



Symbolic Clustering Methods Applied to Interval Estimates of Production Cost Quantiles

Dominique Desbois

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17th Conference of the International Federation of Classification Societies(JRSS) – 19-23 July 2022, Porto

Symbolic Clustering Applied to Quantile Cost Estimates



Fertilizer drill (19th century) *Musée du Vivant*, AgroParisTech photo library

Dominique Desbois

Paris Saclay Applied Economics, INRAE/AgroParisTech, Paris Saclay University

Presentation outline

- Introducing Quantile Cost Estimation
- I) Hierarchical Ascendant Clustering
- II) Divisive Clustering
- Conclusions

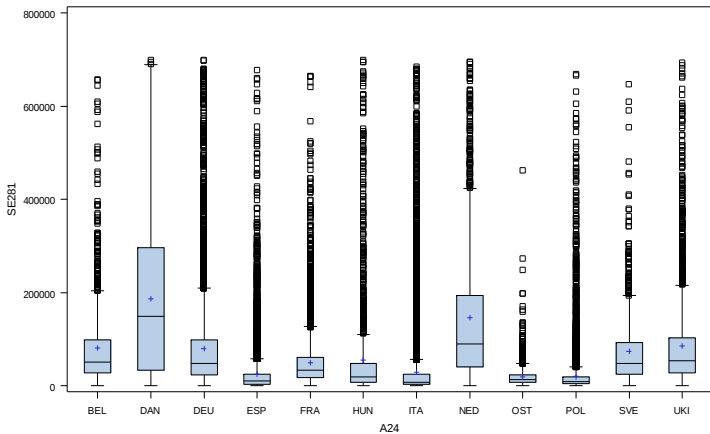
Estimates of Fertilizer Costs: an Input-Output Methodology

- Econometric modeling of agricultural production costs : *choice of a model with constant coefficients*

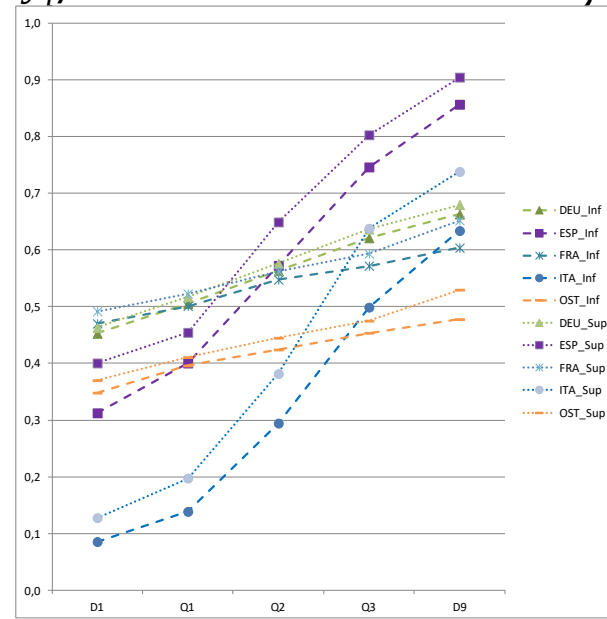
$$X_{ih} = \sum_{k=1}^K \alpha_{ih}^k Y_{kh} + \varepsilon_{ih} \text{ with } \varepsilon_{ih} \text{ i.i.d.}$$

PRODUCTS	CHARGES					TOTAL CHARGE
	Y_{1h}	...	Y_{kh}	...	Y_{Kh}	
X_{1h}	a_{1h}^1	...	a_{1h}^k	...	a_{1h}^K	$\sum X_{1h}$
$\vdots$	$\vdots$		$\vdots$		$\vdots$	$\vdots$
X_{ih}	a_{ih}^1	...	a_{ih}^k	...	a_{ih}^K	$\sum X_{ih}$
$\vdots$	$\vdots$		$\vdots$		$\vdots$	$\vdots$
X_{Ih}	a_{Ih}^1	...	a_{Ih}^k	...	a_{Ih}^K	$\sum X_{Ih}$
TOTAL PRODUIT	$\sum Y_{1h}$	...	$\sum Y_{kh}$	...	$\sum Y_{Kh}$	$\sum_k Y_{kh} = \sum_i X_{ih}$

Quantile Estimates of Production Costs in Agriculture



$$\text{Min}_{\beta} \left\{ \sum_{\vec{i} x_i \geq y_i' \beta} q |x_i - y_i' \beta| + \sum_{\vec{i} x_i \leq y_i' \beta} (1 - q) |x_i - y_i' \beta| \right\}$$



12 Europeans Countries, Fertilisation Costs for 1K € of Gross Product for Yearly Crops

(D.Desbois, FADN-UE 2006)

id	D1I	D1S	Q1I	Q1S	Q2I	Q2S	Q3I	Q3S	D9I	D9S
Bel	0,009	0,019	0,023	0,030	0,038	0,047	0,056	0,080	0,082	0,110
Dan	0,018	0,024	0,035	0,035	0,056	0,056	0,094	0,094	0,140	0,140
Deu	0,004	0,009	0,025	0,033	0,082	0,082	0,140	0,140	0,181	0,181
Esp	0,013	0,017	0,025	0,033	0,058	0,058	0,103	0,103	0,169	0,169
Fra	0,023	0,028	0,053	0,065	0,125	0,125	0,182	0,182	0,232	0,232
Hun	0,020	0,038	0,056	0,071	0,093	0,110	0,138	0,164	0,197	0,197
Ita	0,007	0,011	0,019	0,022	0,041	0,041	0,078	0,078	0,121	0,121
Ned	0,001	0,004	0,004	0,006	0,009	0,012	0,017	0,022	0,026	0,029
Ost	0,000	0,029	0,043	0,057	0,068	0,086	0,106	0,127	0,155	0,179
Pol	0,024	0,032	0,052	0,059	0,088	0,099	0,146	0,165	0,215	0,228
Sve	-0,007	0,016	0,003	0,038	0,100	0,100	0,215	0,215	0,293	0,293
Uki	0,006	0,029	0,036	0,047	0,088	0,088	0,137	0,137	0,171	0,171

Belgium:

