir une partition en 4 groupes (lecture de gauche à droite : juste avant le coude ou changement de pente s'opérant au passage de 4 à 6 groupes)

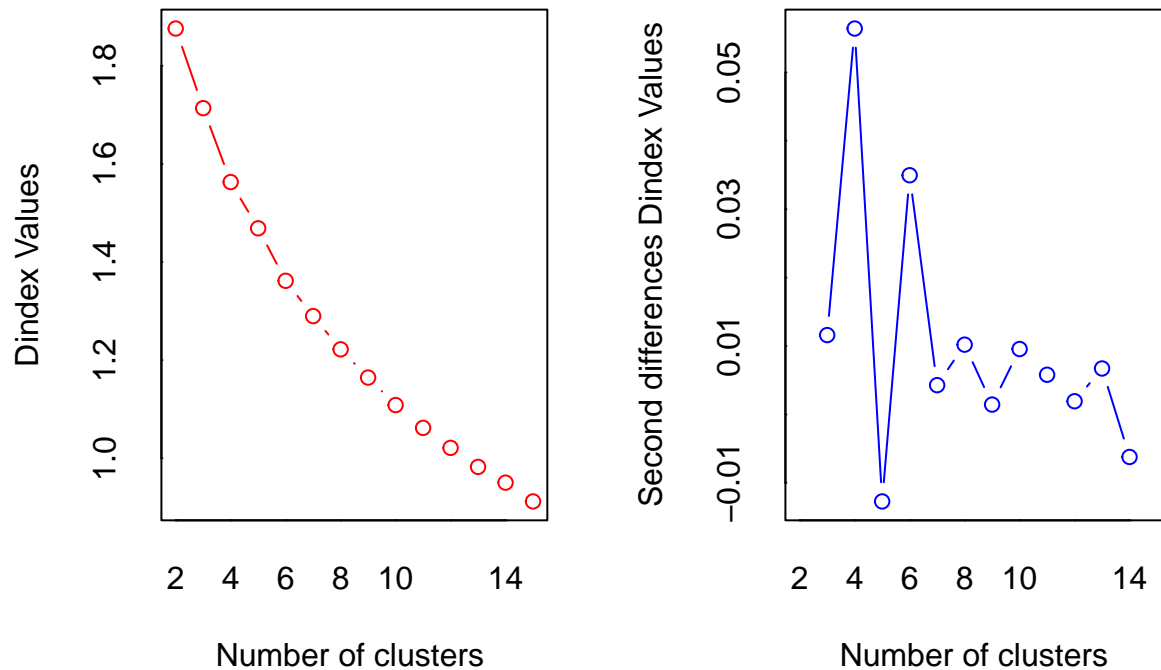
On peut aussi s'aider de critères automatiques calculés dans le package NbClust

```
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.

