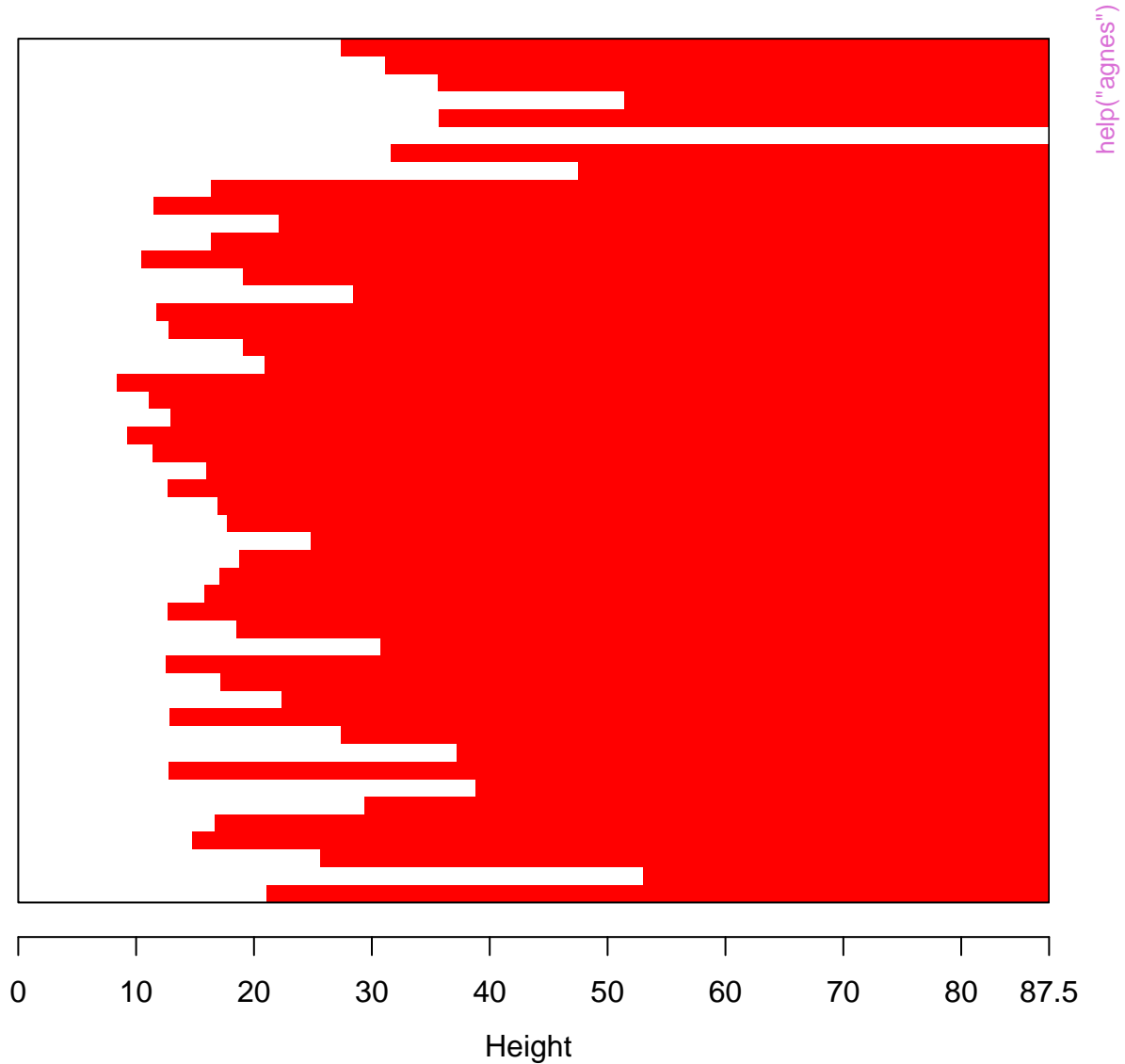
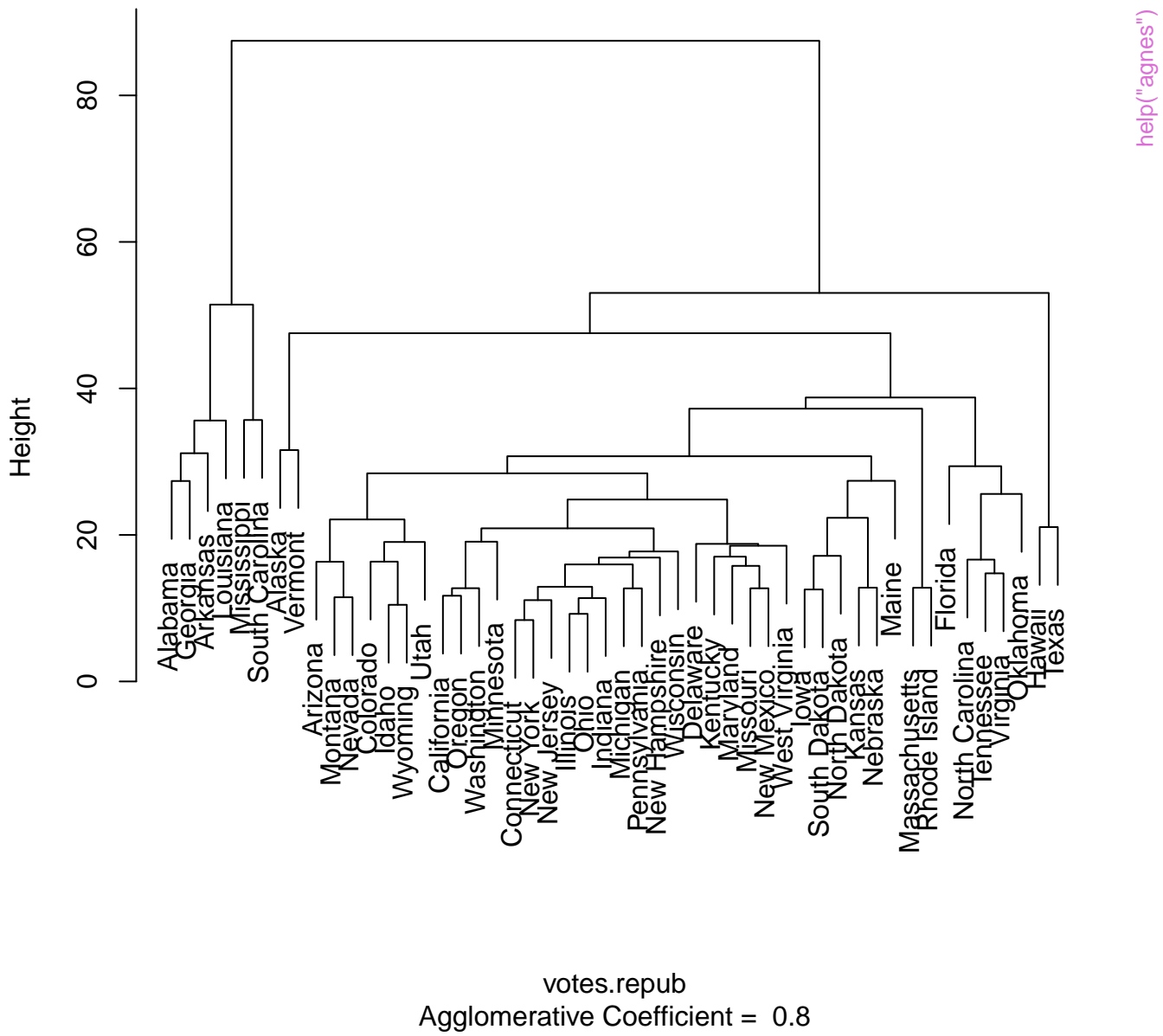


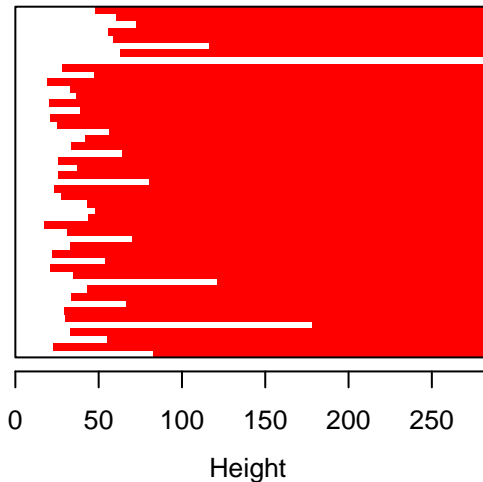
Banner of `agnes(x = votes.repub, metric = "manhattan", stand = TF`



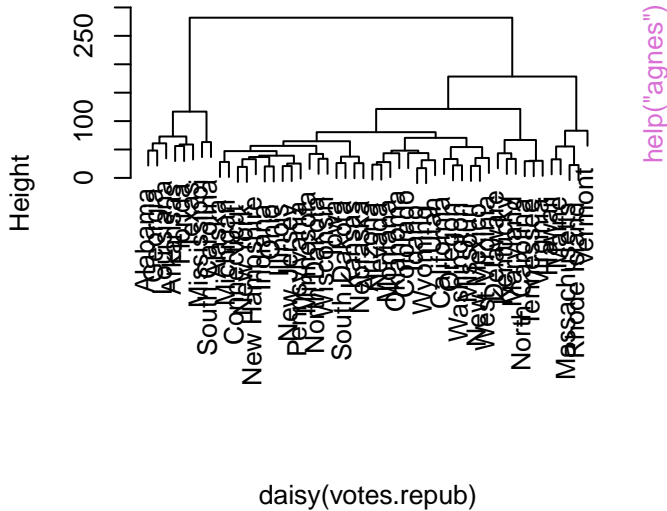
Dendrogram of agnes(x = votes.repub, metric = "manhattan", stand = TRUE)



