# UnsupervisedLearning

July 15, 2020

## 1 Clustering with K-means

#### 1.1 With swiss data

 $\mbox{K-means}$  clustering with 3 clusters of sizes 16, 20, 11

#### Cluster means:

	Fertility	Agriculture	${\tt Examination}$	Education	Catholic	Infant.Mortality
1	80.55000	65.51875	9.43750	6.625	96.15000	20.77500
2	68.32500	55.90500	17.05000	7.850	7.55000	19.67000
3	58.30909	19.50909	25.72727	23.000	22.21455	19.22727

#### Clustering vector:

Courtelary	Delemont	Franches-Mnt	Moutier	Neuveville	Porrentruy
3	1	1	2	2	1
Broye	Glane	Gruyere	Sarine	Veveyse	Aigle
1	1	1	1	1	2
Aubonne	Avenches	Cossonay	Echallens	Grandson	Lausanne
2	2	2	2	2	3
La Vallee	Lavaux	Morges	Moudon	Nyone	Orbe
3	2	2	2	2	2
Oron	Payerne	Paysd'enhaut	Rolle	Vevey	Yverdon
2	2	2	2	3	2
Conthey	Entremont	Herens	Martigwy	Monthey	St Maurice
1	1	1	1	1	1
Sierre	Sion	Boudry	La Chauxdfnd	Le Locle	Neuchatel
1	1	2	3	3	3
Val de Ruz	${\tt ValdeTravers}$	V. De Geneve	Rive Droite	Rive Gauche	
2	3	3	3	3	

Within cluster sum of squares by cluster:

[1] 6532.906 5966.297 9116.894

(between\_SS / total\_SS = 81.8 %)

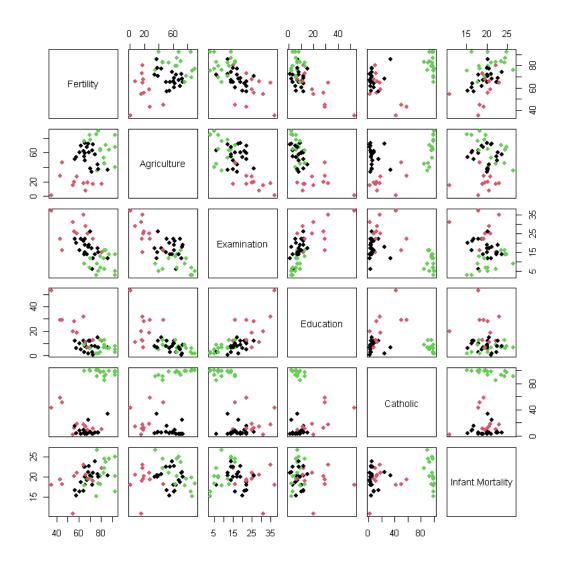
#### Available components:

[1]	"cluster"	"centers"	"totss"	"withinss"	"tot.withinss"
[6]	"betweenss"	"size"	"iter"	"ifault"	

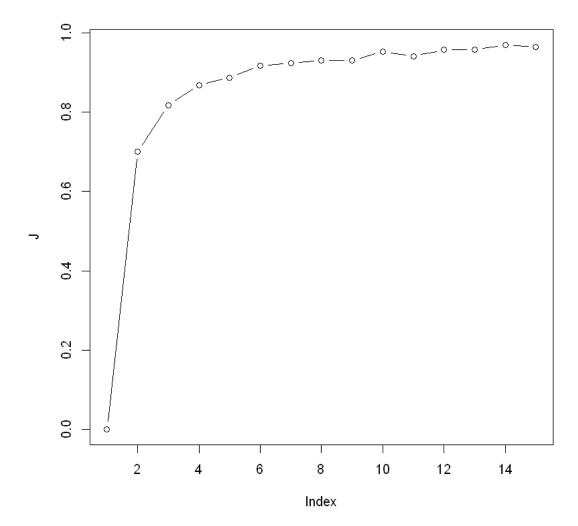
- first size of each group
- then the means of each cluster for each variable = "average guy" for each cluster.
- then assignement to each individuals to each group
- finally the g(K) value.

#### 21616.0973659091

#### 0.817559896131908

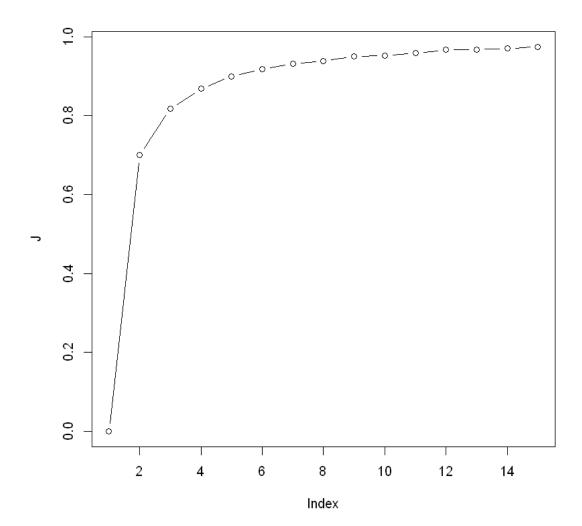


- one cluster for "big" cities
- one cluster for catholic cities
- one cluster for protestant cities



The curve sometime decrease, because the alogrythms change its init points at each time.