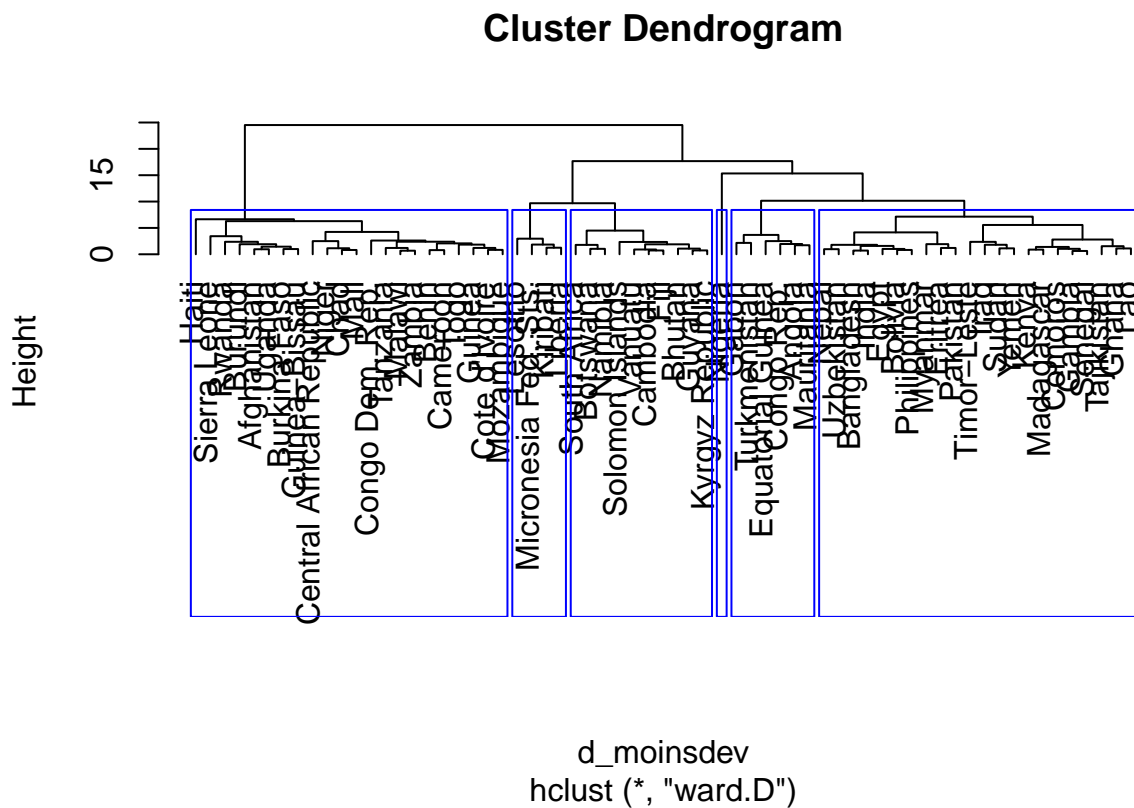
- Partition en 6 groupes

K=6

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

- Representation du dendrogramme avec les différents groupes obtenus

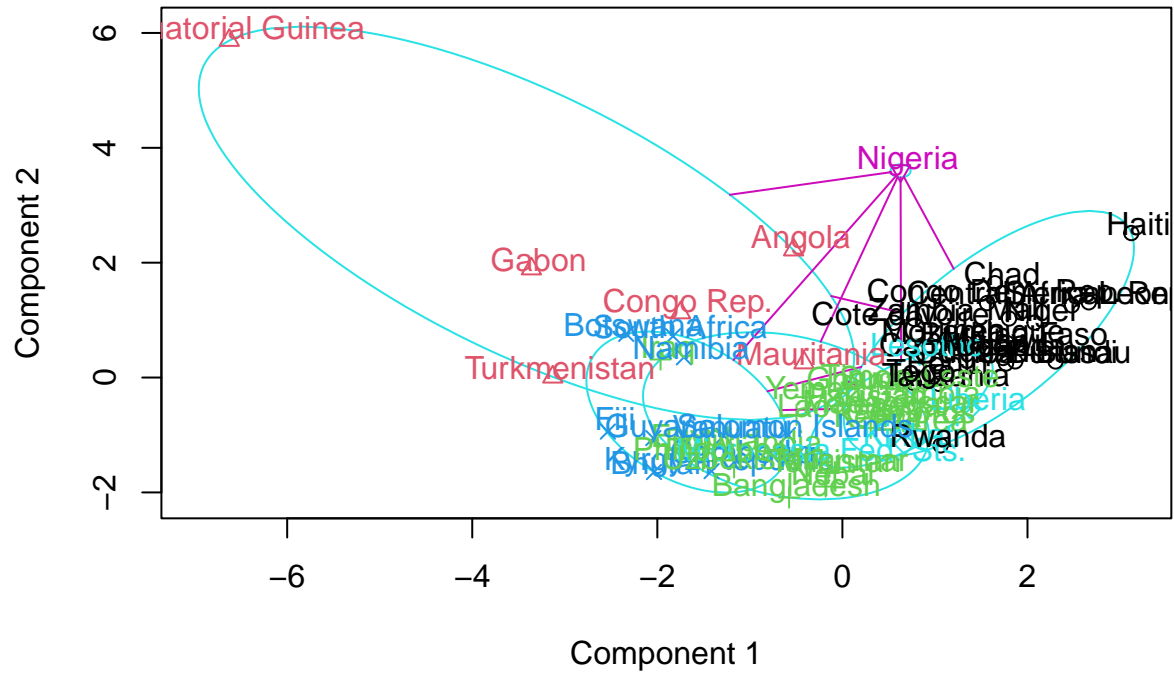
```
plot(cah.ward.moinsdev, hang=-1)
rect.hclust(cah.ward.moinsdev, K, border ="blue")
```