- € 9 to 19 of fertilizers for a € 1,000 € gross product of yearly crops for D1 decile of fertilizer inputs
- € 23 to 30 of fertilizers for a € 1,000 gross product of yearly crops for Q1 quartile of fertilizer inputs
- € 38 to 47 of fertilisers for a € 1,000 € gross product of yearly crops for median of fertilizer inputs
- € 56 to 80 of fertilizers for a € 1,000 € gross product of yearly crops for Q3 quartile of fertilizer inputs
- € 82 to 110 of fertilizers for a € 1,000 gross product of yearly crops for D9 decile of fertilizer inputs

```
syearcrop2<-read.sym.table("~/FERTI/syearcrop2b.txt",header=TRUE,sep='\t',dec=',',row.names=1)
print.data.frame(syearcrop2)
```

I) Hierarchical Ascendant Clustering

- Hausdorff
- Ichino
- Gowda-Diday

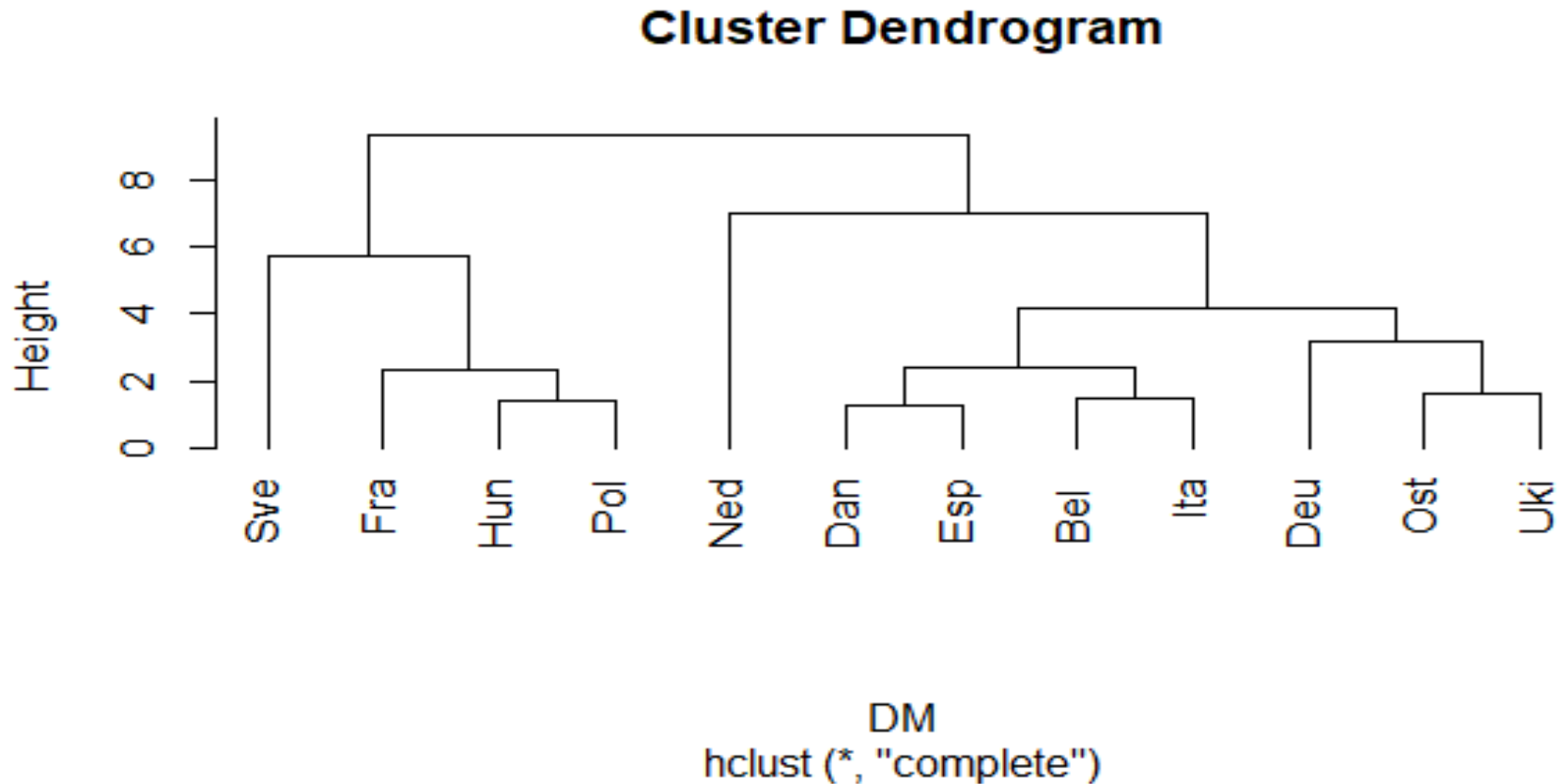
The Hausdorff dissimilarity: [definition for interval data](#)

- For interval estimates, Hausdorff dissimilarity is computed as follows :

$$\delta(z_l, z_{l'}) = \sum_{q=1}^Q \max \left\{ \left| \underline{z}_l^q - \underline{z}_{l'}^q \right| ; \left| \overline{z}_l^q - \overline{z}_{l'}^q \right| \right\}$$

Symbolic HCA («Hausdorff » option) for Quantile Estimates

The Hierarchical Dendrogram for Countries : **Hausdorff Distance**



```
DM <- sym.dist.interval(sym.data = searcrop2[,2:6], gamma = 0.5, method = "Hausdorff",  
                        normalize = FALSE, SpanNormalize = TRUE, euclidean = TRUE, q = 2)  
model <- hclust(DM)  
plot(model, hang = -1)
```

The Hausdorff option of the RSDA `sym.dist.interval` function is adapted from Carvalho F., Souza R., Chavent M., and Lechevallier Y. (2006) Adaptive Hausdorff distances and dynamic clustering of symbolic interval data. *Pattern Recognition Letters Volume 27*, Issue 3, February 2006, pp.167-179.