**Banner of `agnes(x = daisy(votes.repub)`, `diss = "complete"`)**

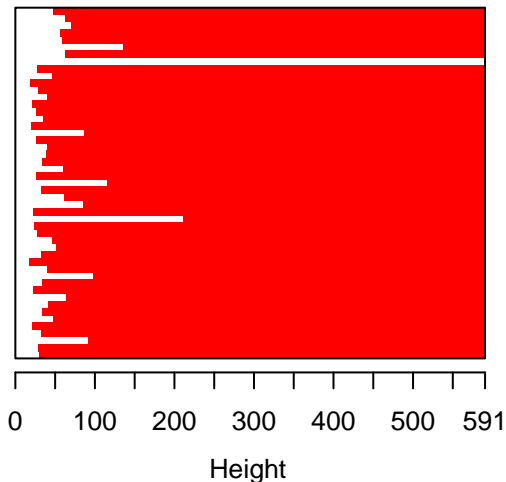


Agglomerative Coefficient = 0.88

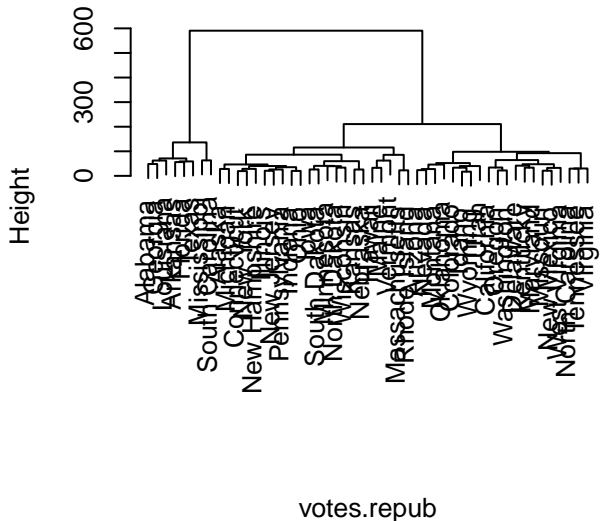


`daisy(votes.repub)`  
Agglomerative Coefficient = 0.88

**Banner of `agnes(x = votes.repub, n of agnes(x = votes.repub, method = "flexible", 0.625)`**

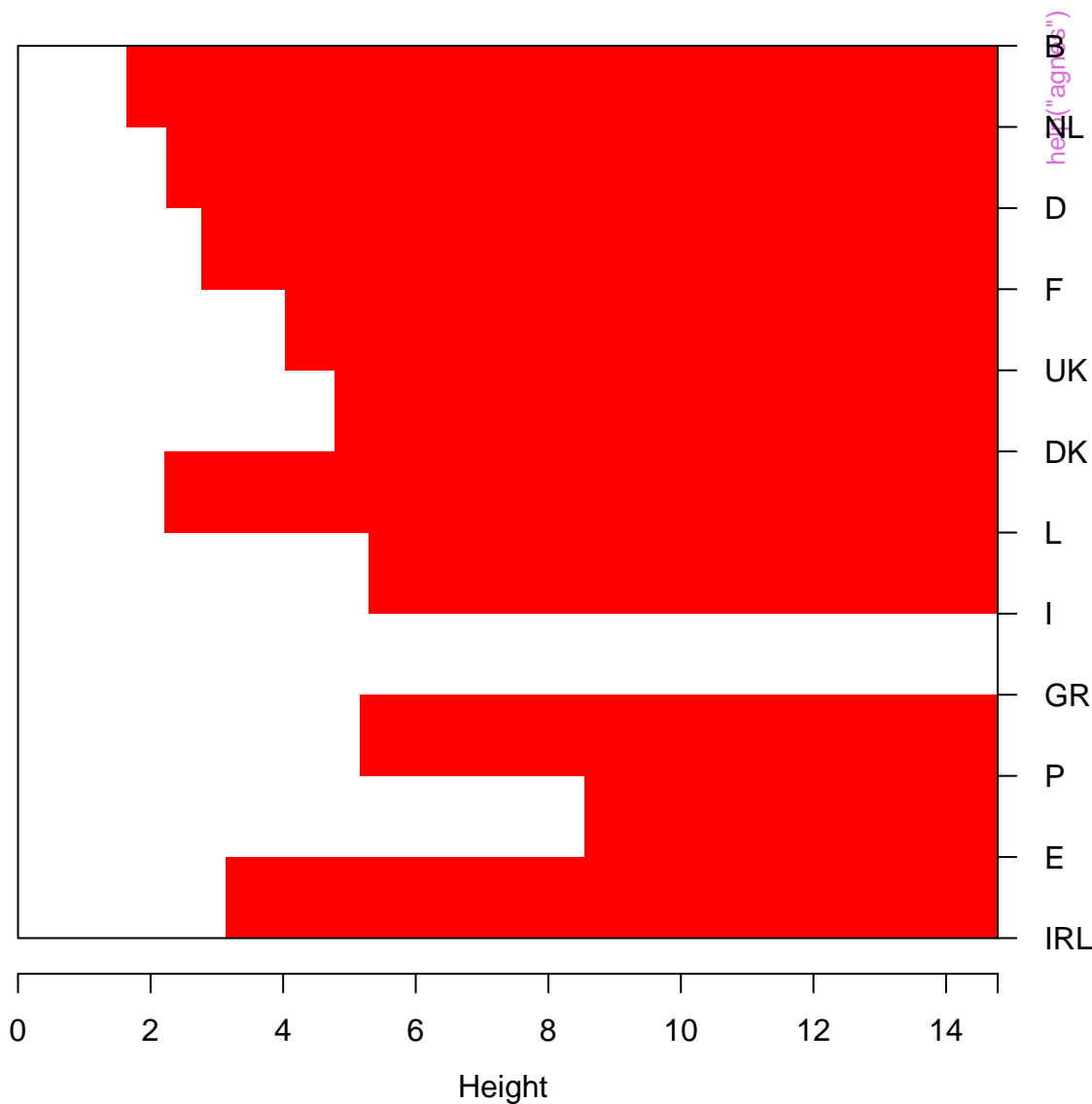


Agglomerative Coefficient = 0.94



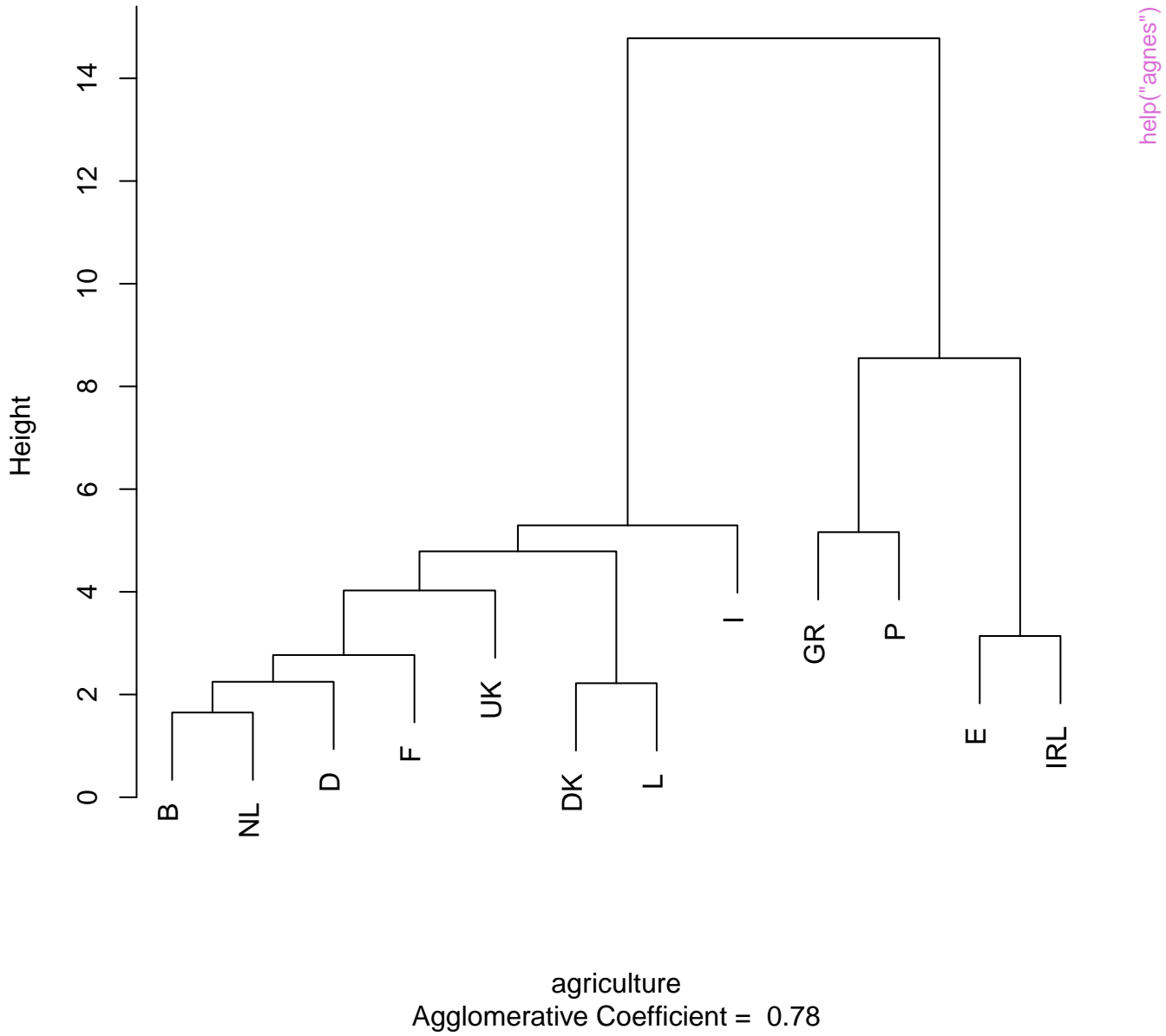
`votes.repub`  
Agglomerative Coefficient = 0.94

# Banner of agnes(x = agriculture)

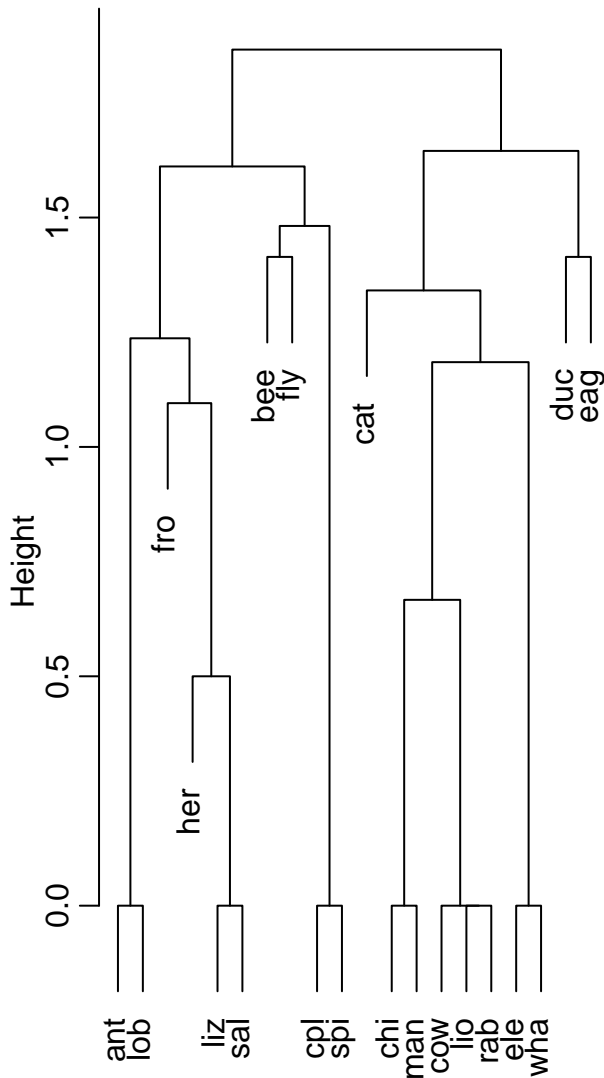


Agglomerative Coefficient = 0.78

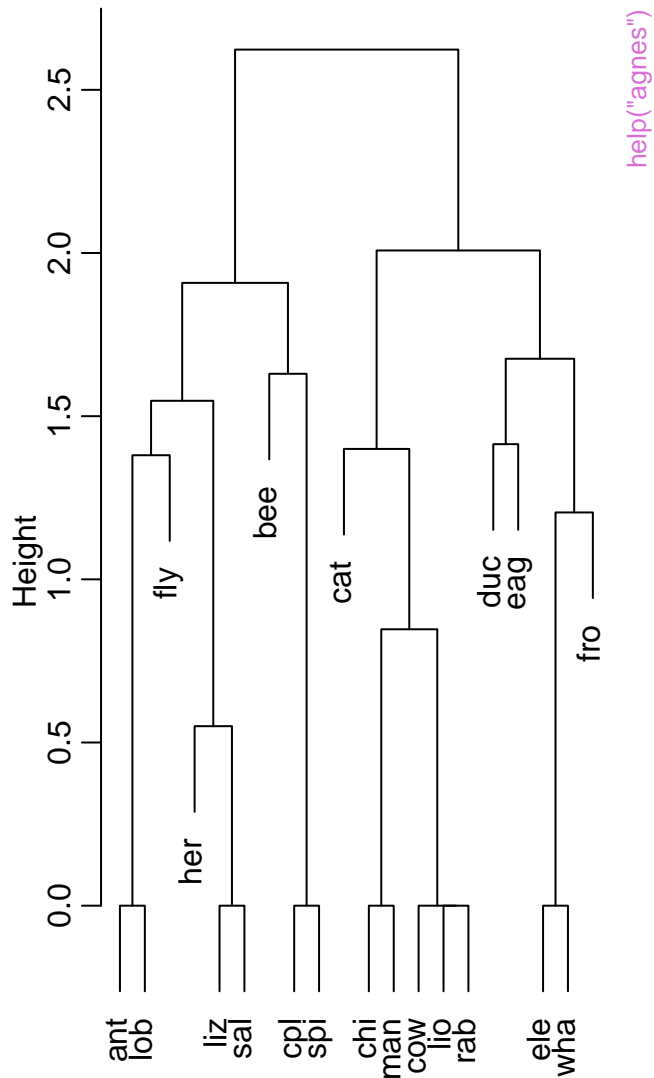
# Dendrogram of agnes(x = agriculture)



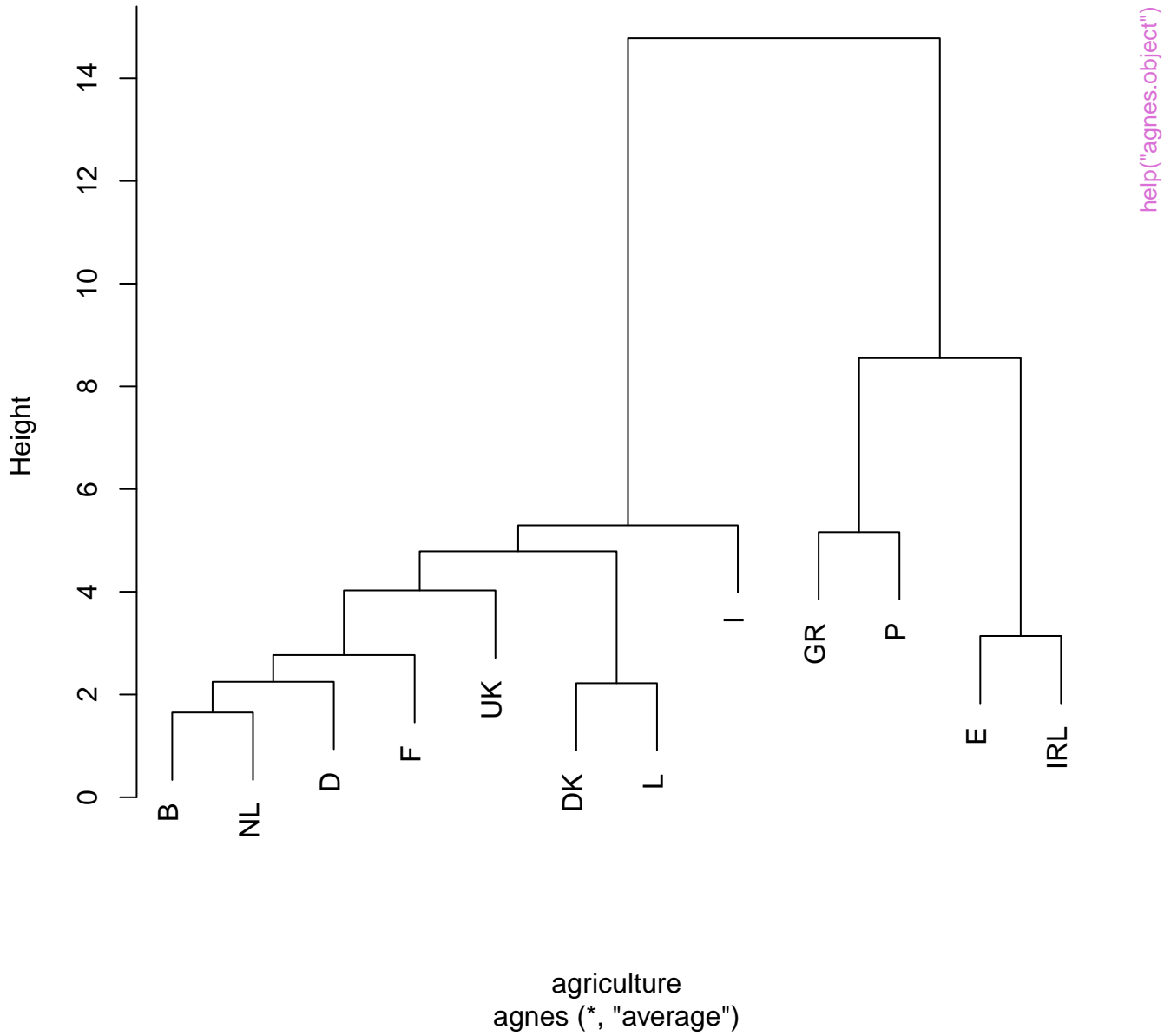
Dendrogram of agnes(x = animals)



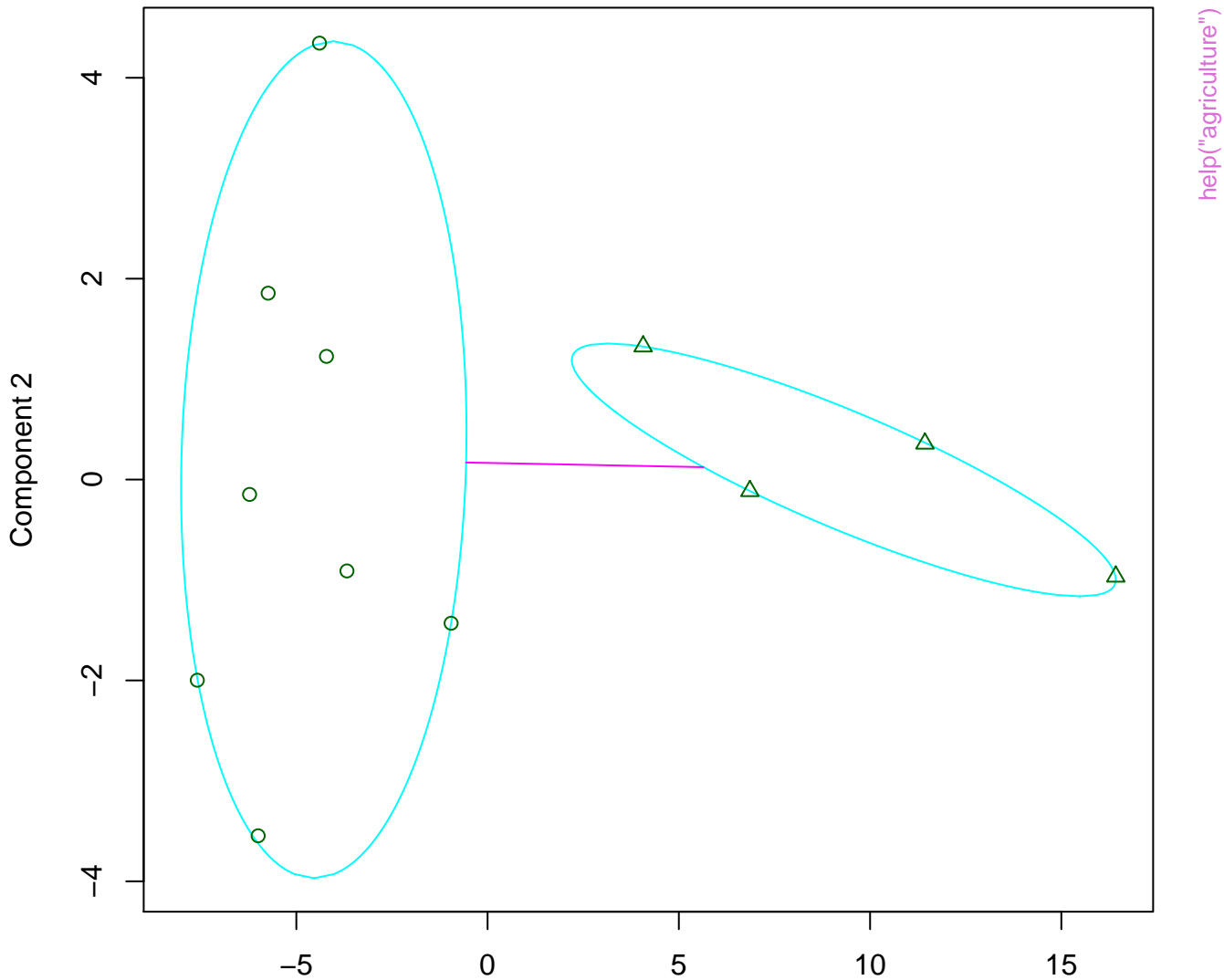
Dendrogram of agnes(x = animals, method = "gaver")



# Dendrogram of agnes(x = agriculture)



**clusplot(pam(x = agriculture, k = 2))**



help("agriculture")

Component 1

These two components explain 100 % of the point variability.