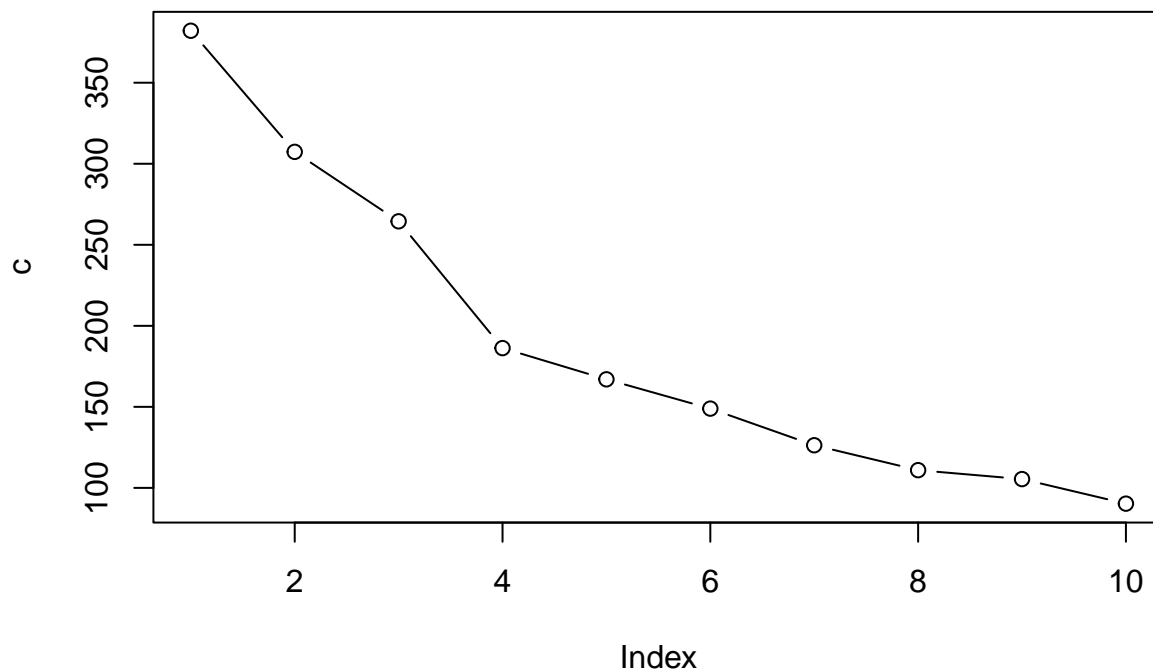
- Clusplot

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

# CLUSPLOT( donnee\_moinsdev )



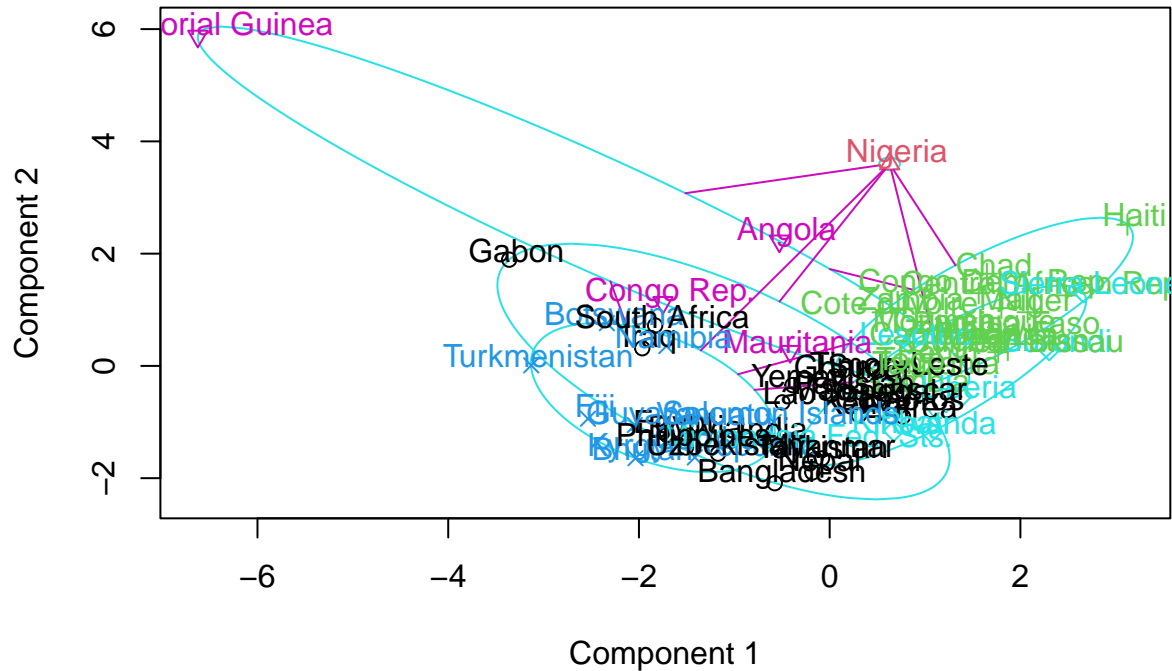
### 3.2 Avec les kmeans :



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 conforte 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)
```