The Gowda – Diday dissimilarity: definition for interval data

- The Gowda – Diday dissimilarity is computed as follows for interval estimates :

$$\delta(z_l, z_{l'}) = \sum_{q=1}^Q \delta(z_l^q, z_{l'}^q)$$

where $\delta(z_l^q, z_{l'}^q) = \delta_p(z_l^q, z_{l'}^q) + \delta_s(z_l^q, z_{l'}^q)$

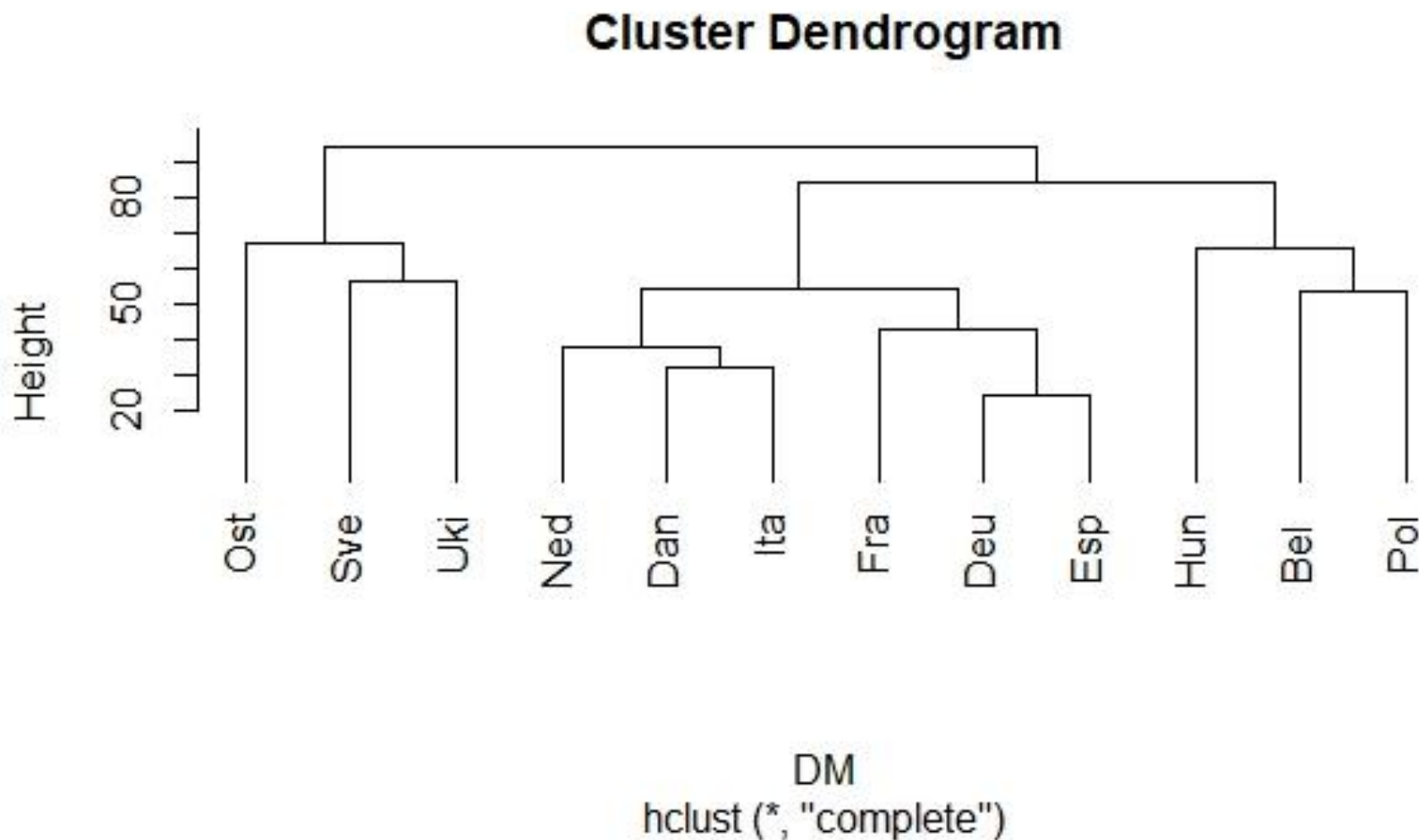
with $\delta_p(z_l^q, z_{l'}^q) = \cos \left[90 \left(1 - \frac{|z_l^q - z_{l'}^q|}{u^q} \right) \right],$

u^q being the length of the maximum interval for the q^{th} quantile;

$$\text{and } \delta_s(z_l^q, z_{l'}^q) = \cos \left[45 \left(\frac{|\overline{z_l^q} - \underline{z_l^q}| + |\overline{z_{l'}^q} - \underline{z_{l'}^q}|}{\max(\overline{z_l^q}, \overline{z_{l'}^q}) - \min(\underline{z_l^q}, \underline{z_{l'}^q})} \right) \right].$$

Symbolic HCA («Gowda-Diday » option) for Quantile Estimates

The Hierarchical Dendrogram for Countries



```
DM <- sym.dist.interval(sym.data = syearcrop2[,2:6], method = "Gowda.Diday")  
model <- hclust(DM)  
plot(model, hang = -1)
```

The Ichino dissimilarity: definition for interval data

- For interval estimates, Ichino dissimilarity is computed as follows :

$$\delta(z_l, z_{l'}) = \sum_{q=1}^Q \delta_I(z_l^q, z_{l'}^q)$$

where

$$\delta_I(z_l^q, z_{l'}^q) = \begin{cases} \mu(z_l^q - z_{l'}^q) / \mu(z_l^q \cup z_{l'}^q) & \text{if } \mu(z_l^q \cup z_{l'}^q) > 0 \\ 0 & \text{if } \mu(z_l^q \cup z_{l'}^q) = 0 \end{cases}$$

i.e.

$$\delta_I(z_l^q, z_{l'}^q) = \frac{\int_{\cup q} |f(z_l^q) - f(-z_{l'}^q)| d\mu}{\int_{\cup q} \sup(f(z_l^q), f(-z_{l'}^q)) d\mu}$$

NB: related to Ichino & Yaguchi's distance between sets, with ($\gamma = 0$), based on symmetric difference between sets