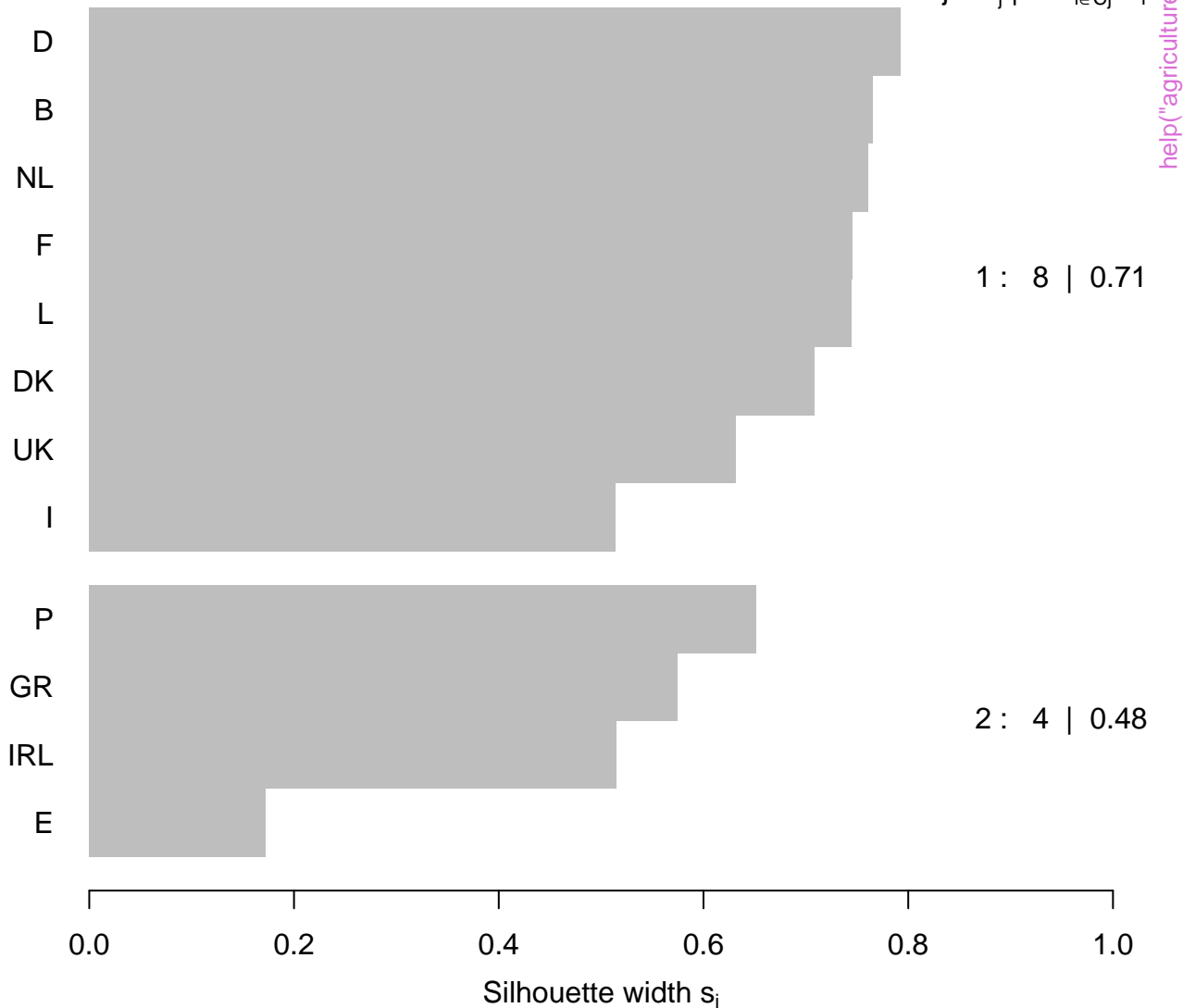


# Silhouette plot of pam(x = agriculture, k = 2)

n = 12

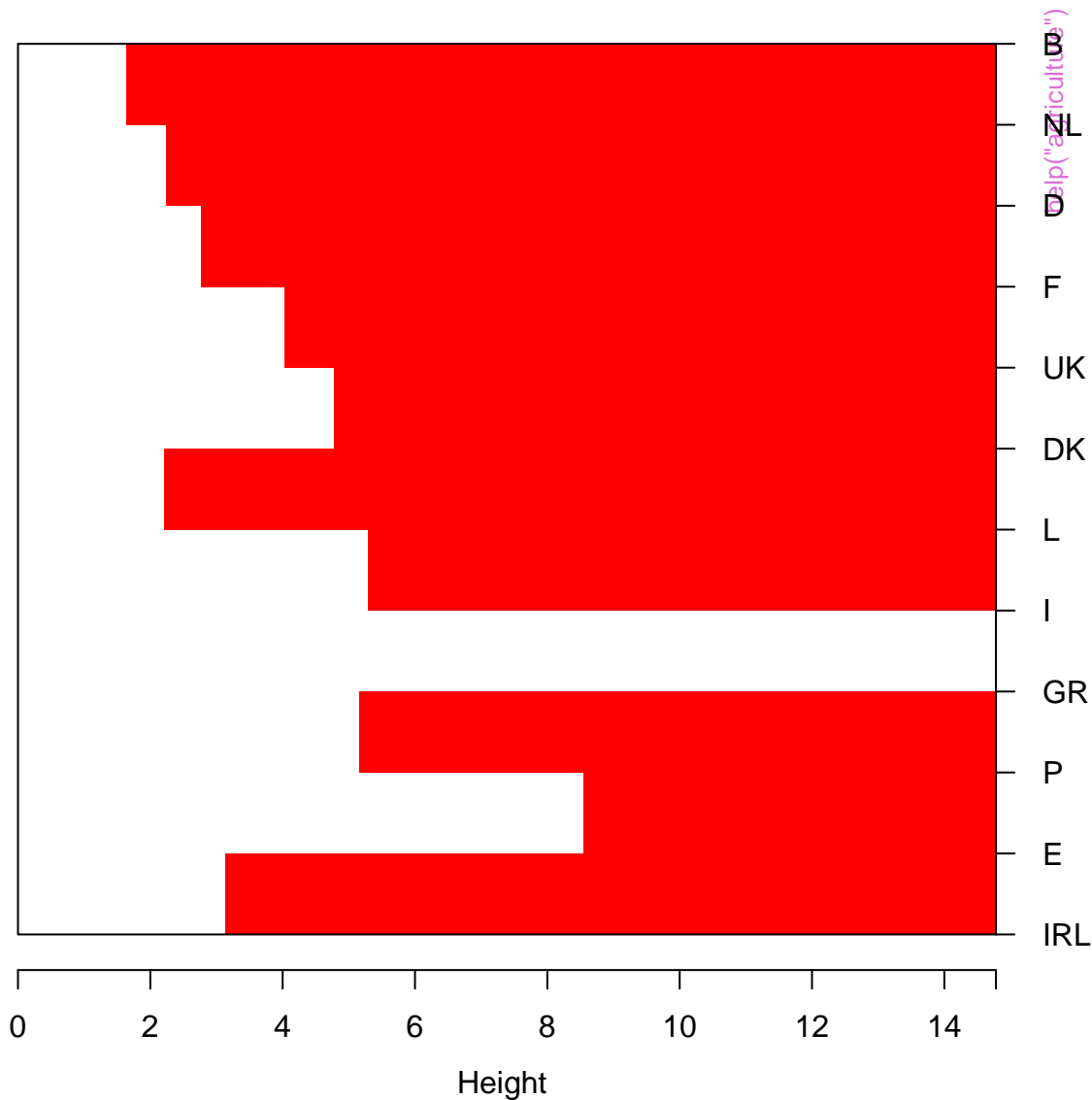
2 clusters  $C_j$

$j : n_j \mid \text{ave}_{i \in C_j} s_i$



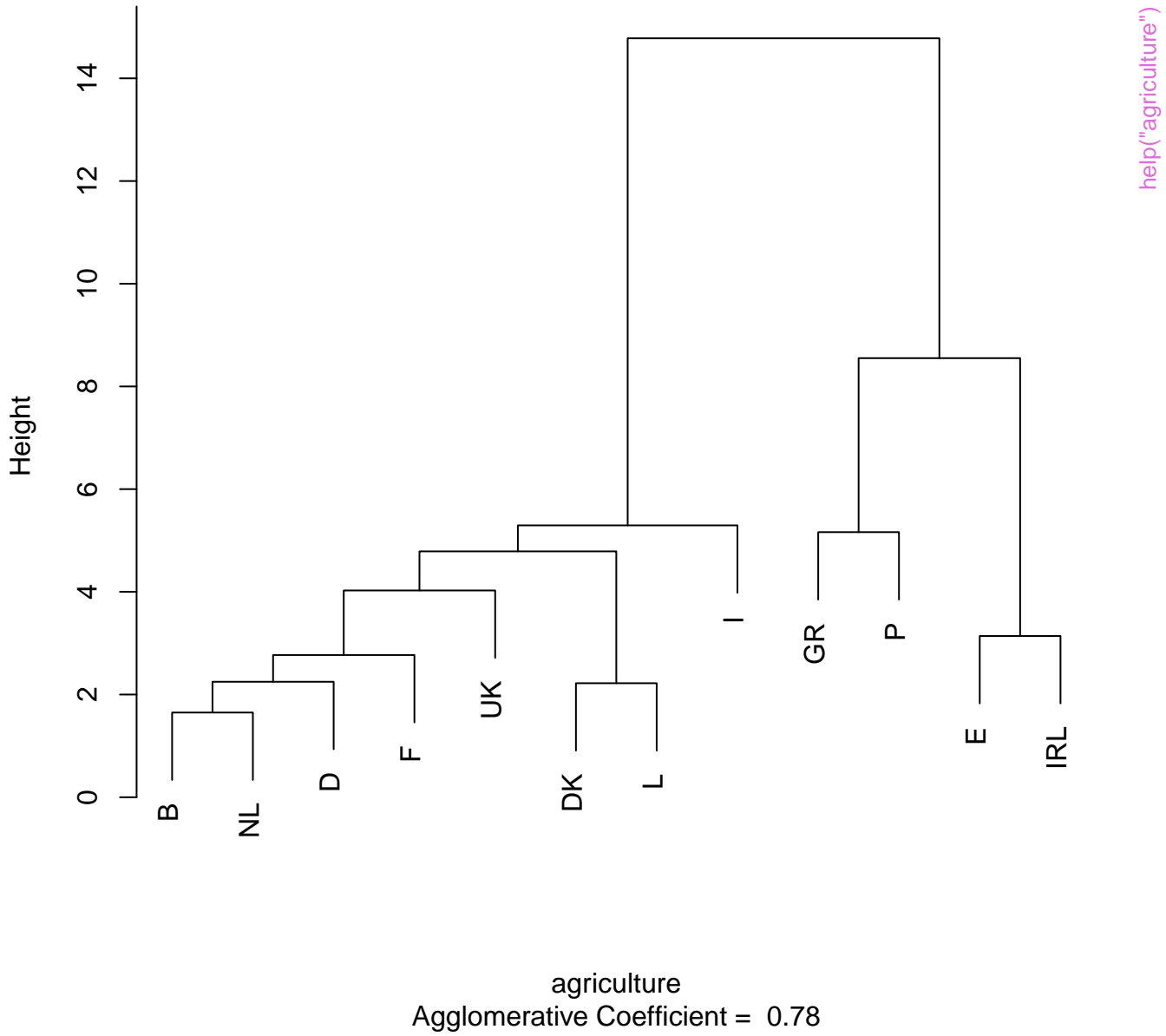
Average silhouette width : 0.63

# Banner of agnes(x = agriculture)

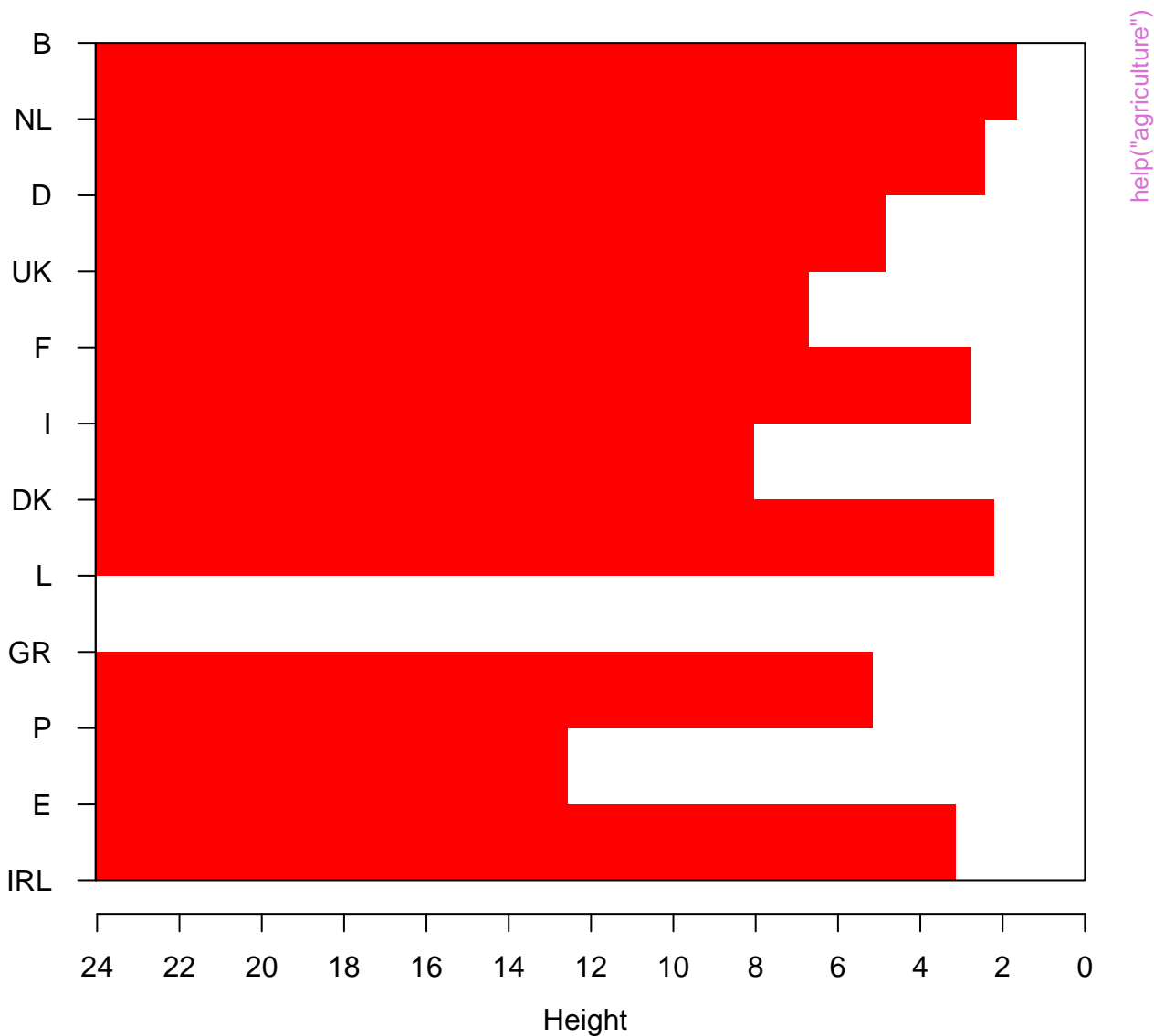


Agglomerative Coefficient = 0.78

# Dendrogram of agnes(x = agriculture)

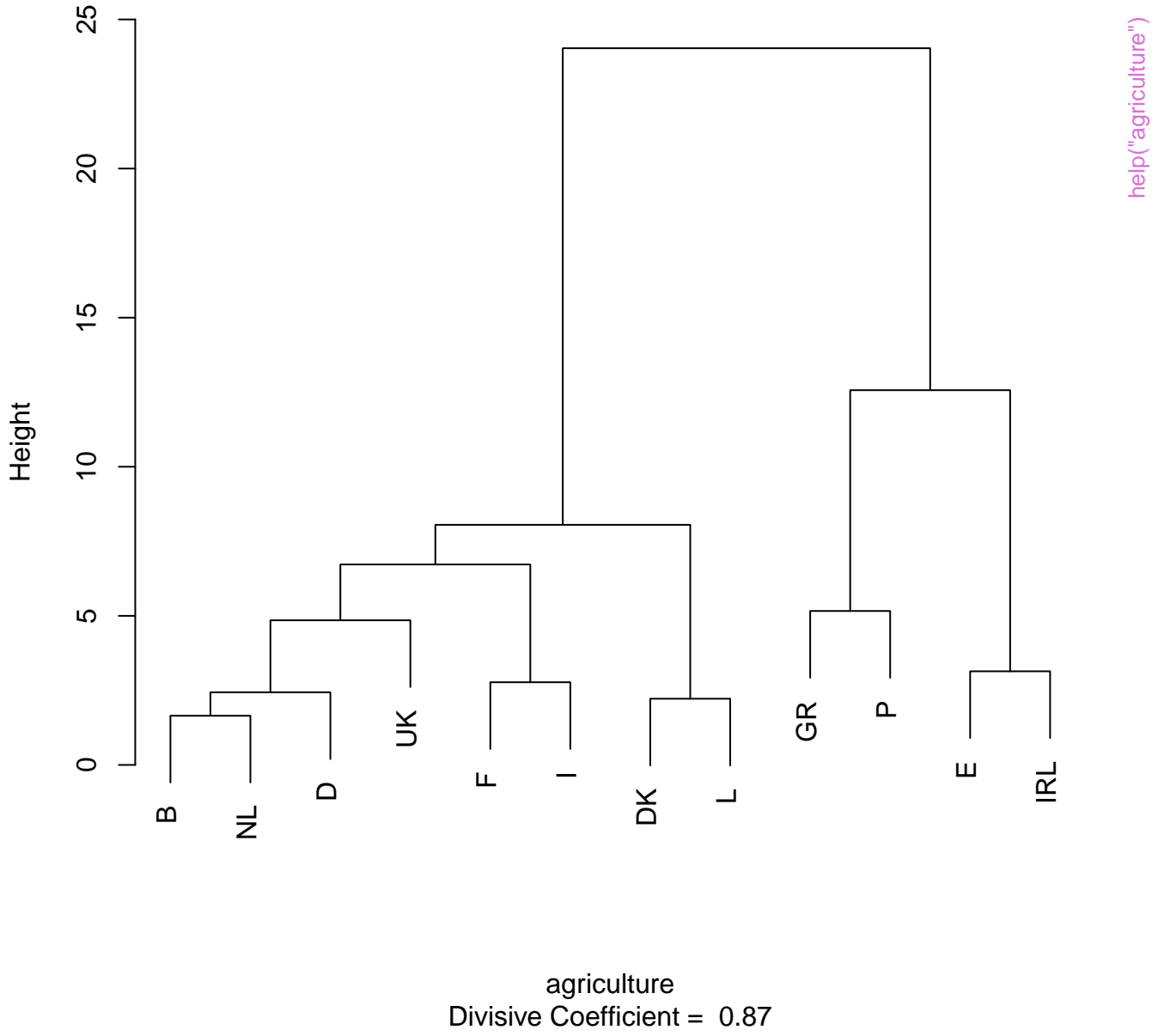