The solution is to run several time with the same k: nstart = 10



The choice could be K=4

When we run ten times (nstart = 10) the result is the clustering with the best j(K) K-means clustering with 4 clusters of sizes 12, 16, 16, 3

#### Cluster means:

	Fertility	Agriculture	Examination	Education	${\tt Catholic}$	Infant.Mortality
1	68.70000	23.80000	23.16667	14.66667	11.74333	19.71667
2	80.55000	65.51875	9.43750	6.62500	96.15000	20.77500
3	66.31250	60.72500	16.93750	7.68750	6.45875	19.55000
4	40.83333	25.16667	25.00000	37.00000	50.36667	18.50000

Clustering vector:

Courtelary	Delemont	${\tt Franches-Mnt}$	Moutier	Neuveville	Porrentruy
1	2	2	1	3	2
Broye	Glane	Gruyere	Sarine	Veveyse	Aigle
2	2	2	2	2	3
Aubonne	Avenches	Cossonay	Echallens	Grandson	Lausanne
3	3	3	3	1	1
La Vallee	Lavaux	Morges	Moudon	Nyone	Orbe
1	3	3	3	3	3
Oron	Payerne	Paysd'enhaut	Rolle	Vevey	Yverdon
3	3	3	3	1	3
Conthey	Entremont	Herens	Martigwy	Monthey	St Maurice
2	2	2	2	2	2
Sierre	Sion	Boudry	La Chauxdfnd	Le Locle	Neuchatel
2	2	1	1	1	1
Val de Ruz	${\tt ValdeTravers}$	V. De Geneve	Rive Droite	Rive Gauche	
1	1	4	4	4	

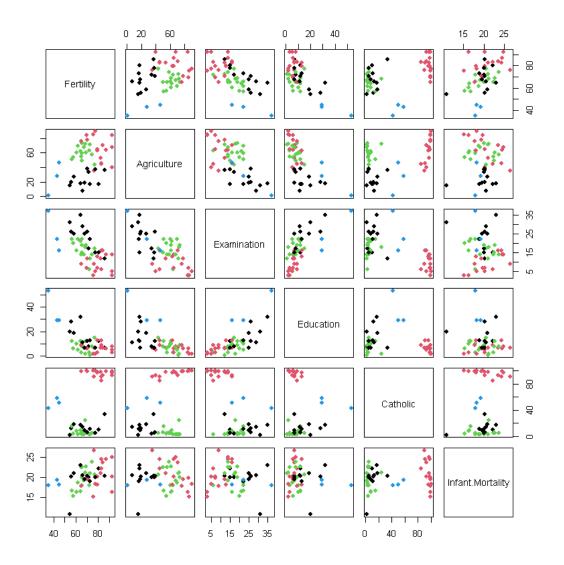
Within cluster sum of squares by cluster: [1] 4490.257 6532.906 2759.445 1839.879

(between\_SS / total\_SS = 86.8 %)

#### Available components:

[1] "cluster" "centers" "totss" "withinss" "tot.withinss" [6] "betweenss" "size" "iter" "ifault"

Now the clustering means : \* catholic \* protestant \* big cities : 3 \* protestant , no agriculture and protestant



## 2 Hierarchical clustering

The input data is not the X variable but a matrices with the distances between the observations

Call:

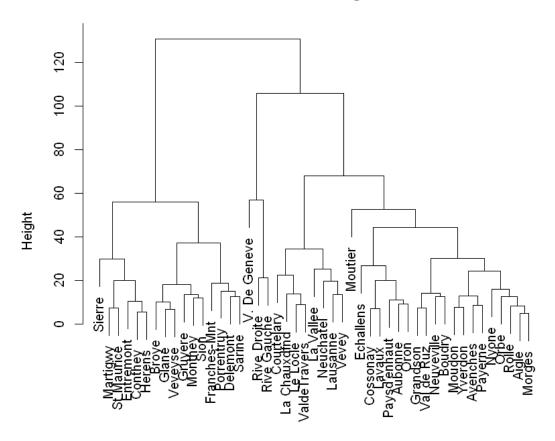
hclust(d = D, method = "complete")

Cluster method : complete
Distance : euclidean

Number of objects: 47

To see the result we have to plot the Dendogram

## **Cluster Dendrogram**



D hclust (\*, "complete")

Here when looking at the Dendogram we may choose to cut the tree at k=3 because it's there that the step is the biggest.