## CLUSPLOT( donnee\_moinsdev )



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

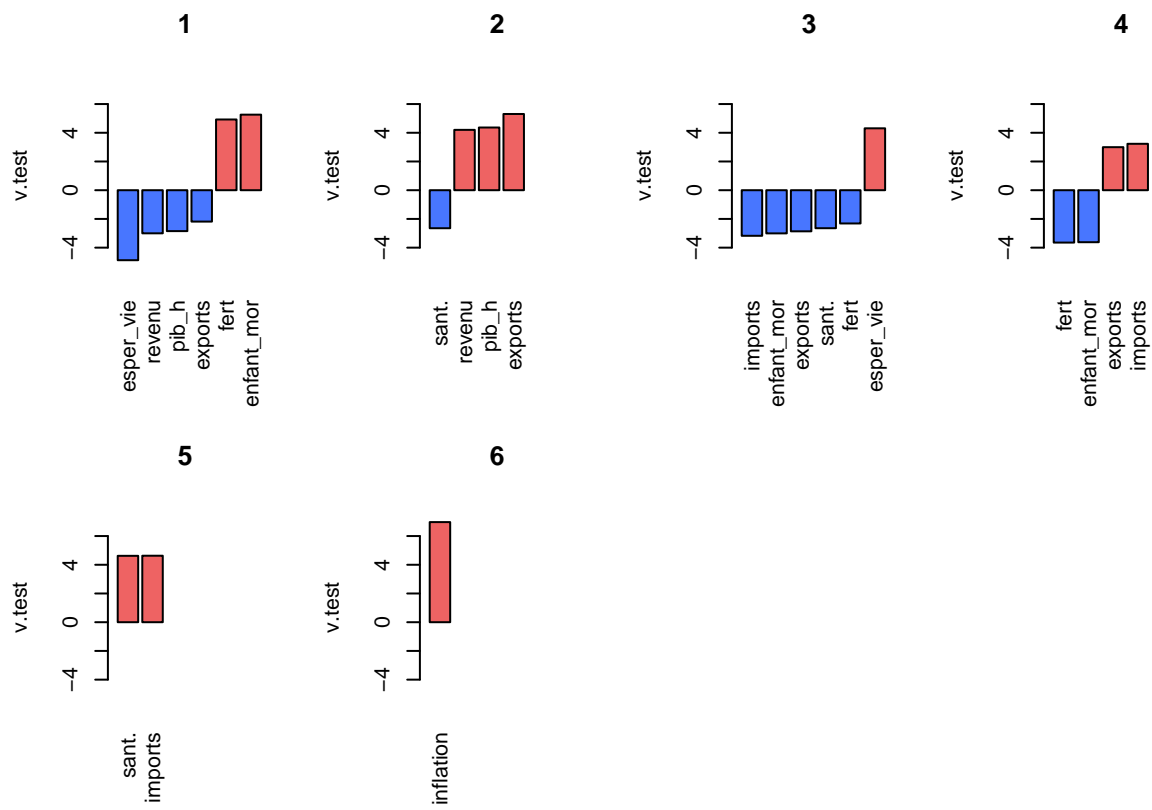
```

```
## 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)
```



## 4 Conclusion vis à vis des choix effectués

Quels points peuvent être critiqués dans votre choix Quelles pistes pourraient être explorées 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-développement. 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 ensuite retraité ce groupe de pays défavorisés afin de pouvoir observer les pays qui étaient le plus en difficulté. Là encore, nous avons dû 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
```