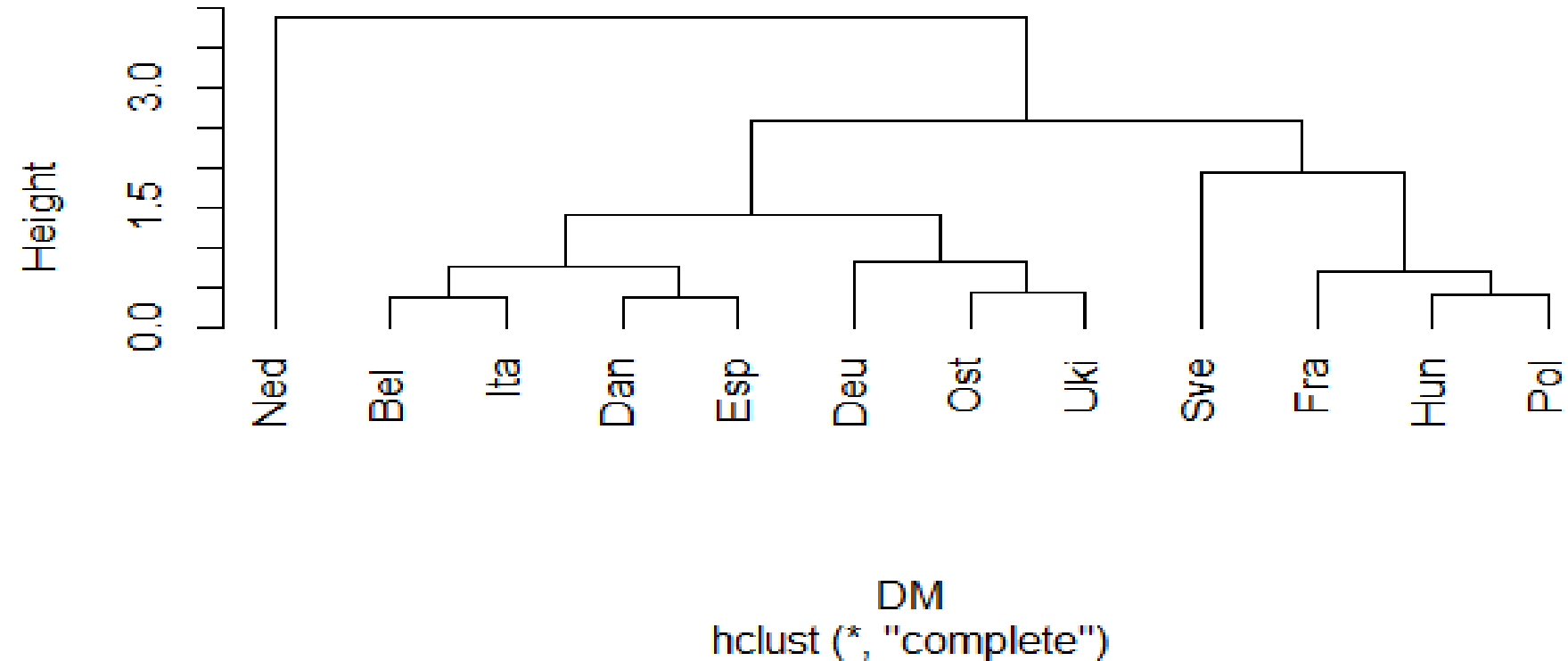
$$\delta_I(z_l^q, z_{l'}^q) = \frac{\pi(z_l^q \oplus z_{l'}^q) - \pi(z_l^q \cap z_{l'}^q) + \gamma |2\pi(z_l^q \cap z_{l'}^q) - \pi(z_l^q) - \pi(z_{l'}^q)|}{R}$$

with R as a normalization term, either $R=1$, or the overall potential of the q^{th} quantile domain, or $R = \pi(z_l \oplus z_{l'})$, the Cartesian joint product.

Symbolic HCA («Ichino » option) for Quantile Estimates

The Hierarchical Dendrogram for Countries

Cluster Dendrogram



```
DM <- sym.dist.interval(sym.data= syearcrop2[,2:6], method = "Ichino")  
model <- hclust(DM)  
plot(model, hang = -1)
```

The « Ichino » Option of the RSDA `sym.dist.interval` function is adapted from Ichino, M. and Yaguchi, H. (1994): Generalized Minkowski metrics for mixed feature type data analysis. *IEEE Transactions on Systems, Man and Cybernetics*, 24 (4), 698–708.

II) Divisive Clustering

The Chavent divisive clustering method:

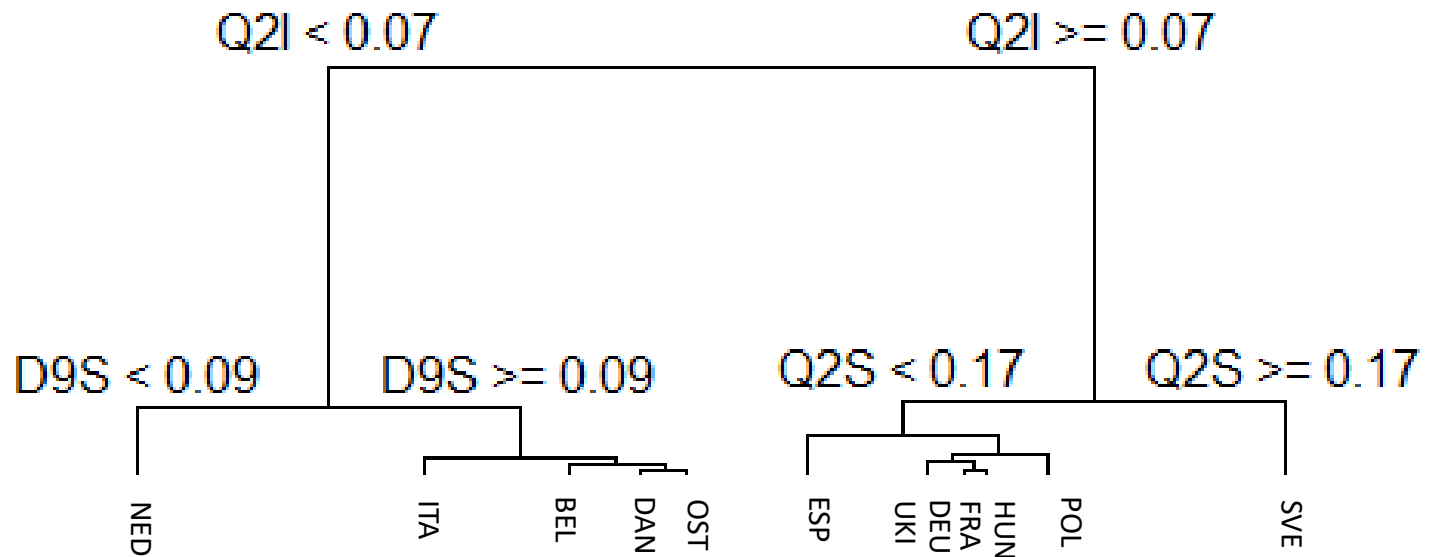
- Generated by the logical binary choice (*yes/no*) to a numerical binary question $\Psi = [Is\ z^q \leq c\ ?]$, let us denote $\{A_k, \overline{A_k}\}$ the induced bipartition of a cluster C_k formed of n_k objects;
- As in Ward method, the “*upper hierarchy*” of partition P_K is indexed by the height h of a cluster C_K , defined by their inter inertia as follows:

$$h(C_k) = B(A_k, \overline{A_k}) = \frac{\mu(A_k)\mu(\overline{A_k})}{\mu(A_k) + \mu(\overline{A_k})} d^2(g(A_k), g(\overline{A_k}))$$

- The DIVCLUS-T algorithm splits the cluster C_K^* that maximises $h(C_K)$, ensuring that the next partition $P_{K+1} = P_K \cup \{A_K, \overline{A_K}\} - C_K^*$ has the minimum intra inertia value, with respect to the following rule

$$W(P_{K+1}) = W(P_K) - h(C_K^*).$$

The DIVCLUST divisive clustering results :

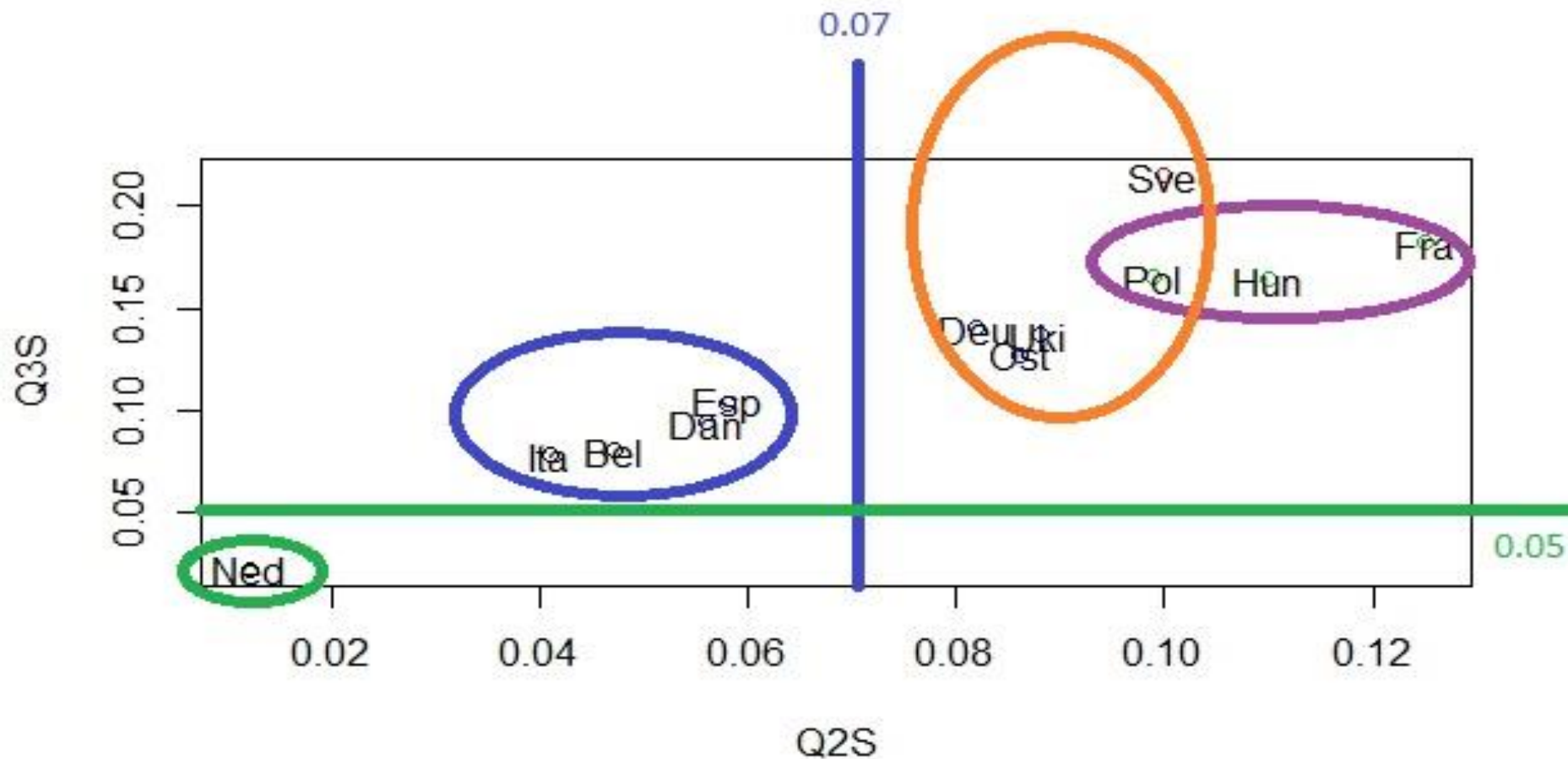


```
year2crop<-read.delim2("~/FERTI/year2crop.txt", row.names=1, stringsAsFactors=FALSE)
tree <- divclust(year2crop[,4:13])
plot(tree)
```

The divisive clustering `divclust` function is issued the `divclust` R library, based on Chavent M., Lechevalier Y., Briant O. (2007) DIVCLUS-T: A monothetic divisive hierarchical clustering method. *Computational Statistics & Data Analysis*, 52, 2, 687-701.

Symbolic Divisive Clustering for Quantile Estimates

The Divisive Tree for Countries : **C4 partition**



```
plot(ysyear2crop[,9:9],ysyear2crop[,11:11],col=cl4$cluster, xlab="Q2S",ylab="Q3S");  
text (ysyear2crop[,9:9], ysyear2crop[,11:11], row.names(ysyear2crop))
```

C4 is one of the best partitions, accordingly with the criterion of the Determinant Ratio Index = $\det(T) / \det(WG)$, where WG is the within-group covariance matrix, and T is the total covariance matrix, BG being the between-group covariance matrix.