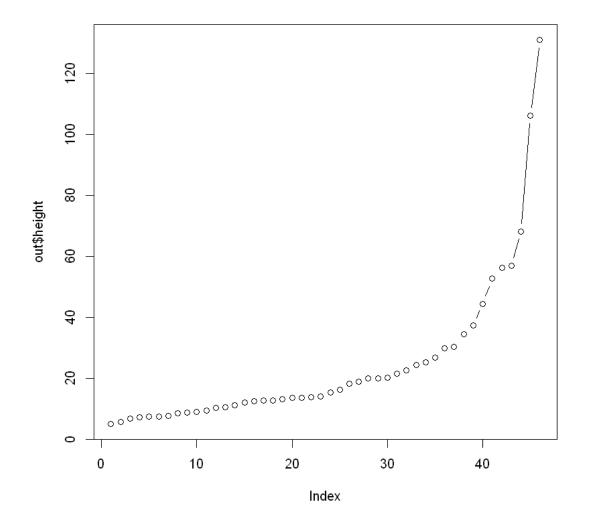
In order to obtain the clustering final partition, we have to cut the tree at the level k=3

Courtelary	Delemont	Franches-Mnt	Moutier	Neuveville	Porrentruy
1	2	2	1	1	2
Broye	Glane	Gruyere	Sarine	Veveyse	Aigle
2	2	2	2	2	1
Aubonne	Avenches	Cossonay	Echallens	Grandson	Lausanne
Aubonne 1	Avenches 1	Cossonay 1	Echallens 1	Grandson 1	Lausanne 1
Aubonne 1 La Vallee	Avenches 1 Lavaux	Cossonay 1 Morges	Echallens 1 Moudon	Grandson 1 Nyone	Lausanne 1 Orbe

Oron	Payerne	Paysd'enhaut	Rolle	Vevey	Yverdon
1	1	1	1	1	1
Conthey	Entremont	Herens	${ t Martigwy}$	Monthey	St Maurice
2	2	2	2	2	2
Sierre	Sion	Boudry	La Chauxdfnd	Le Locle	Neuchatel
2	2	1	1	1	1
Val de Ruz	${\tt ValdeTravers}$	V. De Geneve	Rive Droite	Rive Gauche	
1	1	3	3	3	

We can also use the numeric values in the out to draw a similar curse as for k-means

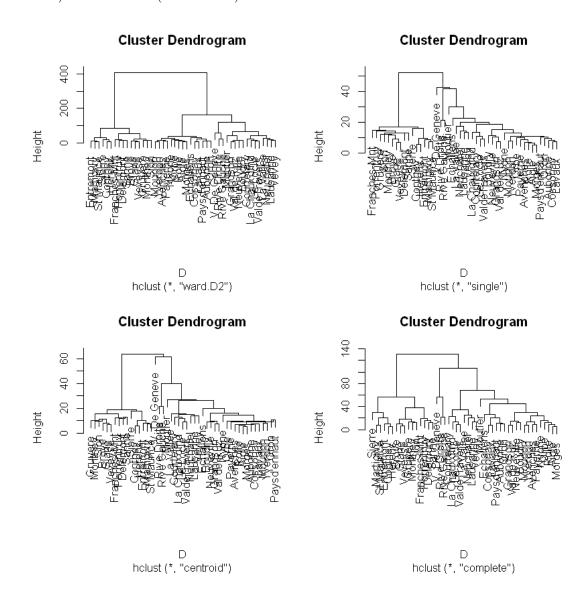
1. 'merge' 2. 'height' 3. 'order' 4. 'labels' 5. 'method' 6. 'call' 7. 'dist.method'



Start to analyse from the right of the curve (curve going from  $k{=}N$  to k=1). With this curve we would surely choose k=4

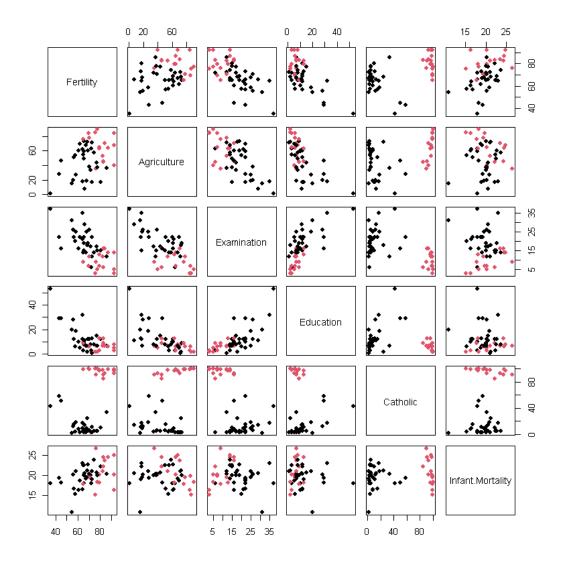
#### 2.0.1 Exercice: Run houst with the different distance, display and show the results.

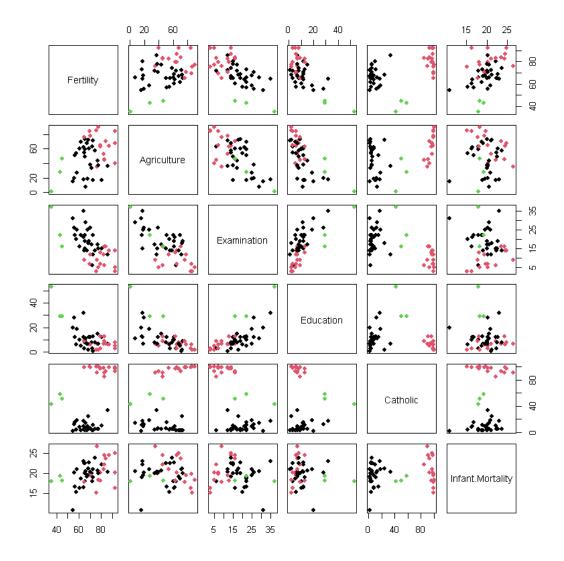
"ward.D2", "single", "complete", "average" (= UPGMA), "mcquitty" (= WPGMA), "median" (= WPGMC) or "centroid" (= UPGMC).