## Banner of diana(x = agriculture)

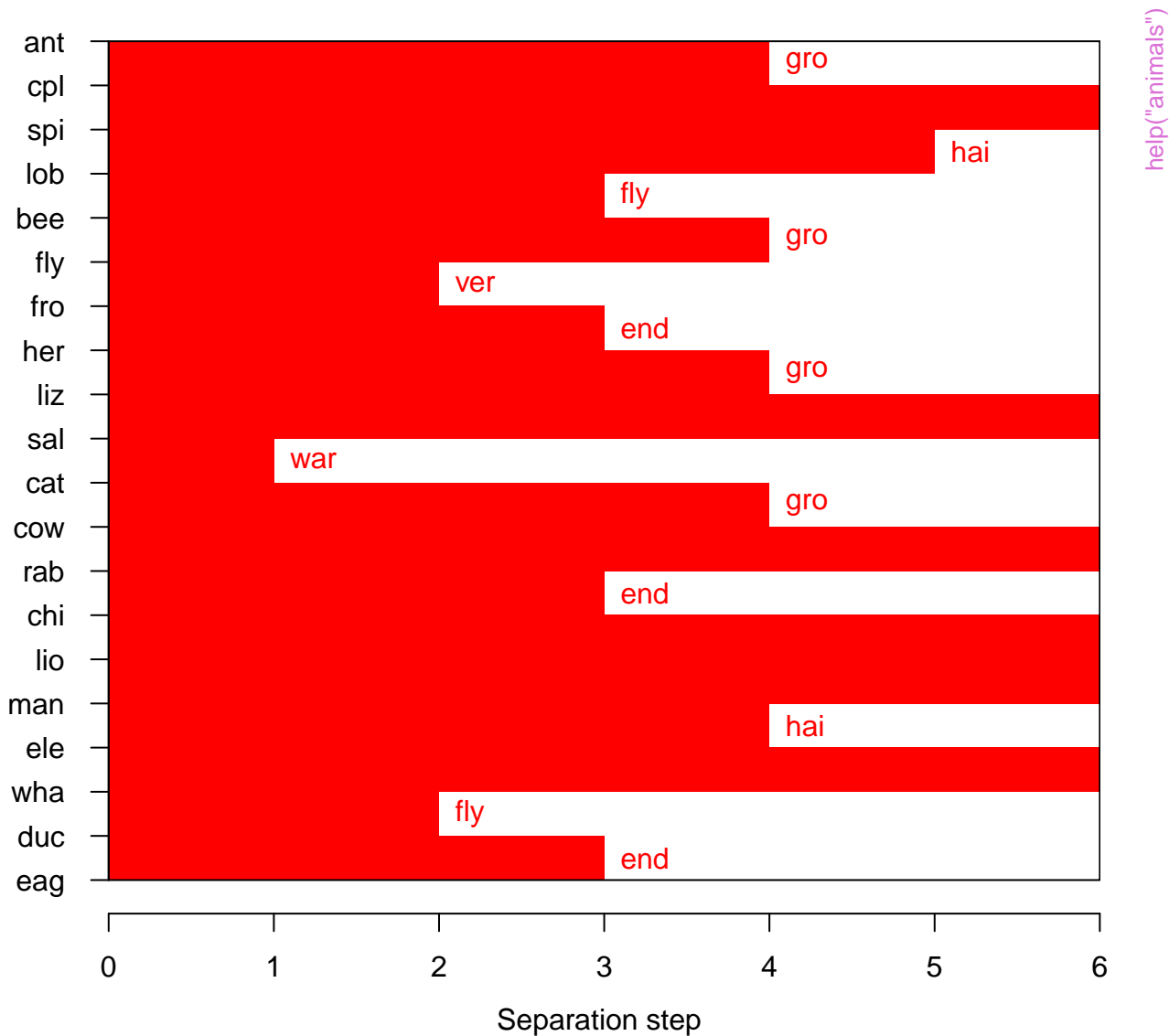


Divisive Coefficient = 0.87

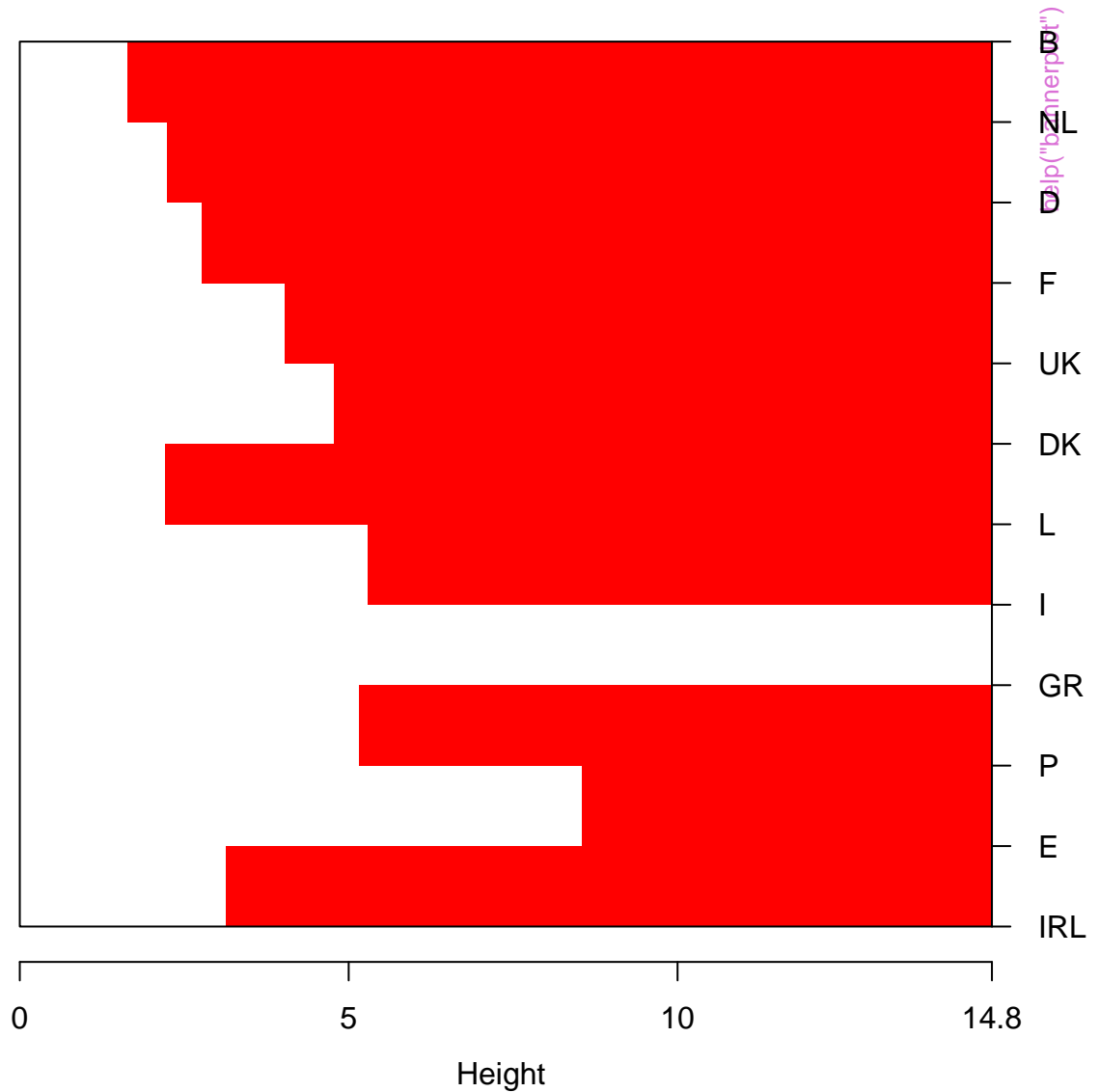
# Dendrogram of diana(x = agriculture)

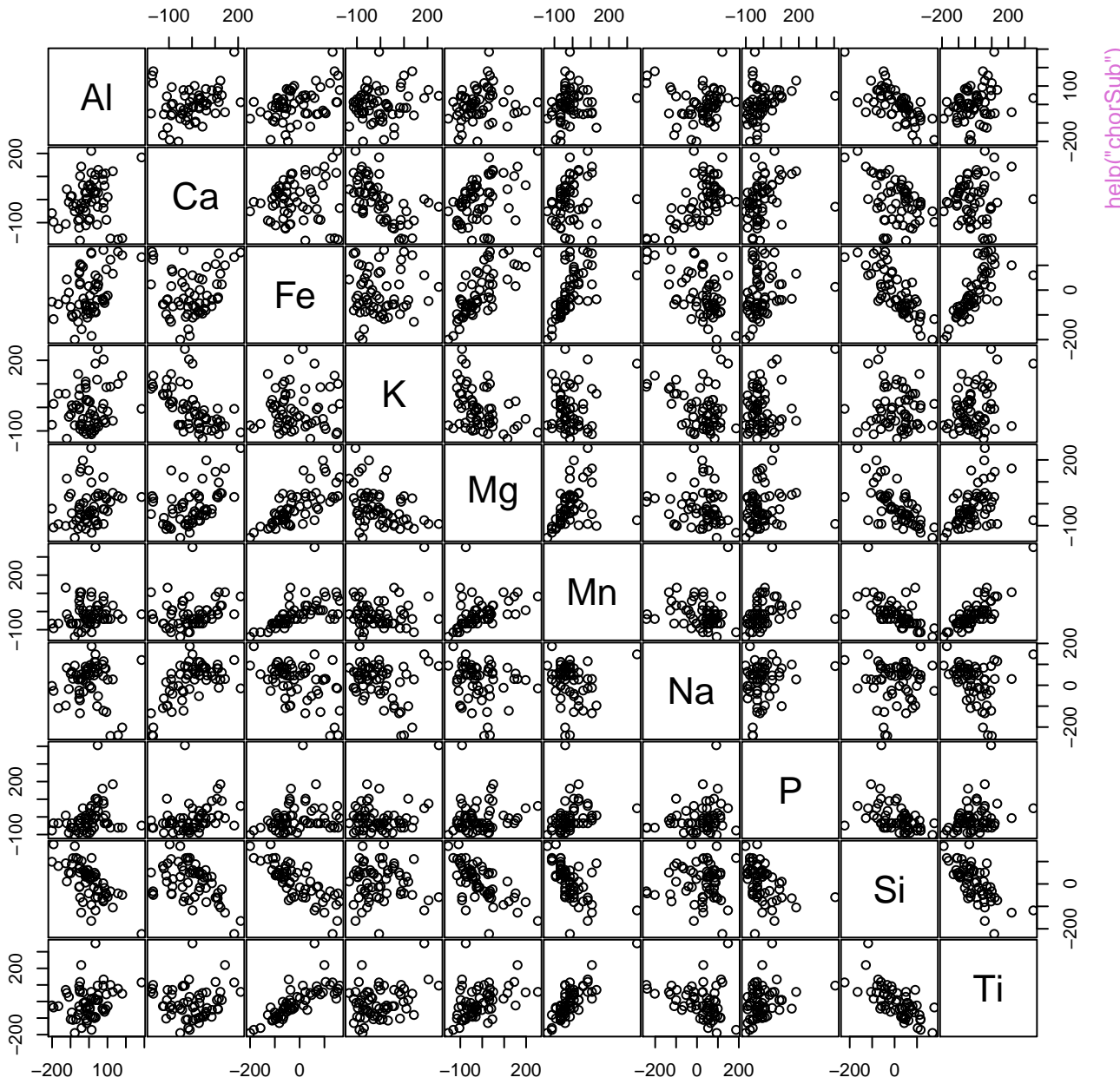


# Banner of mona(x = animals)



# Bannerplot

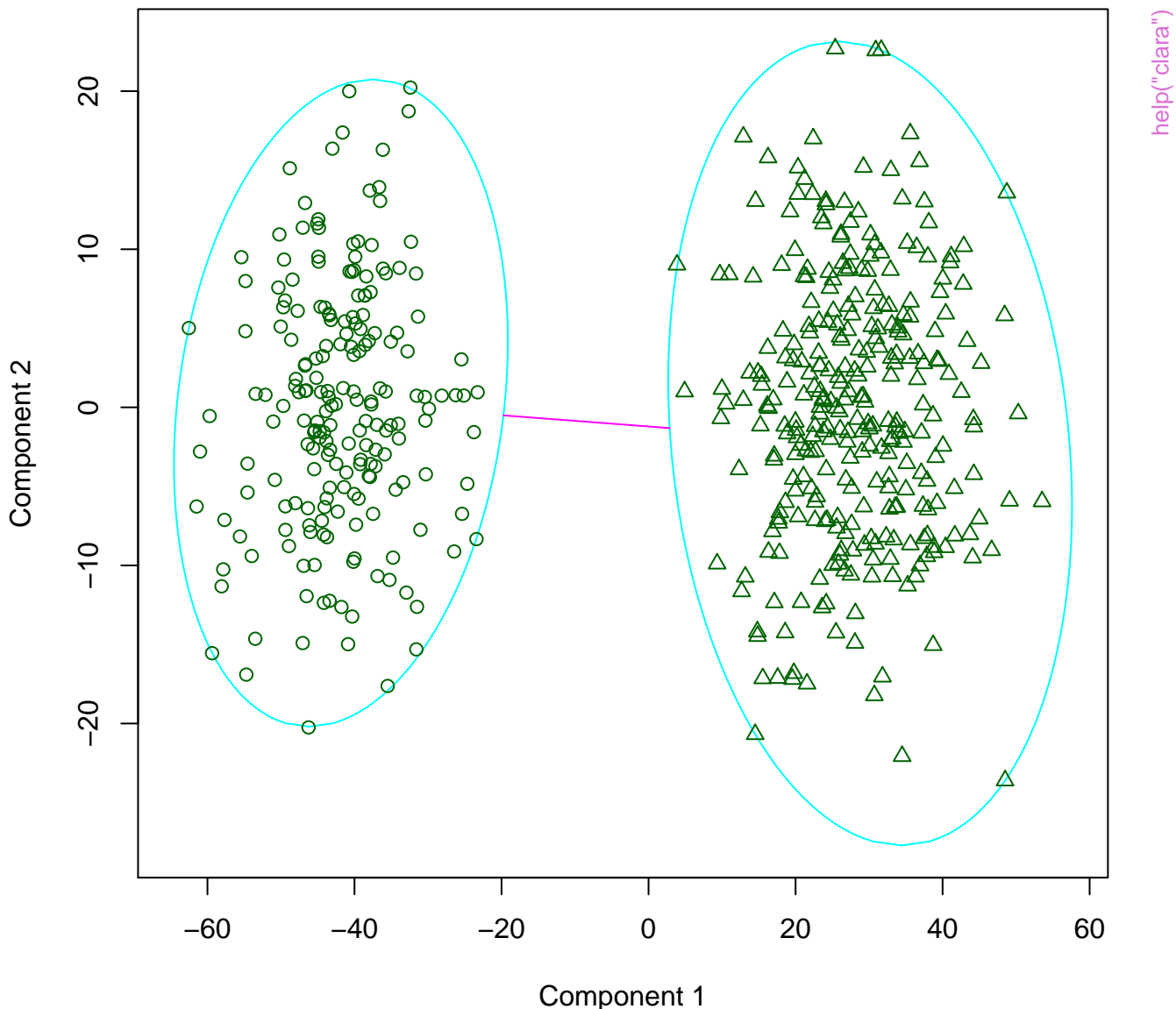




help("chorSub")



**clusplot(clara(x = x, k = 2, samples = 50))**



Component 1

These two components explain 100 % of the point variability.