Symbolic Divisive Clustering for Quantile Estimates

C2 partition : Wilcoxon test on the first PC

G1=X	PC1	Center(PC1)
BEL	[-1.80 : -1.22]	-1,51
DAN	[-0.95 : -0.31]	-0,63
ITA	[-1.57 : -1.19]	-1,38
NED	[-3.16 : -2.96]	-3,06
OST	[-0.60 : 0.47]	-0,07
G2=Y	PC1	Center(PC1)
DEU	[-0.33 : 0.41]	0,04
ESP	[-0.79 : -0.21]	-0,50
FRA	[1.56 : 2.10]	1,83
HUN	[0.58 : 1.62]	1,10
POL	[0.91 : 1.47]	1,19
SVE	[-0.62 : 3.43]	1,40
UKI	[-0.18 : 0.89]	0,36
Wilcoxon rank sum exact test		
data: X and Y		
W = 1, p-value = 0.005051		

>wilcox.test(X,Y)

Symbolic Divisive Clustering for Quantile Estimates

C4 partition : Manova test on the 1st and 2nd PC

CNTY	W=center(PC1)	Z=center(PC2)	G
NED	-3,06	-0,45	C1
ITA	-1,38	-0,26	C2
BEL	-1,51	0,31	C2
DAN	-0,63	0,51	C2
OST	-0,07	0,10	C2
ESP	-0,50	-0,02	C3
UKI	0,36	0,33	C3
DEU	0,04	-0,65	C3
FRA	1,83	0,67	C3
HUN	1,10	1,08	C3
POL	1,19	0,87	C3
SVE	1,40	-1,61	C4

```
>res.man<-manova(cbind(W,Z)
```

```
>summary (resman)
```

	Df	Pillai	approx F		num Df	den Df	Pr(>F)
G	3	1.4369	6.8055		6	16	0.0009996
Residuals	8						
Response W		Sum Sq	Mean Sq		F value	Pr(>F)	
G	3	17.1179	5.7060		9.0294	0.006011	
Response Z		Sum Sq	Mean Sq		F value	Pr(>F)	
G	3	3.7136	1.23786		4.1957	0.04654	

Determine the optimal partition

- In order to determine an optimal partition, we use as the internal quality index for each partition P_K , the log of the determinant ratio computed as follows:

$$\varkappa_K = N \log \left(\frac{\det(T)}{\det(WG^{(K)})} \right)$$

where $T = Z'Z$ is the total scatter matrix (N times the total variance-covariance matrix)

and $WG^{(K)} = \sum_{k=1}^K W^{(k)}$ the sum of the within-group scatter matrices,

$W^{(k)}$ for each group C_k of the partition P_K in K groups.

- The optimal score for the quality index is given by the *min_diff* decision rule:

$$K^* = \arg\min_K \{\partial_K - \partial_{K-1}\}$$

with $\partial_K = \varkappa_{K+1} - \varkappa_K$,

using procedure *ClusterCrit*

Clustering Validation : Internal Indices, optimum

Criterion : c(i)	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
Ball Hall max di	0,006605078	0,002982239	0,002061369	0,000744251	0,000472673	0,000379032	0,000221	0,000140056	6,80E-05	5,28E-05
Banfeld Raftery min	-60,01052	-Inf	-Inf	-Inf	-Inf	-Inf	-Inf	-Inf	-Inf	-Inf
C index min	0,173622	0,1286931	0,0547564	0,01570826	0,01520788	0,02368761	0,002616917	0,003331737	0	0,03623327
Calinski Harabasz max	14,66531	13,20103	16,23248	26,61088	24,73984	24,29827	31,6854	29,31638	32,40501	17,08513
Davies Bouldin min	0,6735817	0,5730269	0,5592225	0,4833014	0,4291948	0,4498311	0,3964471	0,3284583	0,2468822	0,1900374
Det Ratio min di	84,07927	7,59E+14	1,41E+29	-6,02E+45	3,30E+60	1,74E+79	6,03E+98	1,78E+115	3,07E+133	Inf
Dunn max	0,1835137	0,212243	0,2993189	0,5552686	0,5552686	0,567683	0,9208916	0,9208916	1,073963	0,6597068
Gamma max	0,5974265	0,6565854	0,825	0,941358	0,9392857	0,9111111	0,983871	0,978836	1	0,8769231
G plus min	0,1020979	0,08205128	0,03263403	0,008857809	0,007925408	0,007459208	0,000932401	0,000932401	0	0,001864802
GDI max	0,1835137	0,212243	0,2993189	0,5552686	0,5552686	0,567683	0,9208916	0,9208916	1,073963	0,6597068
Sub-Total C	10	0	0	6	0	0	0	0	0	11
Difference : d(i)=c(i)-c(i+1)	D2	D3	D4	D5	D6	D7	D8	D9	D10	
Ball Hall max di	-0,003622839	-0,00091087	-0,001317118	-0,000271579	-9,36408E-05	-0,000158032	-8,09444E-05	-1,52E-05	-1,51796E-05	
Det Ratio min di	7,59322E+14	1,41253E+29	-6,02063E+45	3,29523E+60	1,73602E+79	6,028E+98	1,7791E+115		-6,02063E+45	
Ksq DetW max di	-3,44761E-37	-8,58941E-50	-8,20859E-64	3,00916E-80	-7,91706E-95	-2,0455E-113	-7,694E-133	-2,36E-167	3,00916E-80	
Log Det Ratio min di	357,98028	394,2828			517,299	539,927	455,084			
Log SS Ratio min di	0,6933183	0,729967	0,91552	0,304388	0,346634	0,642745	0,343504	1,58E-01	0,158403	
Trace W max di	-0,03018137	-0,02257986	-0,01584769	-0,003082663	-0,00261525	-0,003082667	-0,001015	-1,98E-04	-0,000198	
Trace WiB max di	4,30809E+29	2,40249E+31	5,19098E+33	2,56285E+34	6,5834E+36	4,0348E+37	-4,69335E+37	0,00E+00	4,0348E+37	
Sub-total D	2	0	1	1	0	1	0	2	1	0
Total (C+D)	12	0	1	7	0	1	0	2	12	6

```
intIdx <- intCriteria(myvar2crop[,4:13],cl4$cluster,"all")
intIdx
```