- if looking like a stair ("single", "centroid"), the method is failing
- "complete" and "ward" are ok for the analysis
- we would choose k=2 for "ward" and k=3 for "complete"

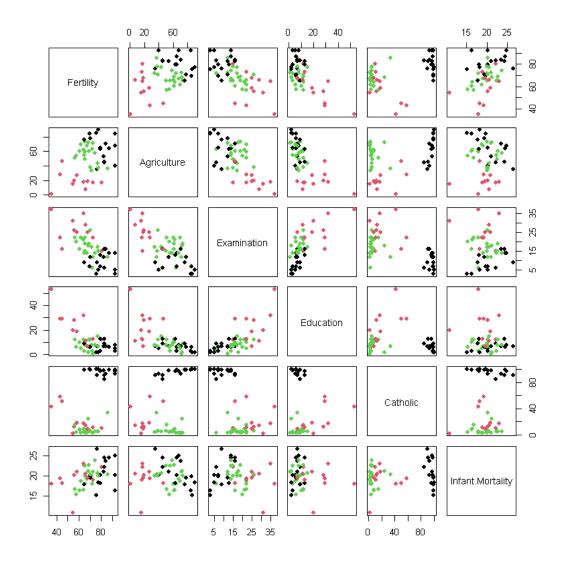
We cut the trees and look at the results using pairs plot in order to understand the data





With 3 groups the green points are well detached to other (for education, fertility) so the interpretation is really more interesting then with k=2: better understanding of the datas

### 2.1 Compare the results of K-Means and HCA both with K=3



#### Better clustering for HClust, but remember that for K-Means the best k was 4

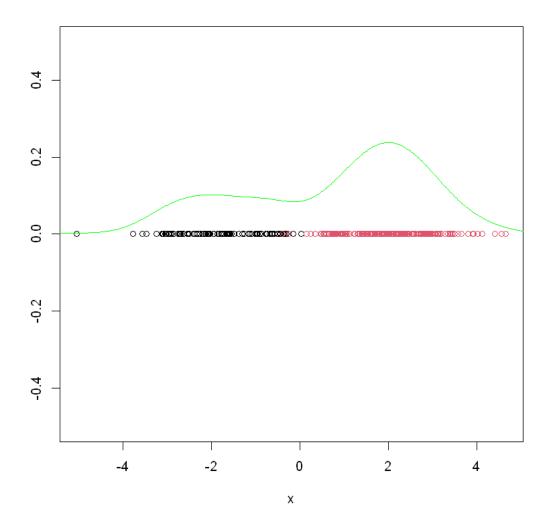
In conclusion: \* k= 3 HCA is better \* k= 4 K-Means is interesting because the protestant group is divided in an interesting way

## 3 EM Algorythm with Gaussian Mixture Model (GMM)

# 3.1 Try to code simple EM algorythm of GMM with fixed covariances matrices to simplify

identity matrix

We simulate some data



This is P(x)

View the effect of each iteration of the EM on the mean, the proportions and the cluster membership

#### 3.1.1 With swiss data and Mclust package

Warning message:

"package 'mclust' is in use and will not be installed"

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Gaussian finite mixture model fitted by EM algorithm

Mclust EEE (ellipsoidal, equal volume, shape and orientation) model with 3 components:

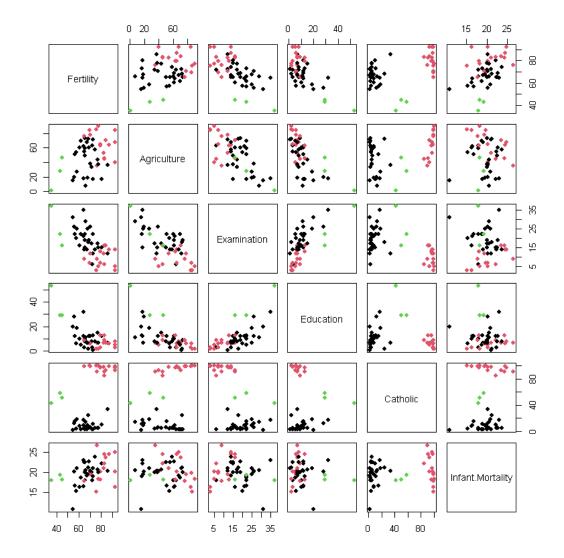
log-likelihood n df BIC ICL -934.9916 47 41 -2027.839 -2027.839

Clustering table:

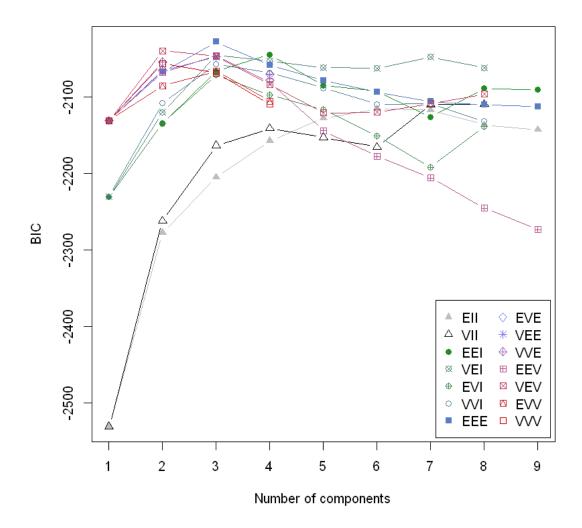
1 2 3 28 16 3

1. 'call' 2. 'data' 3. 'modelName' 4. 'n' 5. 'd' 6. 'G' 7. 'BIC' 8. 'loglik' 9. 'df' 10. 'bic' 11. 'icl' 12. 'hypvol' 13. 'parameters' 14. 'z' 15. 'classification' 16. 'uncertainty'

Courtelary 1 Delemont 2 Franches-Mnt 2 Moutier 1 Neuveville 1 Porrentruy 2 Broye 2 Glane 2 Gruyere 2 Sarine 2 Veveyse 2 Aigle 1 Aubonne 1 Avenches 1 Cossonay 1 Echallens 1 Grandson 1 Lausanne 1 La Vallee 1 Lavaux 1 Morges 1 Moudon 1 Nyone 1 Orbe 1 Oron 1 Payerne 1 Paysd'enhaut 1 Rolle 1 Vevey 1 Yverdon 1 Conthey 2 Entremont 2 Herens 2 Martigwy 2 Monthey 2 St Maurice 2 Sierre 2 Sion 2 Boudry 1 La Chauxdfnd 1 Le Locle 1 Neuchatel 1 Val de Ruz 1 ValdeTravers 1 V. De Geneve 3 Rive Droite 3 Rive Gauche 3

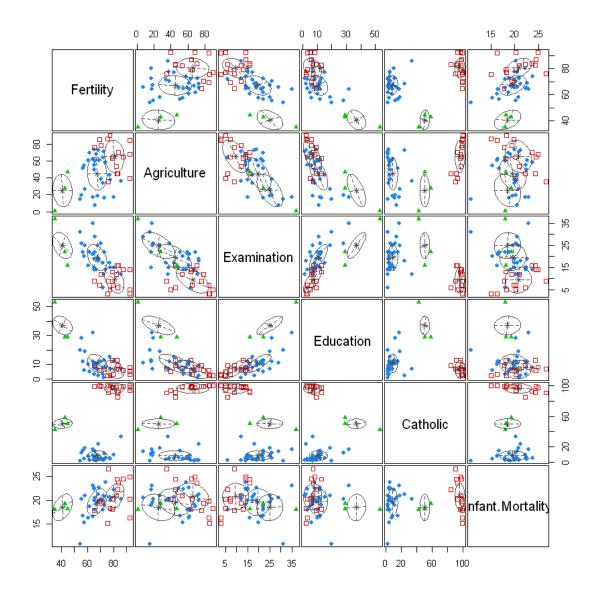


With default parameter, very close to result of HAC with complete linkage



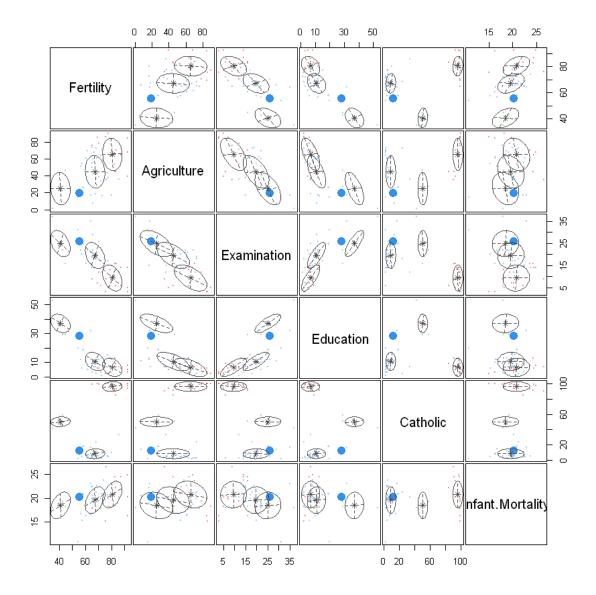
How to to understand this plot : \* the EEE model : E = equal, EEE : proportion equal, mean , variance \* best of the best : EEE for 3 component \* 14 models \* 9 values of K tested ! \* pos 1 : proportion : E : Equal, V = Free \* pos 2 : covariance matrix : V : free, I = identity, E : equal \* pos 3 : ??

If you are expert, it can be intersting to change k and find the best model with a different k



We can also visualize the estimated Gaussian with the previous graph Access also to the probability

The bigger the point is the bigger the uncertainty to belong to the choosen cluster is.