# Silhouette plot of clara(x = x, k = 2, samples = 50)

n = 44

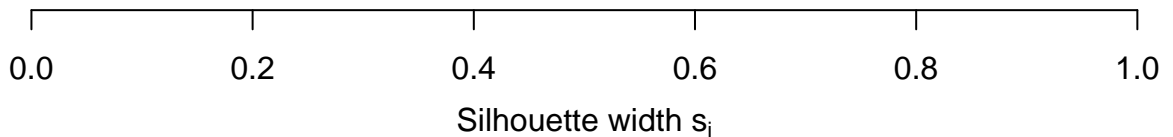
2 clusters  $C_j$

$j : n_j \mid \text{ave}_{i \in C_j} s_i$

help("clara")

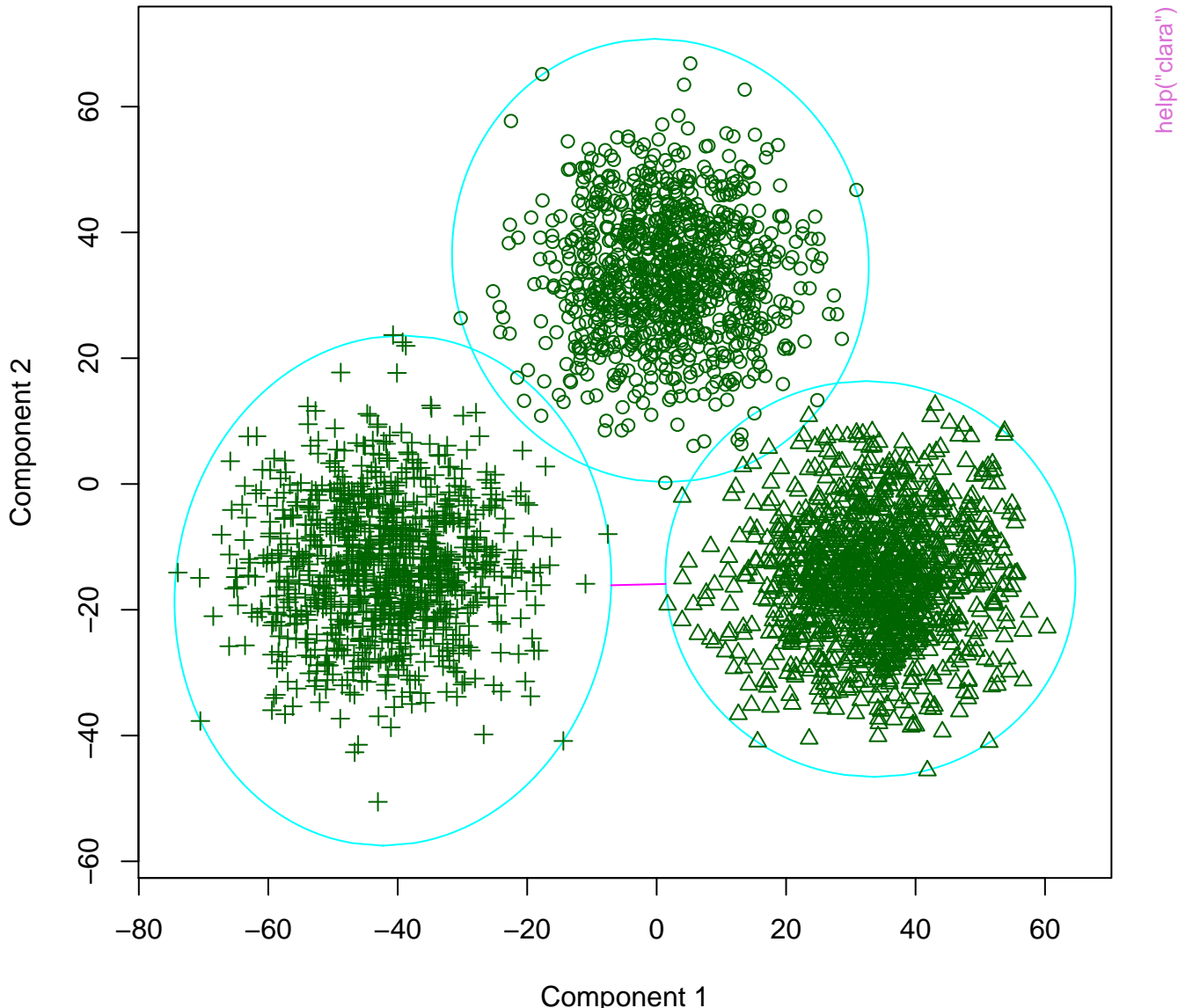
1 : 21 | 0.80

2 : 23 | 0.77



Average silhouette width : 0.78

**clusplot(clara(x = xclara, k = 3))**



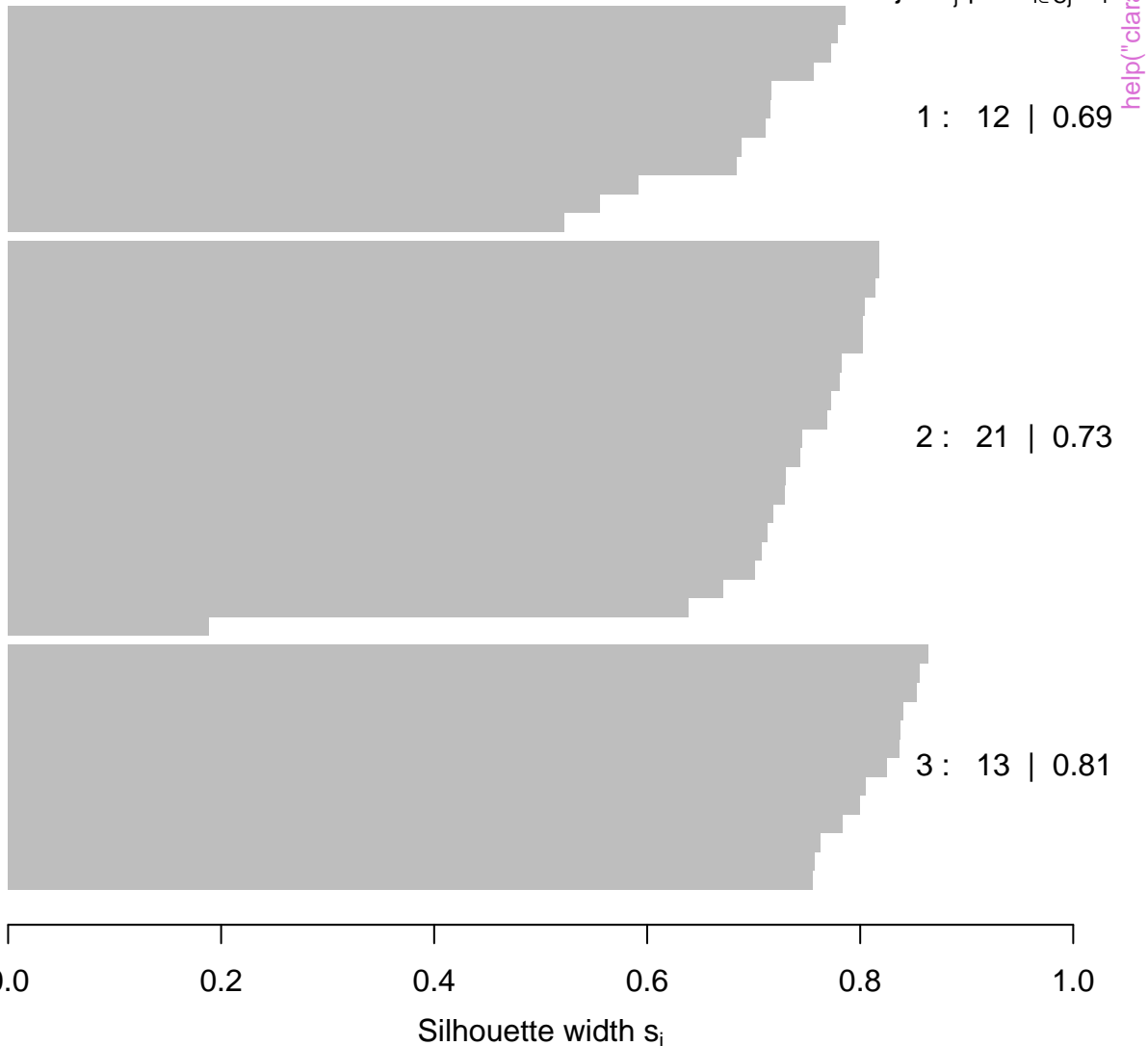
These two components explain 100 % of the point variability.

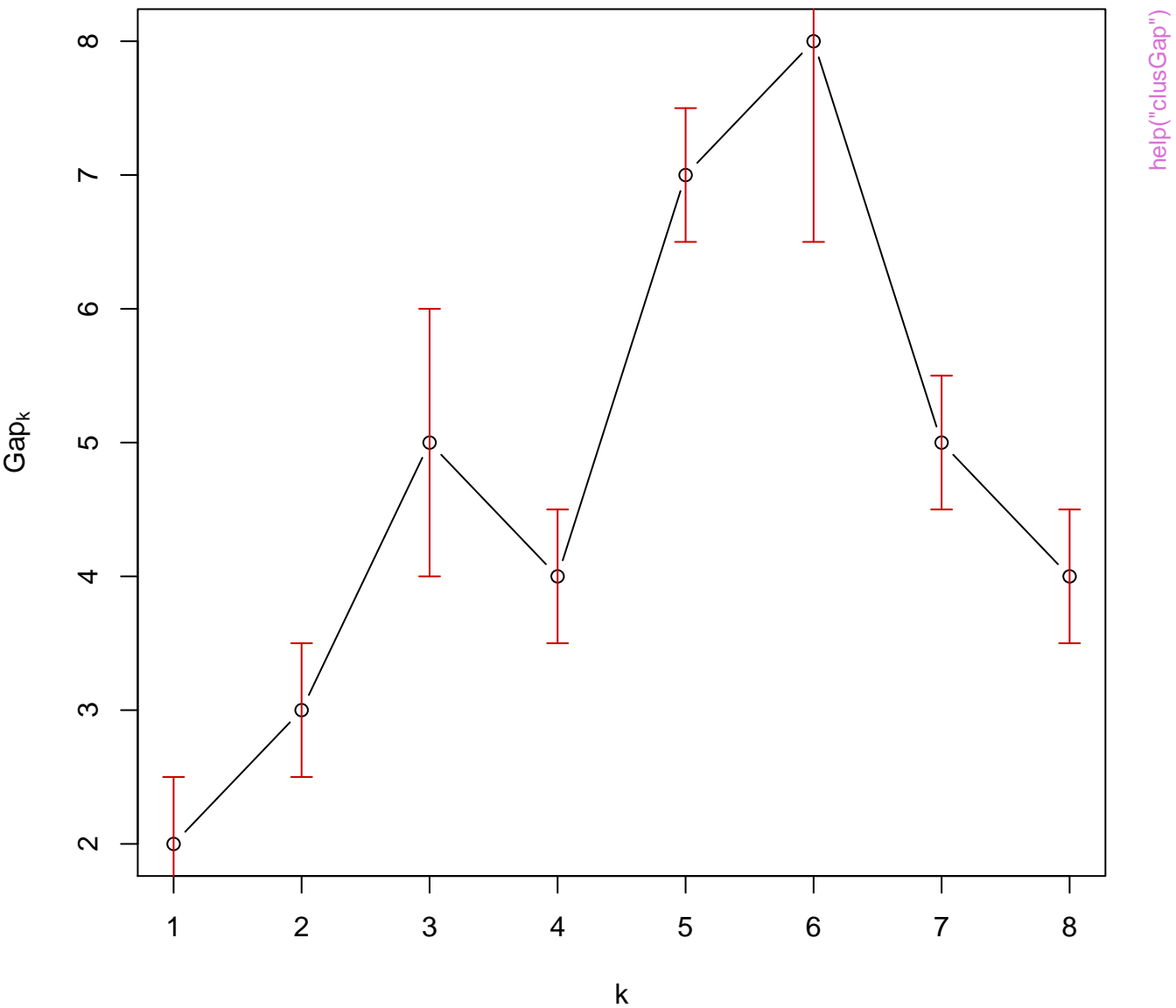
# Silhouette plot of clara(x = xclara, k = 3)

n = 46

3 clusters  $C_j$

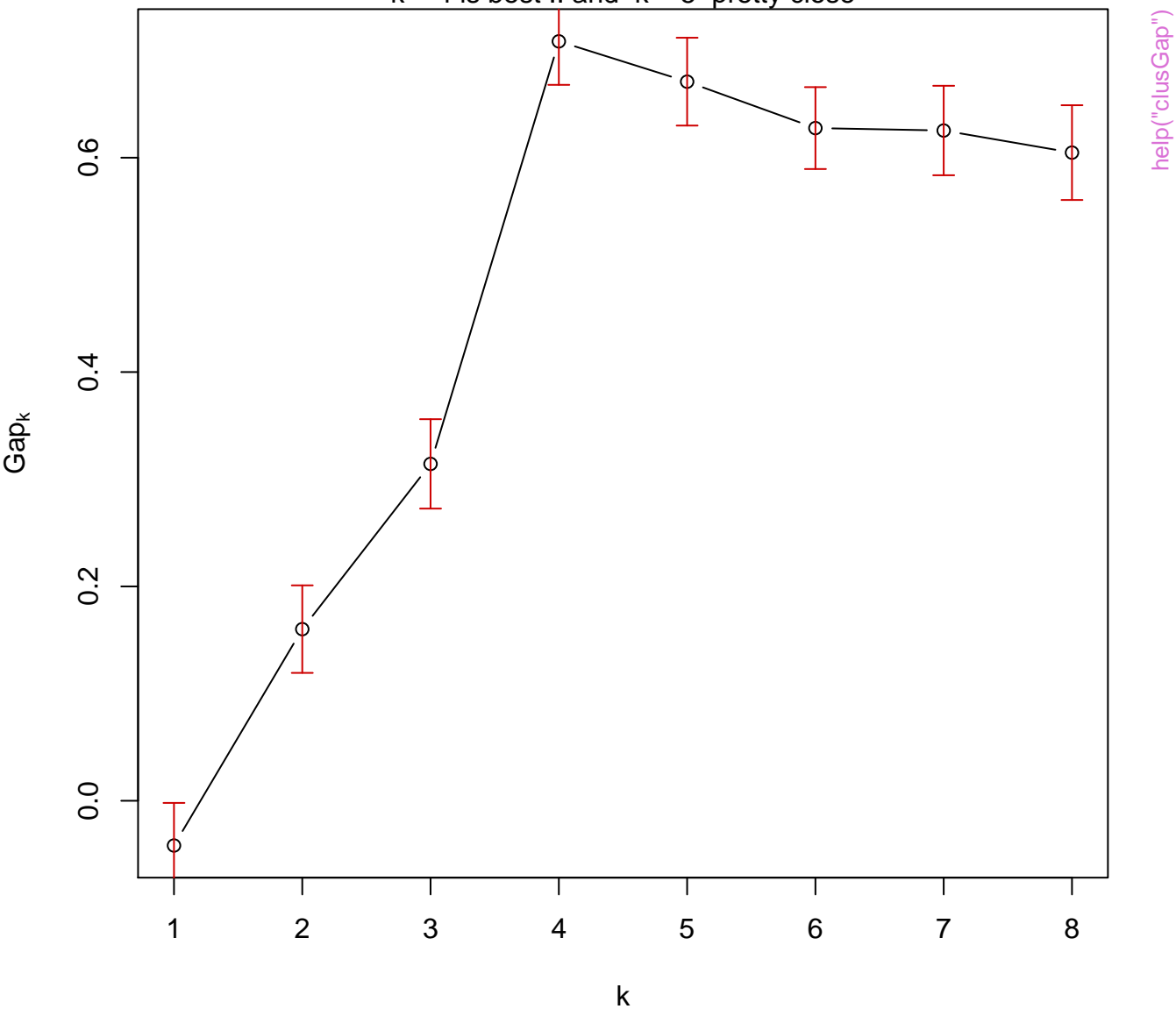
$j : n_j \mid \text{ave}_{i \in C_j} s_i$