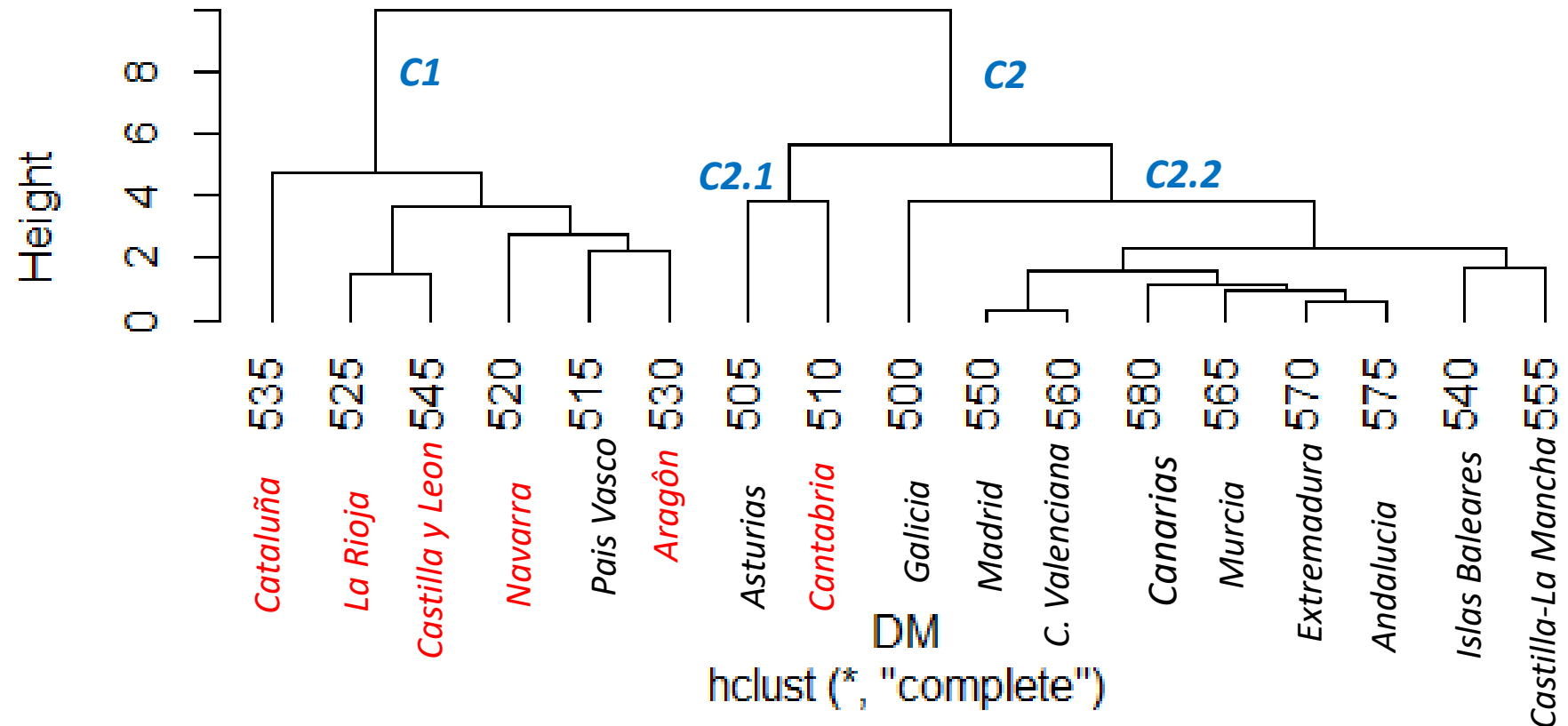
Maria Halkidi, Yannis Batistakis, and Michalis Vazirgiannis. On clustering validation techniques. *J. Intell. Inf. Syst.*, 17(2-3):107{145, 2001.