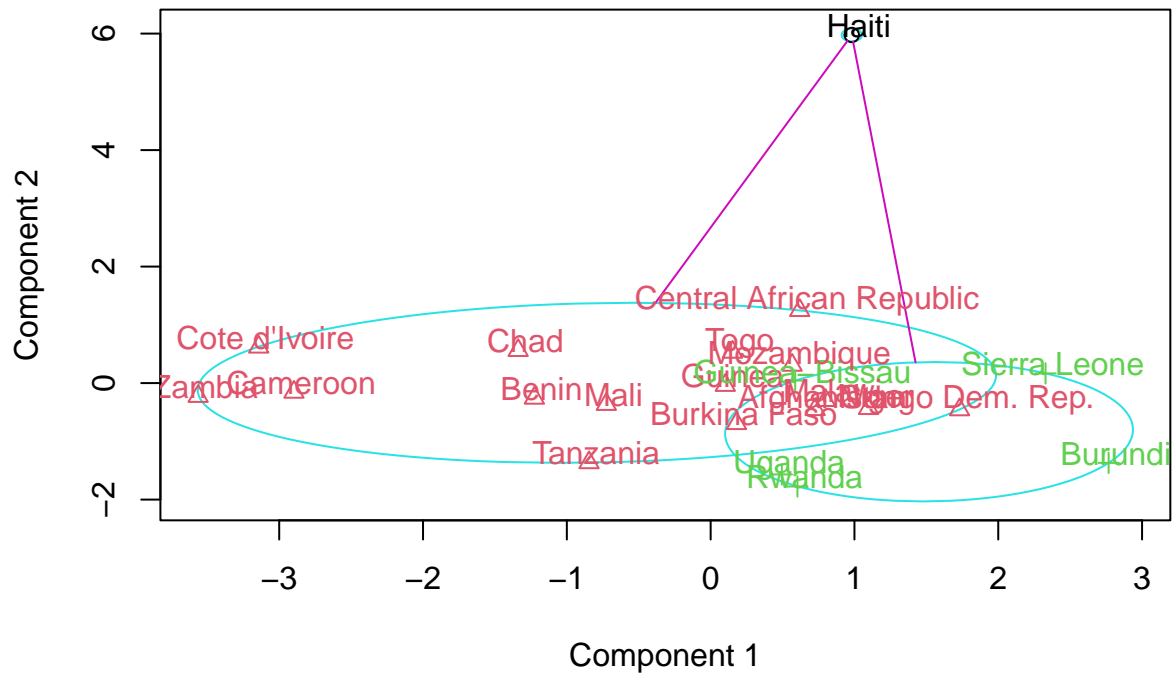
On va réaliser une méthode rapide des K-means pour choisir ce que l'on alloue comme budget pour nos 22 pays. Nous allons fixer  $K = 3$ .

On préférera utiliser l'option `nstart` du `kmeans` pour stabiliser les résultats. En relançant le code plusieurs fois, on observe que les résultats sont stables.

```
aide <- aide[1:9]
c = kmeans(aide,3,nstart=50)
gpe_22 = c$cluster
clusplot(aide,gpe_22,labels=3,col.p=gpe_22)
```



## CLUSPLOT( aide )



```
table(gpe_22)
```

```
## gpe_22
## 1 2 3
## 1 16 5
```

Le groupe 1 est le plus nécessiteux avec un pays en grande difficulté, tandis que le groupe 2 comprend 5 pays en difficulté et le groupe 3 comprend 16 pays avec des besoins moindres.