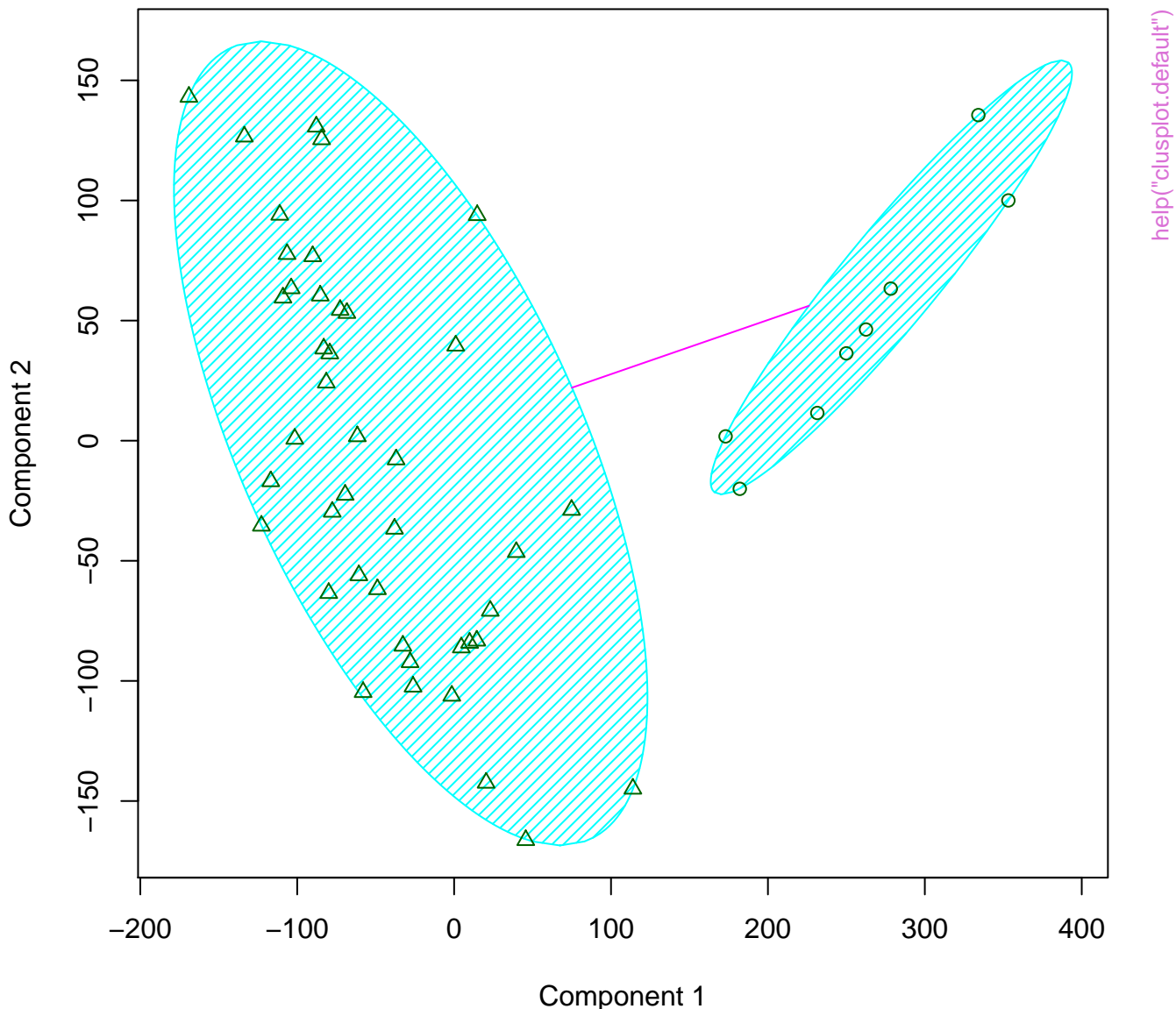


## Gap statistic for the 'ruspini' data

k = 4 is best .. and k = 5 pretty close

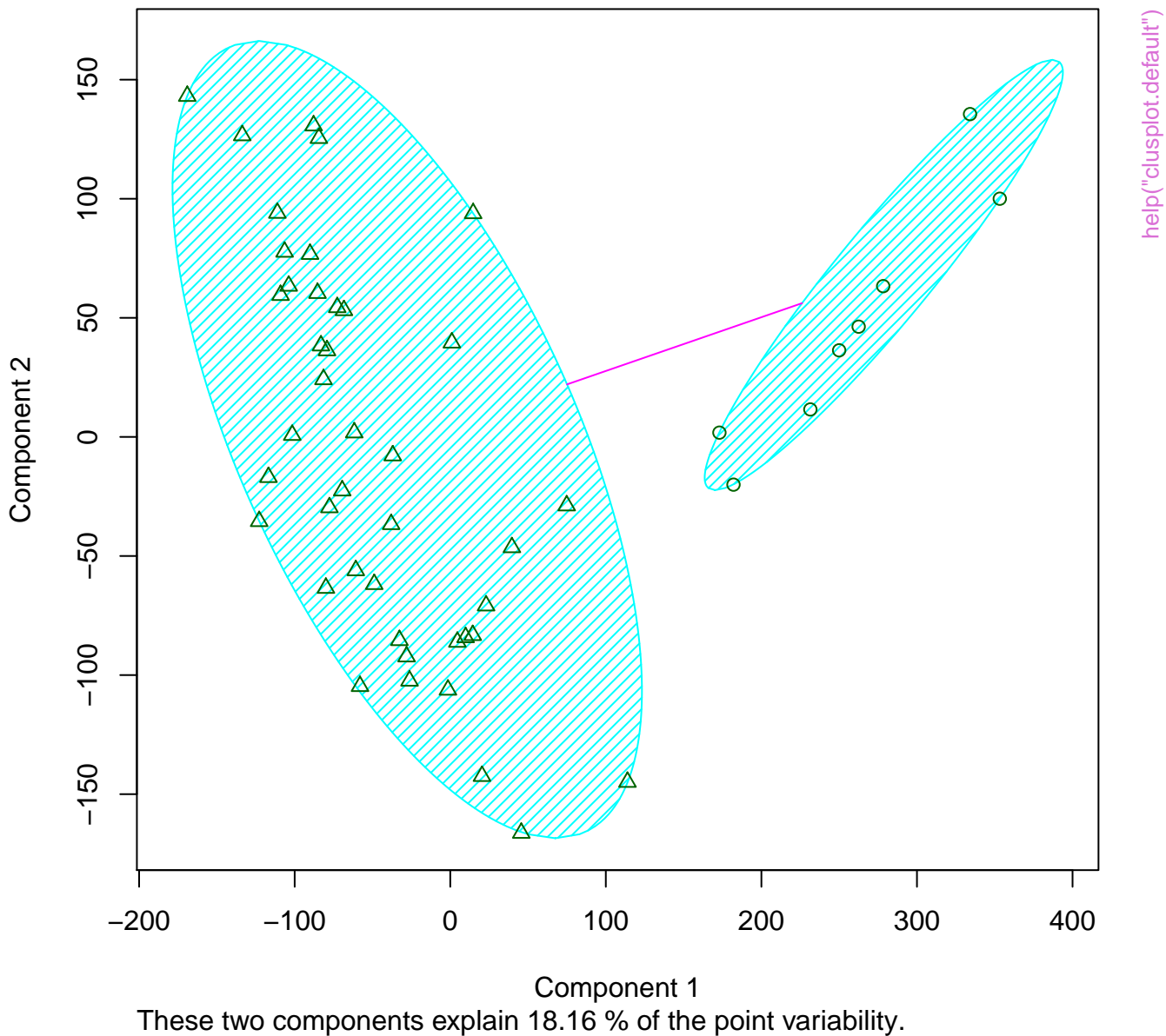


**clusplot(pam(x = votes.diss, k = 2, diss = TRUE))**



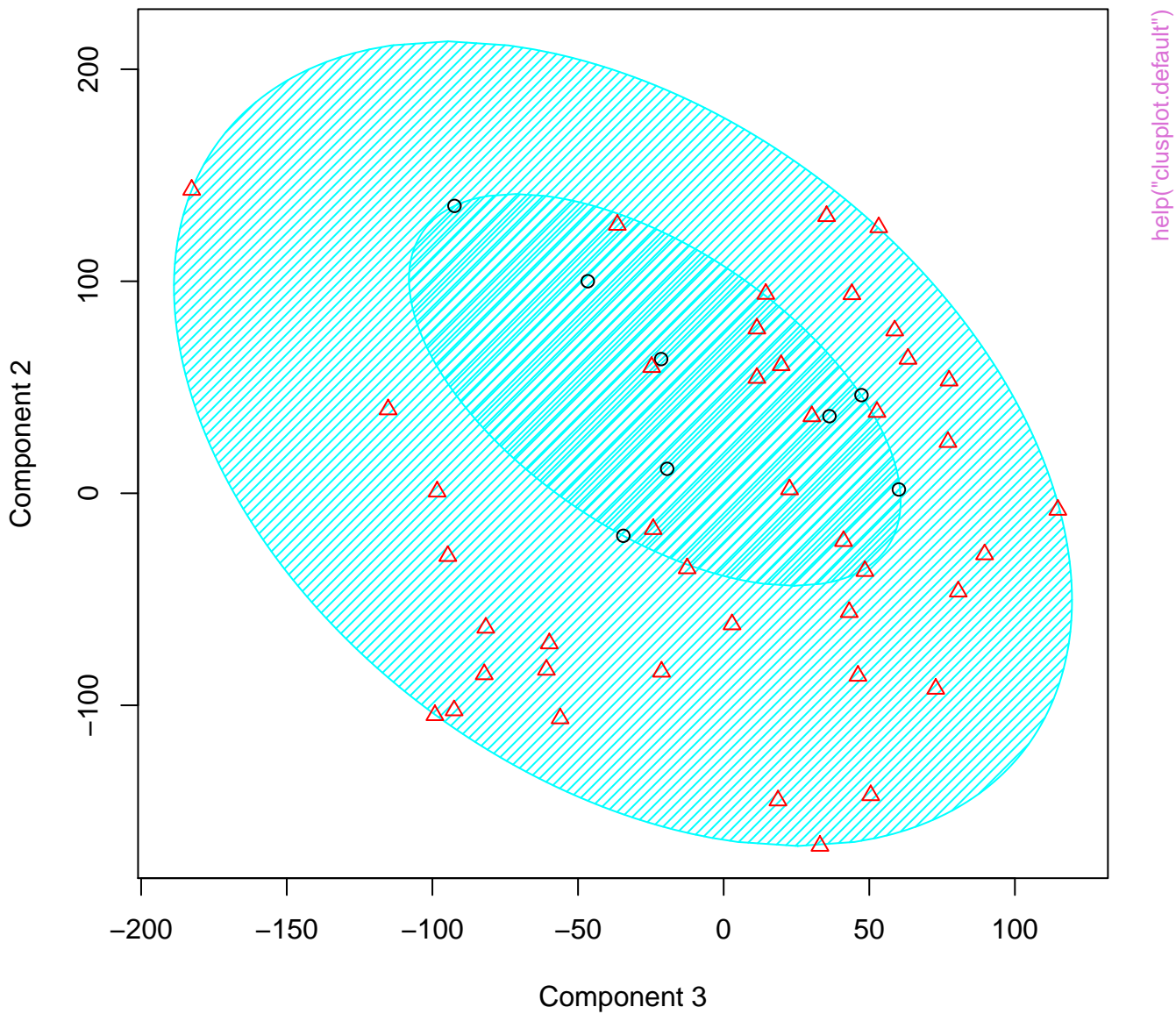
These two components explain 18.16 % of the point variability.