This information is directly extract from the output of the Algorythm.

	G 1	l	1 000	<b></b>
	Courtelary	1.000000e+00	1.936575e-41	7.572986e-21
	Delemont	4.918818e-33	1.0000000e+00	3.020169e-14
	Franches-Mnt	4.930018e-40	1.000000e+00	4.121262e-22
	Moutier	1.000000e+00	5.704706e-19	1.283381e-12
	Neuveville	1.000000e+00	2.002089e-45	2.831415e-22
	Porrentruy	6.729864e-38	1.000000e+00	1.657370e-15
	Broye	1.373874e-38	1.000000e+00	2.197023e-22
	Glane	3.066321e-43	1.000000e+00	1.218175e-25
	Gruyere	2.375623e-43	1.000000e+00	9.018504e-23
	Sarine	1.099925e-37	1.000000e+00	2.392042e-18
	Veveyse	2.954360e-44	1.000000e+00	2.005166e-25
	Aigle	1.000000e+00	1.457455e-43	1.282937e-21
	Aubonne	1.000000e+00	4.430158e-48	1.016653e-23
	Avenches	1.000000e+00	3.607653e-46	2.536988e-22
	Cossonay	1.000000e+00	8.688952e-50	2.364852e-27
	Echallens	1.000000e+00	7.755727e-29	1.065739e-17
	Grandson	1.000000e+00	1.478713e-48	2.309841e-25
	Lausanne	1.000000e+00	3.814979e-39	3.869423e-10
	La Vallee	1.000000e+00	1.470315e-52	4.020816e-24
	Lavaux	1.000000e+00	3.806609e-48	2.532751e-24
	Morges	1.000000e+00	4.013728e-47	7.548107e-25
	Moudon	1.000000e+00 1.000000e+00	1.991294e-46	3.822450e-23
A matrix: $47 \times 3$ of type dbl	Nyone Orbe	1.000000e+00 1.000000e+00	1.179617e-37 1.321625e-48	2.005990e-16 1.535777e-24
A matrix: $47 \times 3$ of type dbl	Oron	1.000000e+00 1.000000e+00	3.224140e-48	5.153818e-27
	Payerne	1.000000e+00	7.294973e-45	1.117981e-22
	Paysd'enhaut	1.000000e+00 1.000000e+00	7.474317e-47	3.158982e-23
	Rolle	1.000000e+00 1.000000e+00	2.267946e-43	2.938428e-19
	Vevey	1.000000e+00 1.000000e+00	3.564403e-34	6.222807e-12
	Yverdon	1.000000e+00	1.696589e-44	2.529561e-20
	Conthey	7.303432e-47	1.00000000+00	1.053782e-22
	Entremont	2.668420e-47	1.0000000e+00	5.984137e-20
	Herens	3.734582e-47	1.000000e+00	1.192764e-23
	Martigwy	4.178559e-45	1.0000000e+00	2.812089e-21
	Monthey	1.023760e-44	1.0000000e+00	1.288274e-22
	St Maurice	2.720172e-46	1.000000e+00	7.009389e-18
	Sierre	1.557015e-46	1.000000e+00	6.786755e-27
	Sion	3.215546e-43	1.000000e+00	2.654542e-20
	Boudry	1.0000000e+00	9.048151e-48	1.521805e-26
	La Chauxdfnd	1.0000000e+00	1.195468e-41	5.775682e-23
	Le Locle	1.0000000e+00	3.803771e-42	4.647618e-22
	Neuchatel	1.0000000e+00	4.741972e-36	1.602488e-12
	Val de Ruz	1.0000000e+00	1.077673e-46	7.180907e-26
	ValdeTravers	1.0000000e+00	4.633954e-46	2.245377e-26
	V. De Geneve	1.931260e-19	2.996057e-28	1.000000e+00
	Rive Droite	8.232250e-19	9.681768e-18	1.000000e+00
	Rive Gauche	1.927605e-20	1.019775e-13	1.000000e+00

Other package implement the EM algorithm for continuous but also categorical one. Rmixmod package allows to deal with both.

#### It is also possible to get the datas of the 'average guy' of each cluster

```
80.55000
                                    Fertility
                                              67.335714
                                                                    40.83333
                                 Agriculture
                                              44.900000
                                                          65.51875
                                                                    25.16667
                               Examination
                                              19.607143
                                                          9.43750
                                                                     25.00000
A matrix: 6 \times 3 of type dbl
                                                                     37.00000
                                  Education
                                              10.678571
                                                          6.62500
                                    Catholic
                                              8.723571
                                                          96.15000
                                                                    50.36667
                            Infant.Mortality | 19.621429
                                                          20.77500
                                                                    18.50000
```

Ex: cluster the wine data and evaluate the quality of the clustering regarding the know labels

Gaussian finite mixture model fitted by EM algorithm

\_\_\_\_\_

Mclust EVI (diagonal, equal volume, varying shape) model with 3 components:

Clustering table:

1 2 3 65 63 50

1. 'call' 2. 'data' 3. 'modelName' 4. 'n' 5. 'd' 6. 'G' 7. 'BIC' 8. 'loglik' 9. 'df' 10. 'bic' 11. 'icl' 12. 'hypvol' 13. 'parameters' 14. 'z' 15. 'classification' 16. 'uncertainty'