Compte tenu de ces informations, j'ai décidé de répartir l'argent de la manière suivante :

- Groupe 1 : 3 millions d'euros
- Groupe 2 : 3 millions d'euros
- Groupe 3 : 4 millions d'euros

Nous allons maintenant expliquer notre raisonnement pour cette répartition. Le groupe 1 avec un seul pays en grande difficulté nécessite une aide urgente et importante. Nous avons donc alloué une plus grande partie de l'argent disponible à ce groupe pour répondre à ses besoins pressants.

Pour le groupe 2, bien que les besoins soient moins urgents que dans le groupe 1, il y a tout de même 5 pays qui ont besoin d'une aide financière. Nous avons alloué une somme significative à ce groupe pour les aider à surmonter leurs difficultés.

Enfin, pour le groupe 3, bien qu'il y ait un plus grand nombre de pays dans le besoin, nous avons alloué une somme plus petite car les besoins sont moins pressants et moins graves. Cela ne veut pas dire que ces pays n'ont pas besoin d'aide, mais plutôt qu'ils ont des besoins moins critiques que les autres groupes.

```
## Warning in text.default(1.1 * P$x, 1.1 * P$y, labels[i], xpd = TRUE, adj =
## ifelse(P$x < : "explode" n'est pas un paramètre graphique

## Warning in text.default(1.1 * P$x, 1.1 * P$y, labels[i], xpd = TRUE, adj =
## ifelse(P$x < : "startangle" n'est pas un paramètre graphique

## Warning in text.default(1.1 * P$x, 1.1 * P$y, labels[i], xpd = TRUE, adj =
## ifelse(P$x < : "explode" n'est pas un paramètre graphique

## Warning in text.default(1.1 * P$x, 1.1 * P$y, labels[i], xpd = TRUE, adj =
## ifelse(P$x < : "startangle" n'est pas un paramètre graphique

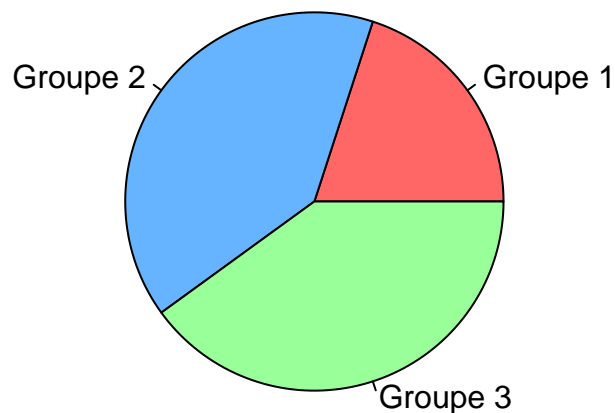
## Warning in text.default(1.1 * P$x, 1.1 * P$y, labels[i], xpd = TRUE, adj =
## ifelse(P$x < : "explode" n'est pas un paramètre graphique

## Warning in text.default(1.1 * P$x, 1.1 * P$y, labels[i], xpd = TRUE, adj =
## ifelse(P$x < : "startangle" n'est pas un paramètre graphique

## Warning in title(main = main, ...): "explode" n'est pas un paramètre graphique

## Warning in title(main = main, ...): "startangle" n'est pas un paramètre
## graphique
```

## Répartition de l'argent entre les groupes



Nous vous présentons donc si dessous, les sommes à alloué parmi les 22 pays dans le grand besoin.

- Haiti : 2 millions de dollars

- Siera Leone : 800 000 dollars
- Guinea- Bissau : 800 000 dollars
- Uganda : 800 000 dollars
- Rwanda : 800 000 dollars
- Burundi : 800 000 dollars
- Côte d’ivoire : 250 000 dollars
- Kambi : 250 000 dollars
- Cameroon : 250 000 dollars
- Chad : 250 000 dollars
- Benin : 250 000 dollars
- Mali : 250 000 dollars
- Tanzani : 250 000 dollars
- Central African Republic : 250 000 dollars
- Togo : 250 000 dollars
- Mozambique : 250 000 dollars
- Guinea : 250 000 dollars
- Malawi : 250 000 dollars
- Burkina Faso : 250 000 dollars
- Afghanistan : 250 000 dollars
- Congo : 250 000 dollars
- Dem Rep : 250 000 dollars

## **6 Pour aller plus loin**

### **6.1 Améliorations**

### **6.2 Pistes**