Symbolic HCA («Hausdorff » option) for Quantile Estimates

The Hierarchical Dendrogram for Spanish Regions

Hausdorff Distance

Cluster Dendrogram

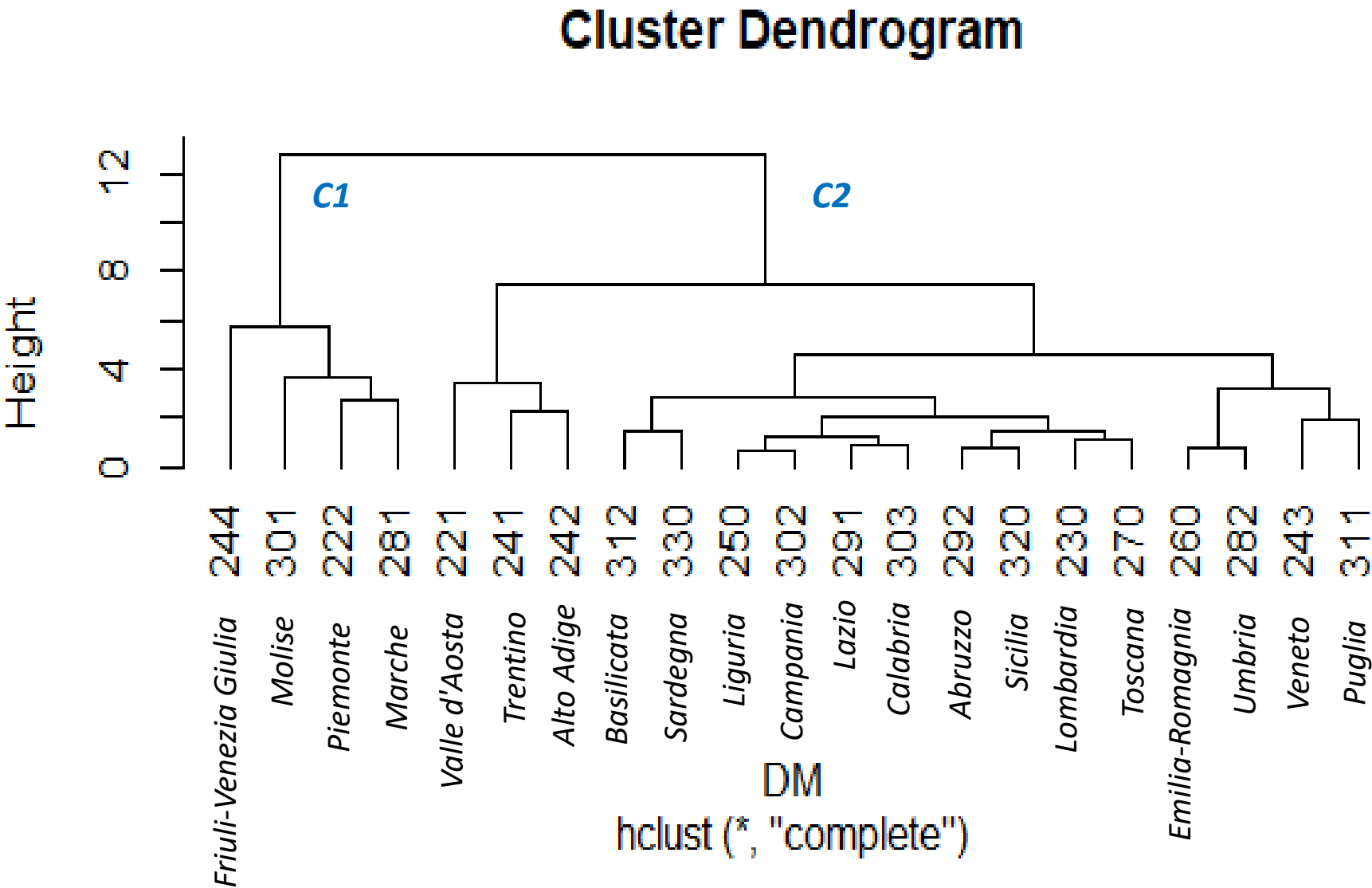


Cantabria: Spanish region belonging to the Ebro watershed

(D.Desbois, FADN-UE, 2006)

Symbolic HCA («Hausdorff » option) for Quantile Estimates

The Hausdorff Distance Hierarchical Dendrogram for Italian Regions

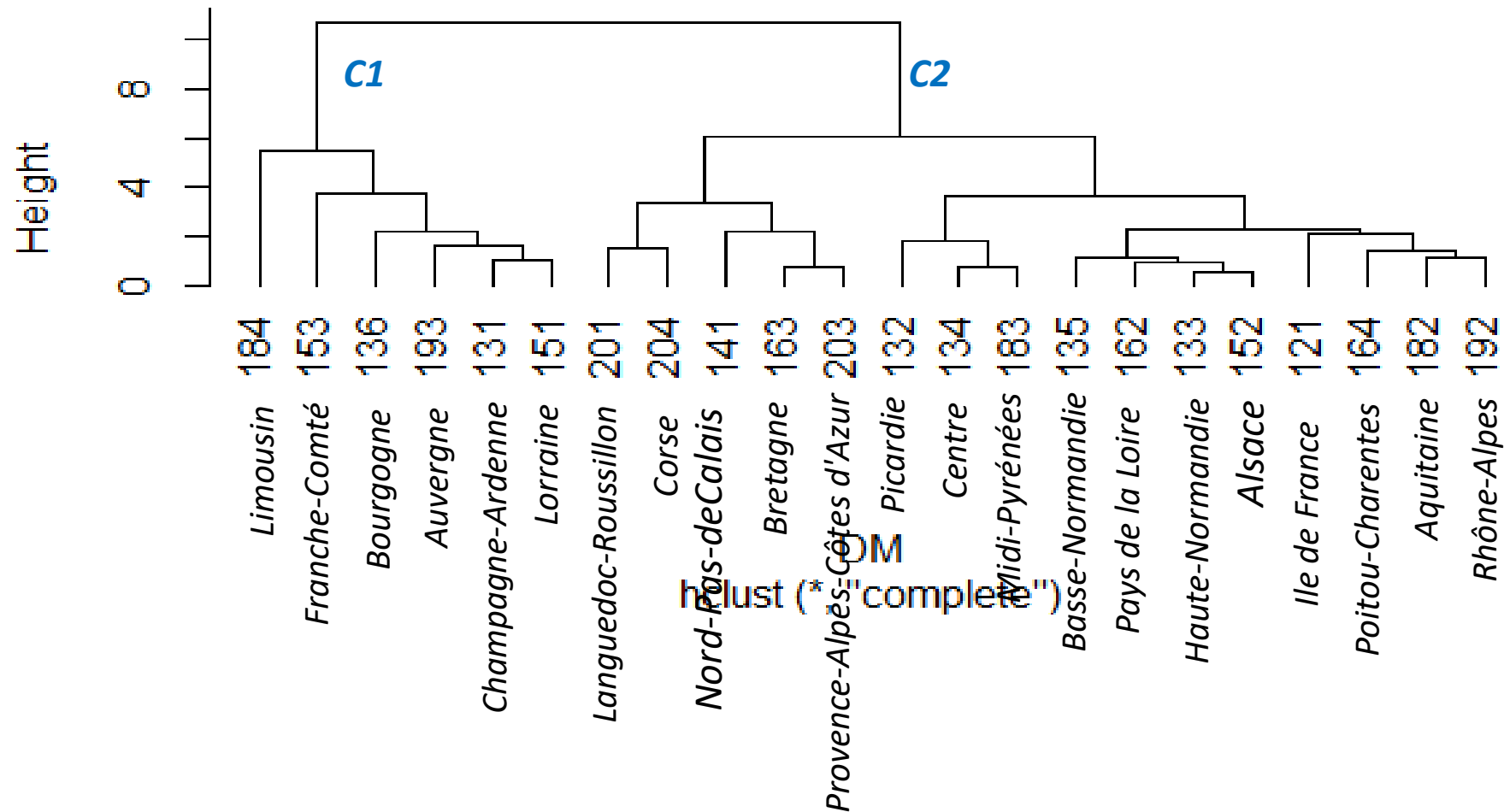


Symbolic HCA («Hausdorff » option) for Quantile Estimates

The Hierarchical Dendrogram for French Regions

Hausdorff Distance

Cluster Dendrogram



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As a personal tribute to my PhD advisor:

Emeritus Prof. Yves Surry (SLU, The Royal Swedish Academy of Agriculture)
who passed away during the Covid crisis.