#### Mclust find by itself the three clusters

A way to compare: confusion matrix

1 2 3
Barbera 0 0 48
Barolo 58 1 0
Grignolino 7 62 2

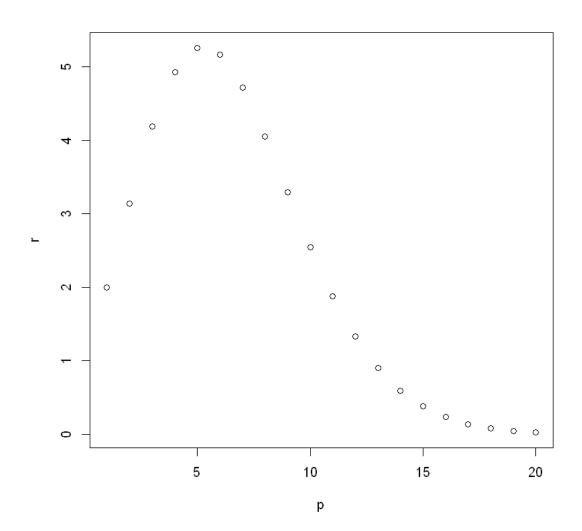
Globaly the result is very good: error = 10 errors over 178 = 5%

#### Try the same classification with K-Means

1. 'cluster' 2. 'centers' 3. 'totss' 4. 'withinss' 5. 'tot.withinss' 6. 'betweenss' 7. 'size' 8. 'iter' 9. 'ifault'

Barbera 6 0 42 Barolo 32 24 3 Grignolino 6 0 65

With Kmeans the error ratio is 25% (5% with Hclust)



# 4 Dimension Reduction with PCA

Warning message:

"package 'FactoMineR' is in use and will not be installed"

		$100 \mathrm{m}$	Long.jump	Shot.put	High.jump	$400 \mathrm{m}$	110m.hurdle	Discu
		<dbl $>$	<dbl $>$	<dbl $>$	<dbl $>$	<dbl $>$	<dbl $>$	<dbl></dbl>
-	SEBRLE	11.04	7.58	14.83	2.07	49.81	14.69	43.75
A data.frame: $6 \times 13$	CLAY	10.76	7.40	14.26	1.86	49.37	14.05	50.72
A data.frame. $0 \times 15$	KARPOV	11.02	7.30	14.77	2.04	48.37	14.09	48.95
	BERNARD	11.02	7.23	14.25	1.92	48.93	14.99	40.87
	YURKOV	11.34	7.09	15.19	2.10	50.42	15.31	46.26
	WARNERS	11.11	7.60	14.31	1.98	48.68	14.23	41.10

We just take the 10 first columns

Run PCA on those datas

#### Call:

princomp(x = X)

#### Standard deviations:

```
    Comp.1
    Comp.2
    Comp.3
    Comp.4
    Comp.5
    Comp.6

    11.61065403
    4.78910847
    3.12206072
    1.05698409
    0.58972067
    0.36425523

    Comp.7
    Comp.8
    Comp.9
    Comp.10

    0.24917123
    0.22222732
    0.15825005
    0.07006272
```

10 variables and 41 observations.

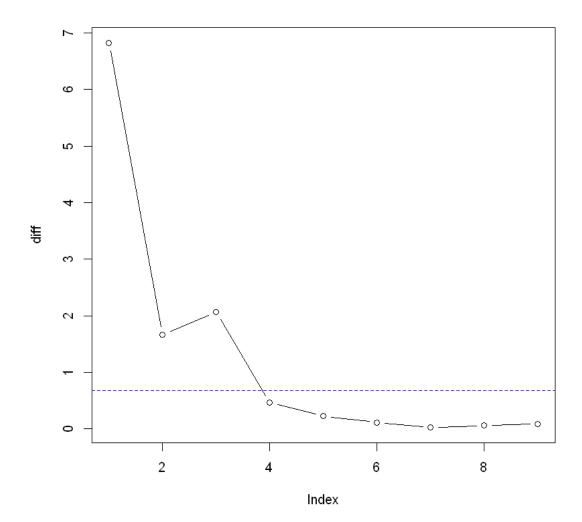
#### Now we have to select the number of dimension component to retain

1) look at the summary and use the cumulative proportion regarding 90% => we should here keep 2 components (93,2%)

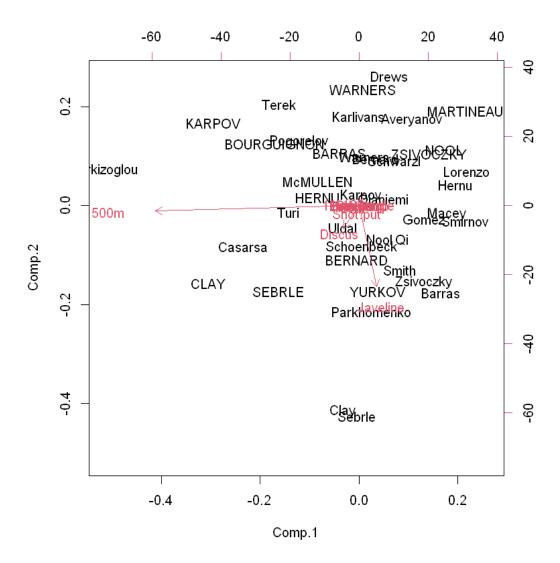
#### Importance of components:

	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5
Standard deviation	11.6106540	4.7891085	3.1220607	1.056984087	0.589720672
Proportion of Variance	0.7965959	0.1355296	0.0575980	0.006601788	0.002055026
Cumulative Proportion	0.7965959	0.9321255	0.9897235	0.996325247	0.998380274
	Comp.	6 Con	np.7 (	Comp.8	Comp.9
Standard deviation	0.364255234	0 0.249171	1229 0.2222	227318 0.1582	2500495
Proportion of Variance	0.000784036	5 0.000366	8877 0.0002	291823 0.0003	1479832
Cumulative Proportion	0.999164310	0.999531	1187 0.9998	323010 0.9999	9709933
	Comp.1	.0			
Standard deviation	7.006272e-0	2			
Proportion of Variance	2.900673e-0	5			
Cumulative Proportion	1.000000e+0	0			

- 2) use the screeplot Applying the rule of the break, the choice could be 3. screeplot(pc)
  - 3) with scree-test of Cattel, the choice is also d= 3



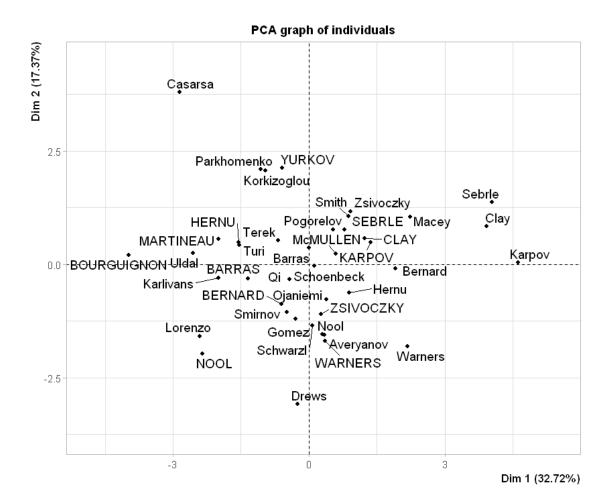
We can now look art the correlation circle

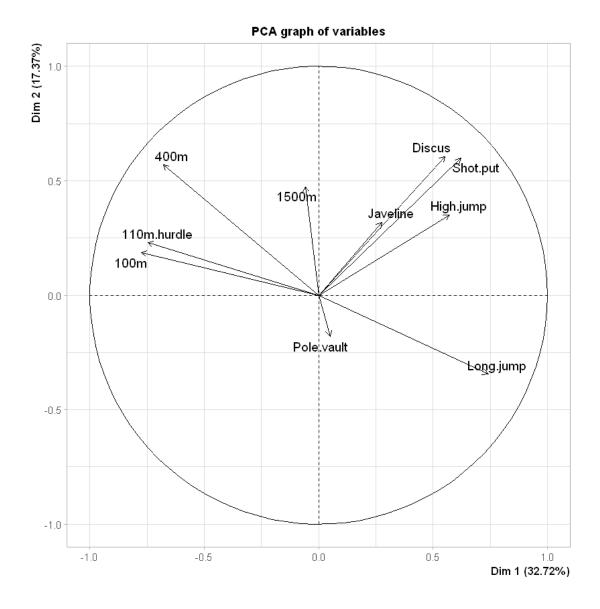


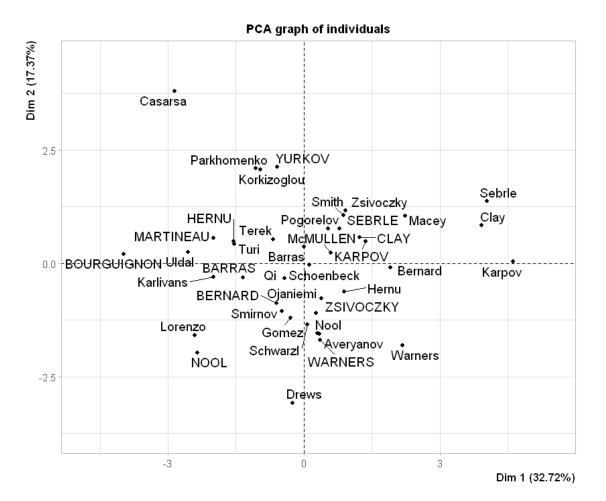
in red : correlation circle  $\,$ 

in black: score plot: projection of the datas on the two best coponent

To have a clearer view of correlation circle, it's better to use (FactoMineR package)







# 5 Clustering with HDclassif

```
Warning message:
"package 'HDclassif' is in use and will not be installed"

Y 1 2 3

Barbera 0 0 48

Barolo 58 1 0

Grignolino 2 68 1
```

With this HDCC algorythme the result is even better then with: 2.2% of error