# CLUSPLOT( votes.diss )

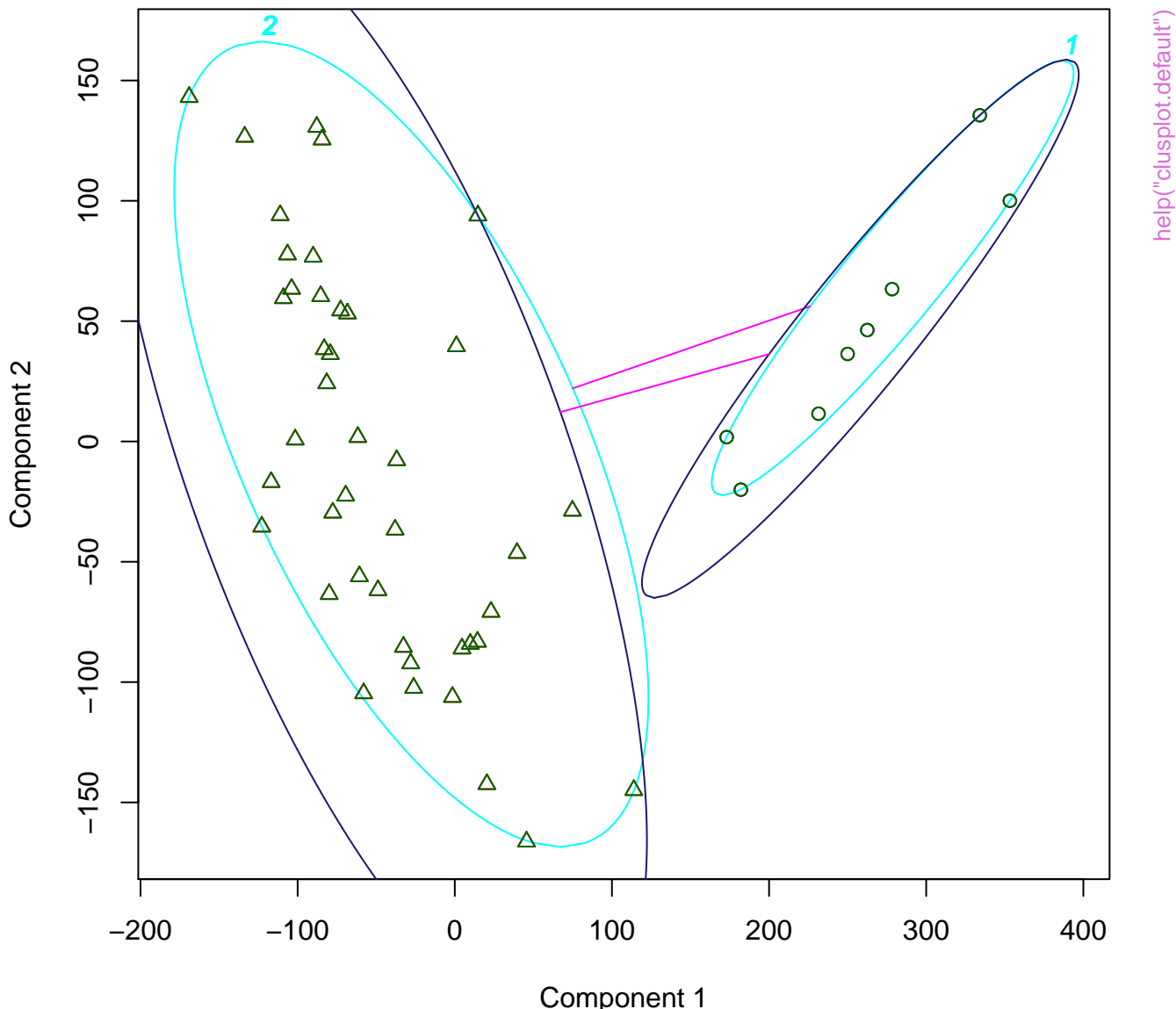




**clusplot(pam(x = votes.diss, k = 2, diss = TRUE))**

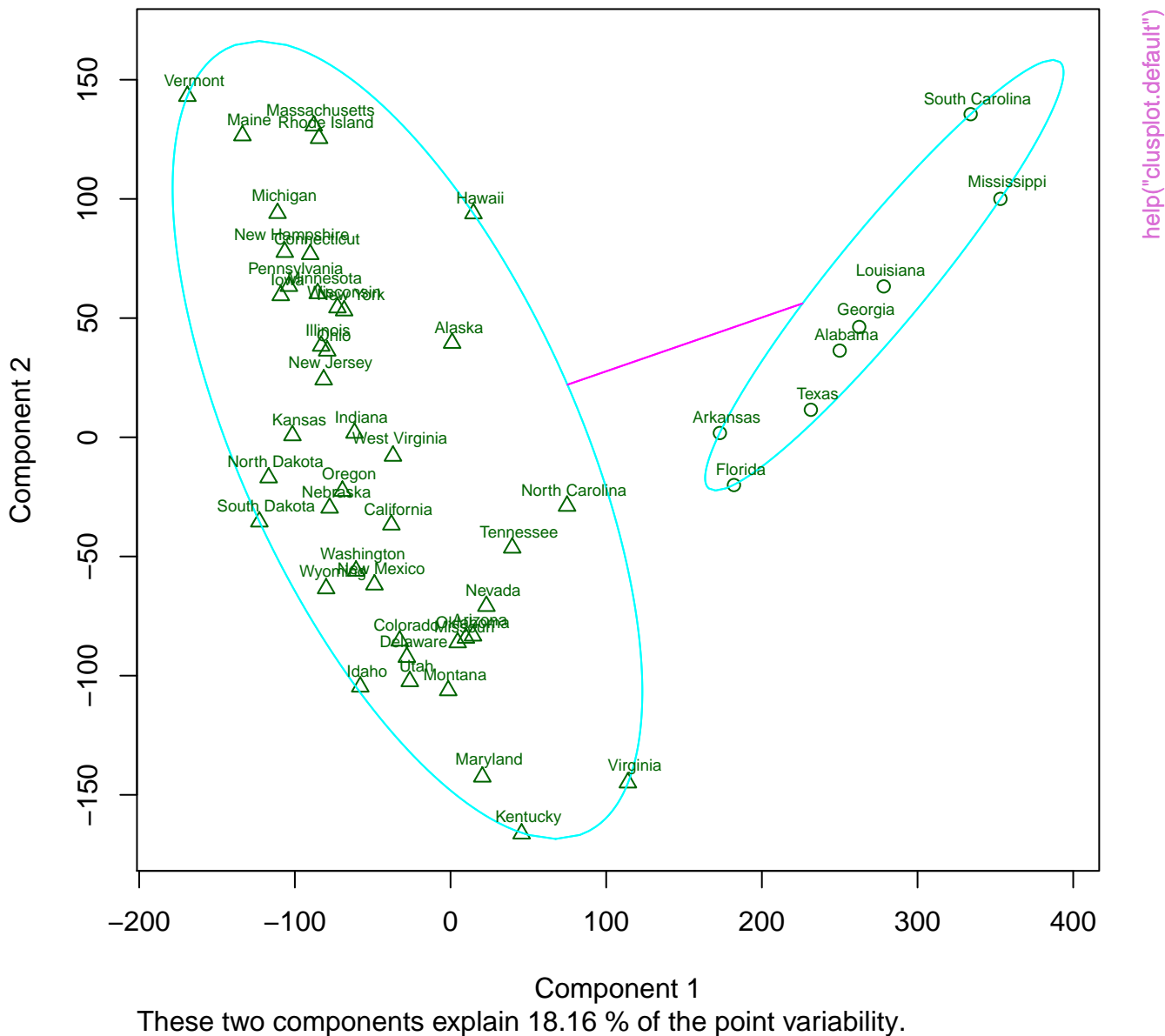


**clusplot(pam(x = votes.diss, k = 2, diss = TRUE))**

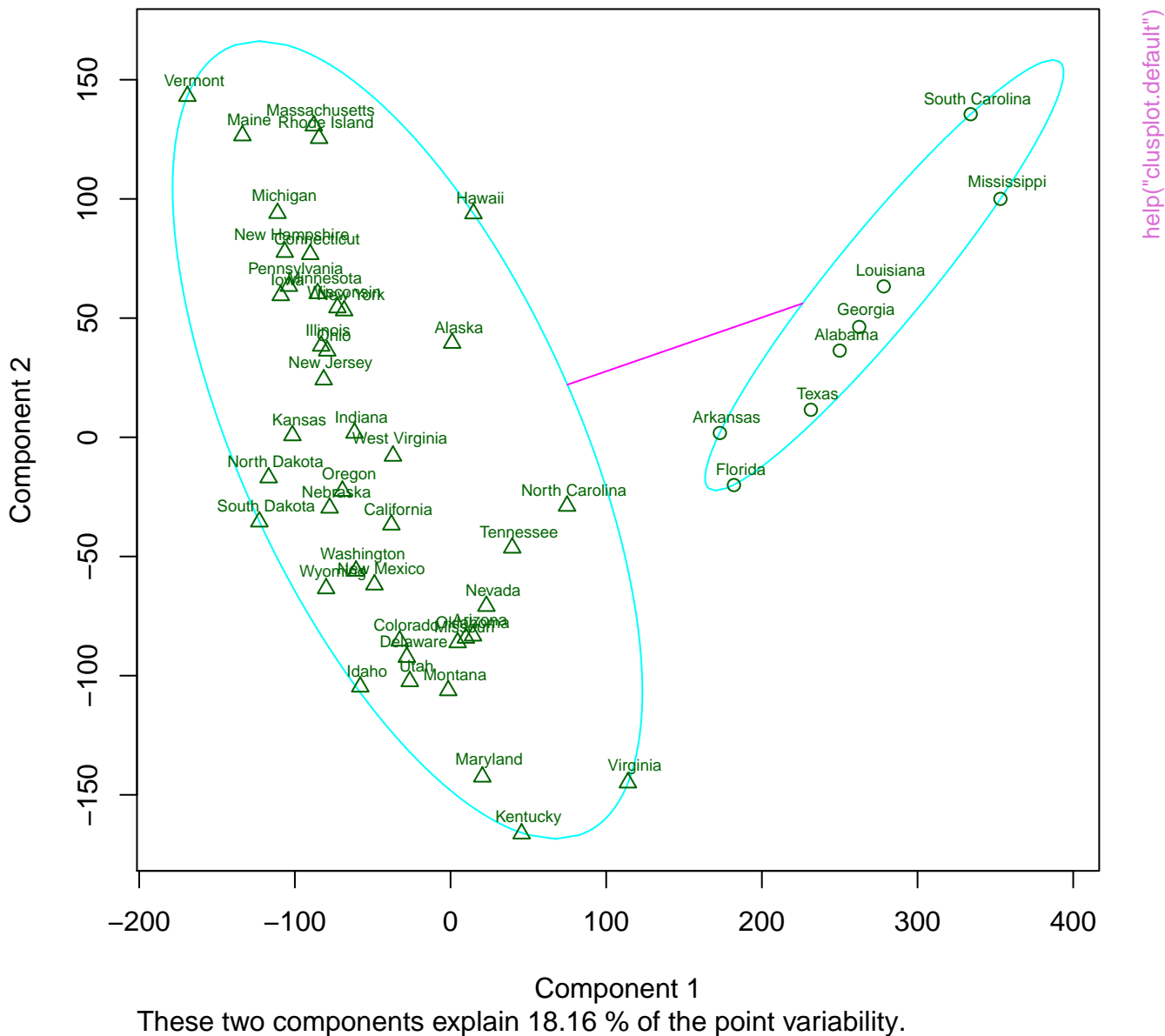


These two components explain 18.16 % of the point variability.

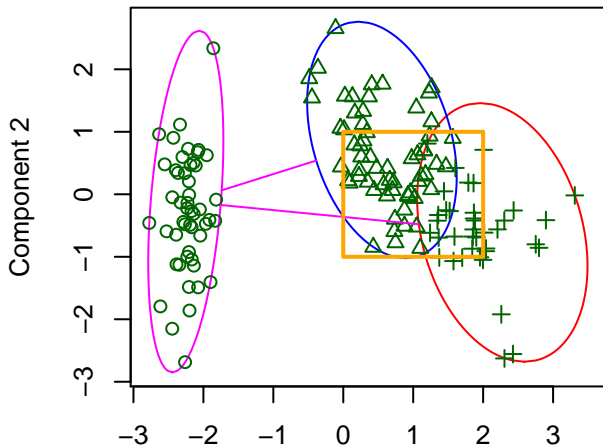
# CLUSPLOT( votes.diss )



# CLUSPLOT( votes.diss )

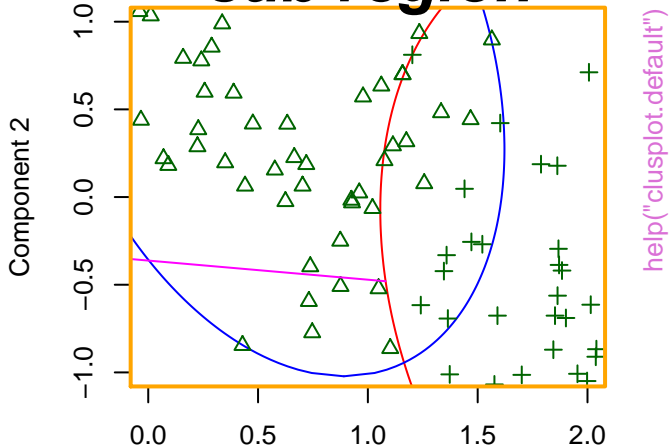


CLUSPLOT( iris.x )



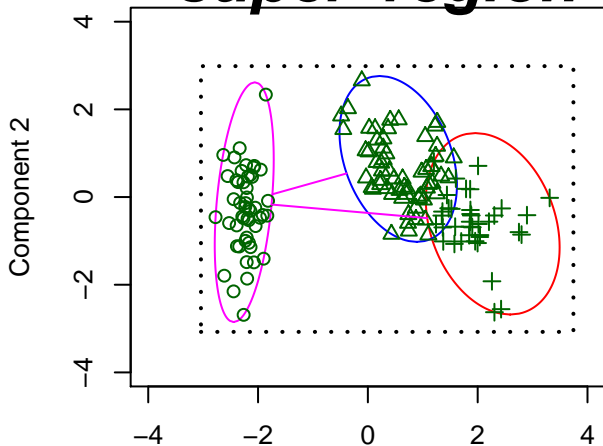
Component 1  
These two components explain 95.81 % of the

CLUSPLOT( iris.x )  
*sub region*



Component 1  
These two components explain 95.81 % of the

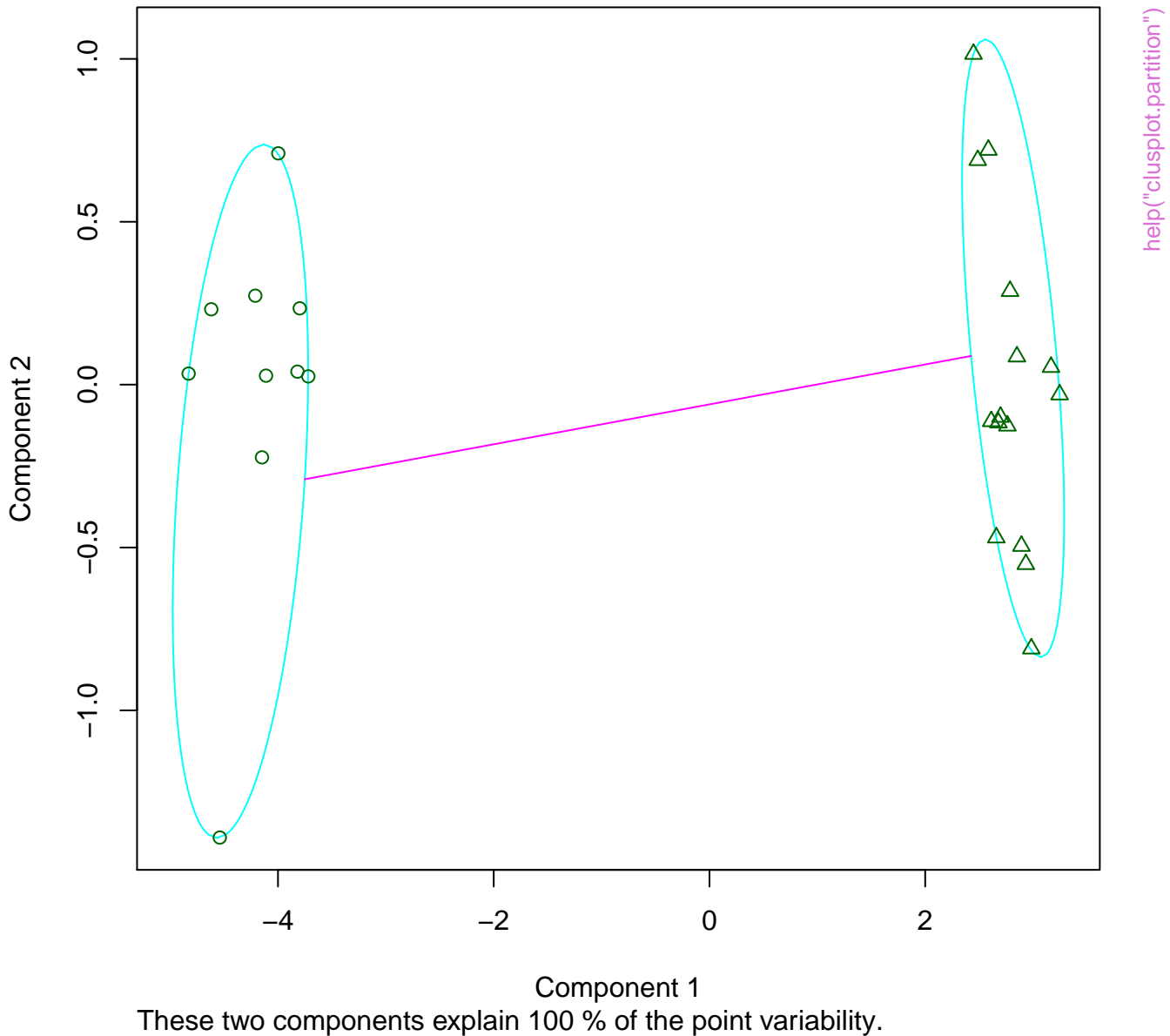
CLUSPLOT( iris.x )  
*'super' region*



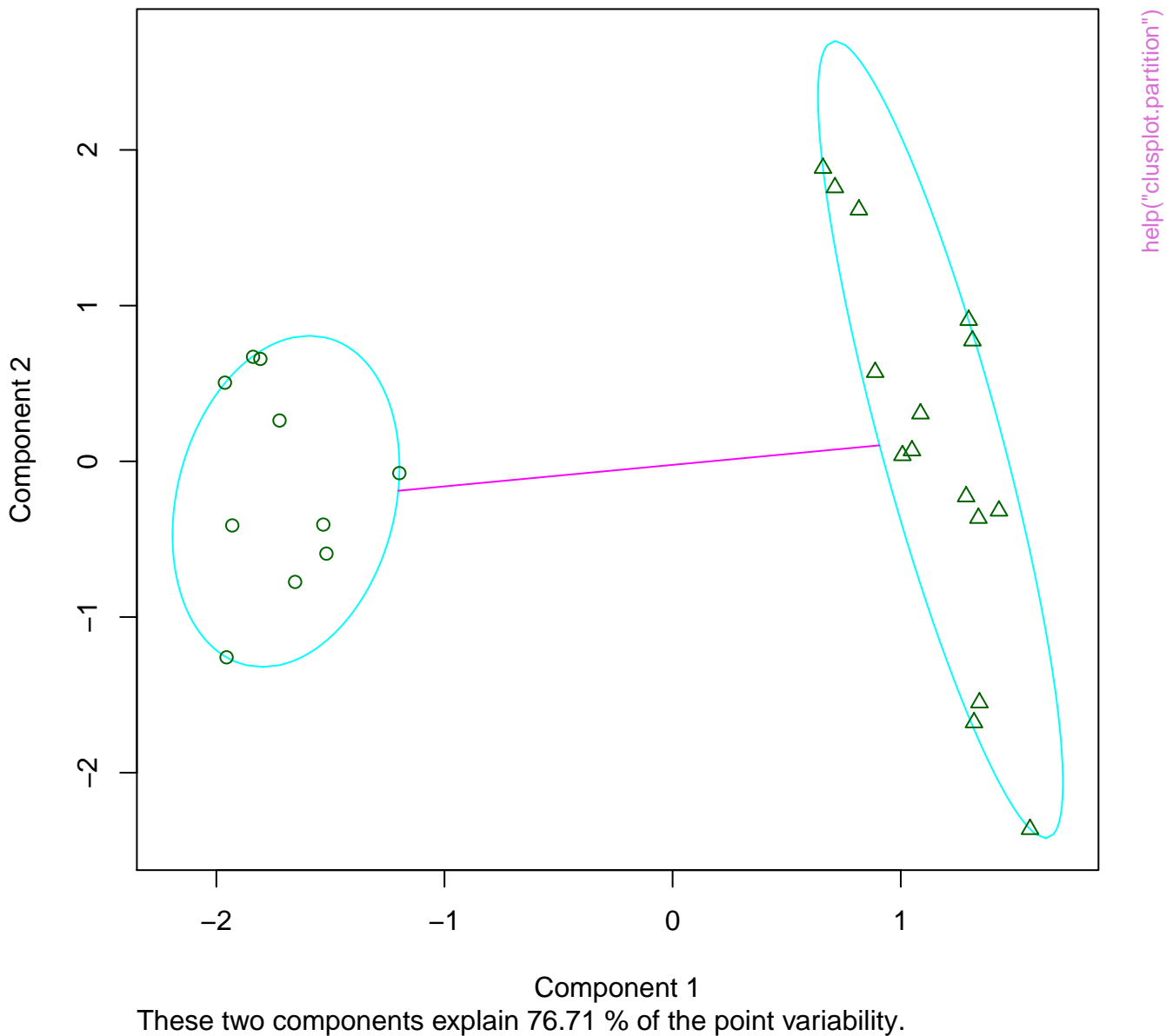
Component 1  
These two components explain 95.81 % of the

help("clusplot default")

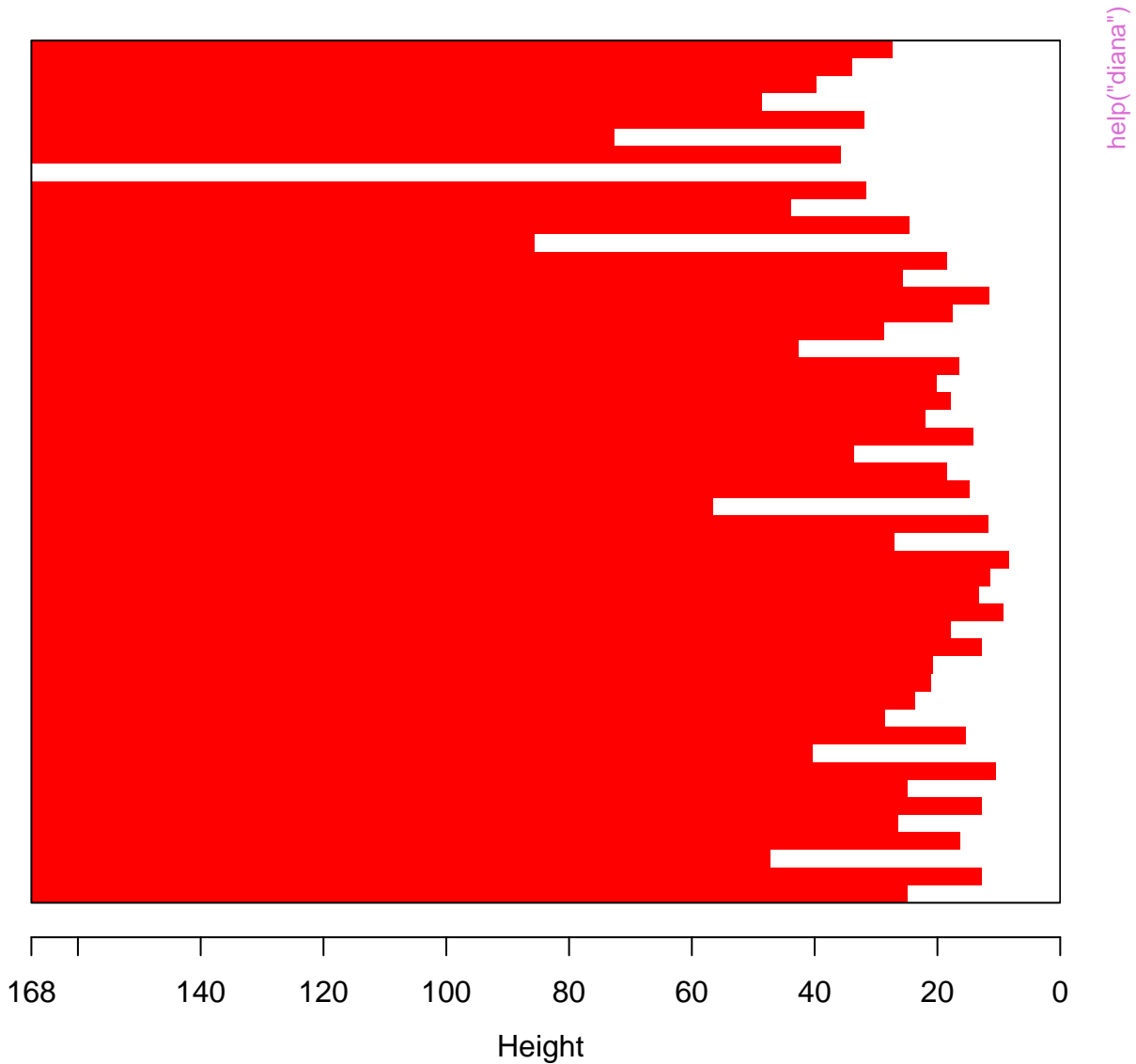
**clusplot(pam(x = x, k = 2))**



**clusplot(pam(x = x4, k = 2))**



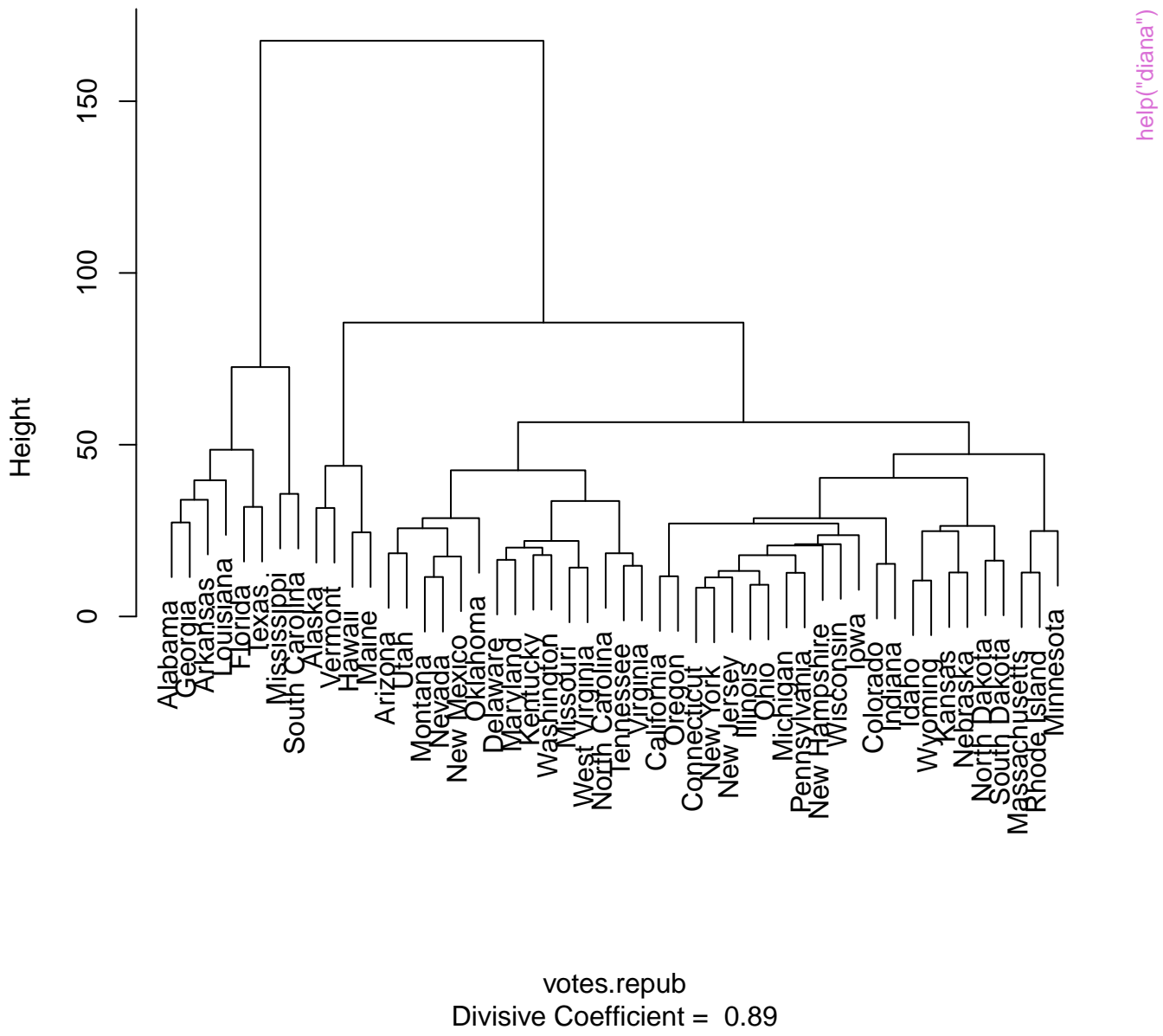
Banner of `diana(x = votes.repub, metric = "manhattan", stand = TR`



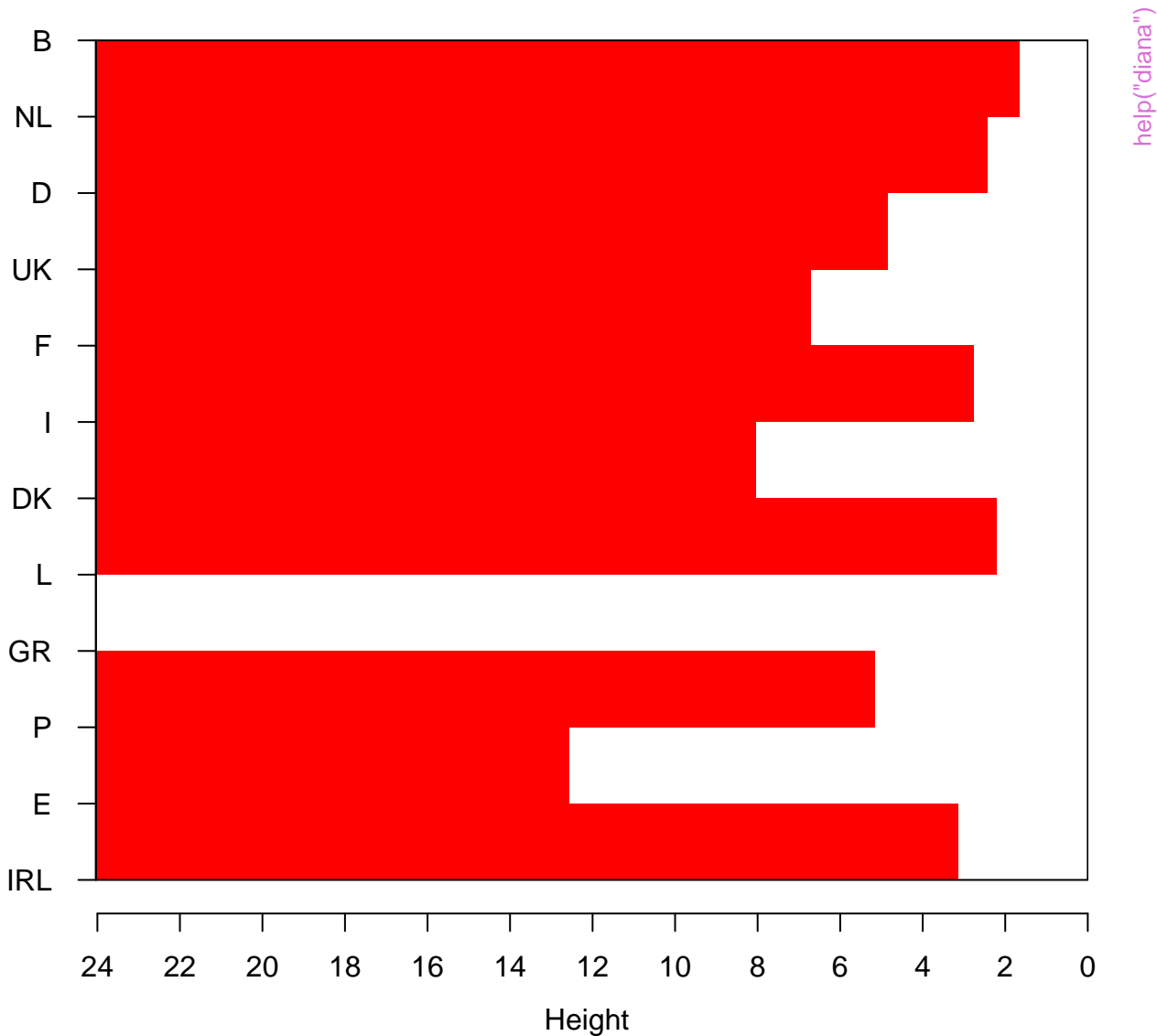
Divisive Coefficient = 0.89



Dendrogram of `diana(x = votes.repub, metric = "manhattan", stand = TRUE)`

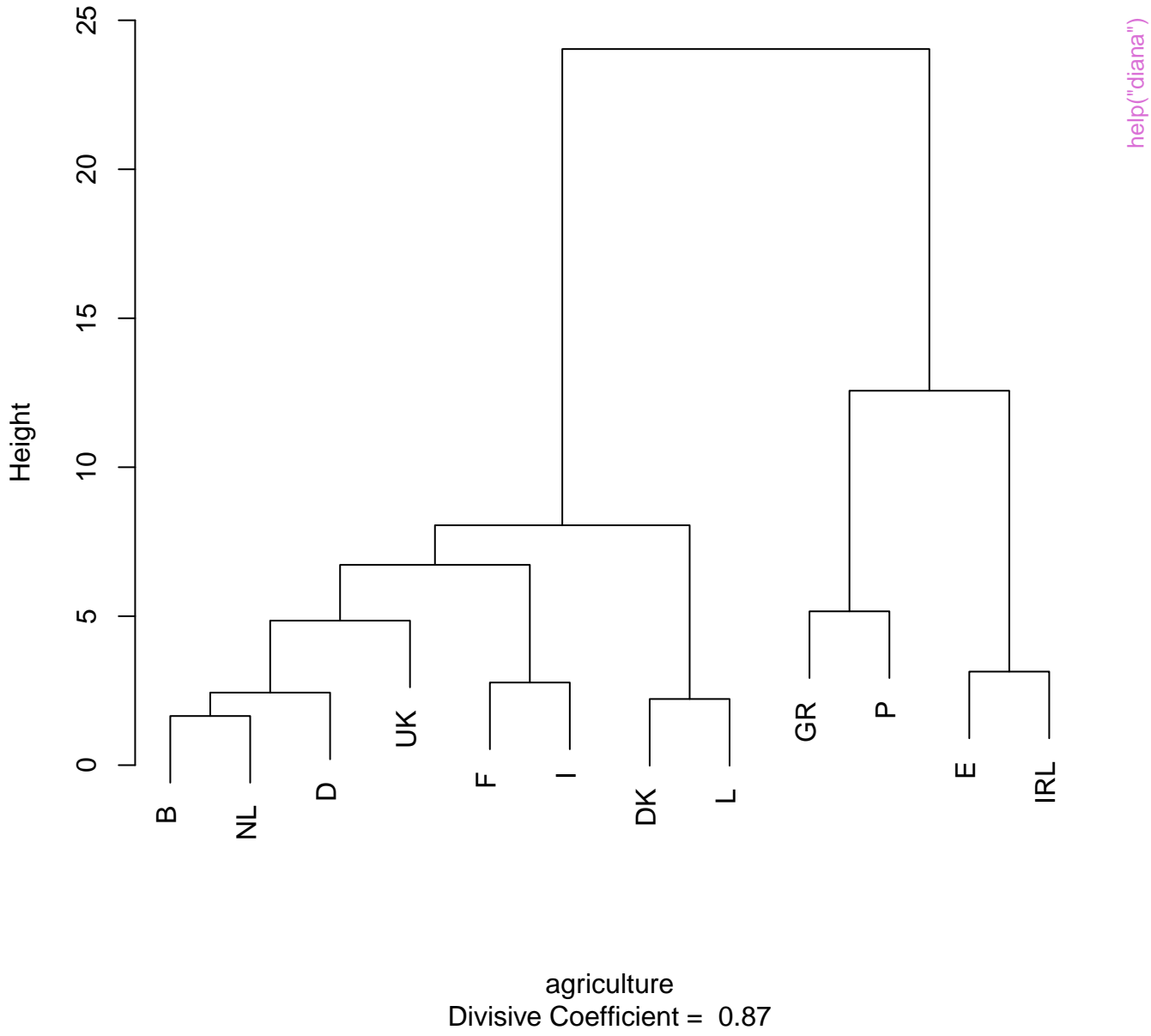


# Banner of diana(x = agriculture)

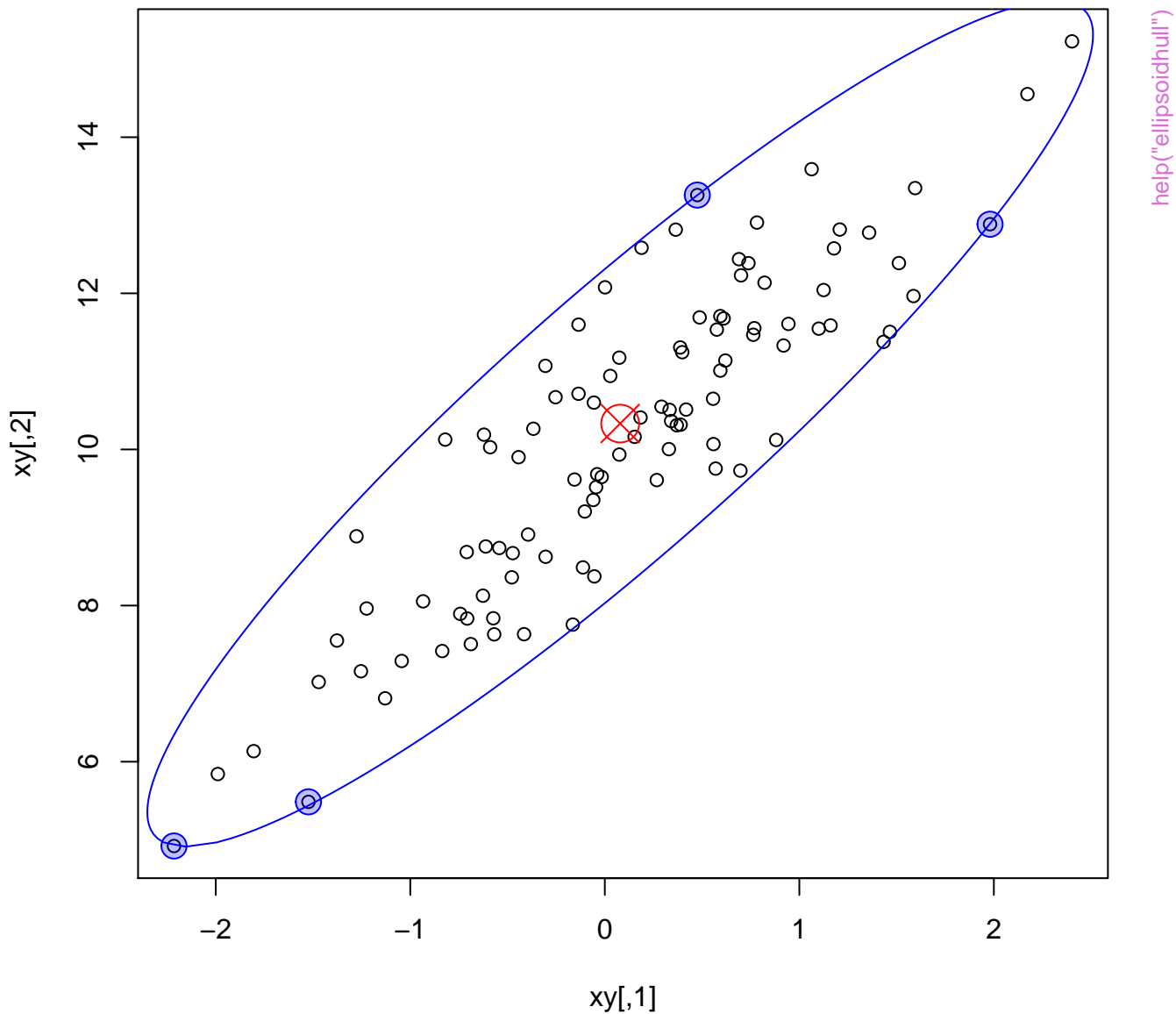


Divisive Coefficient = 0.87

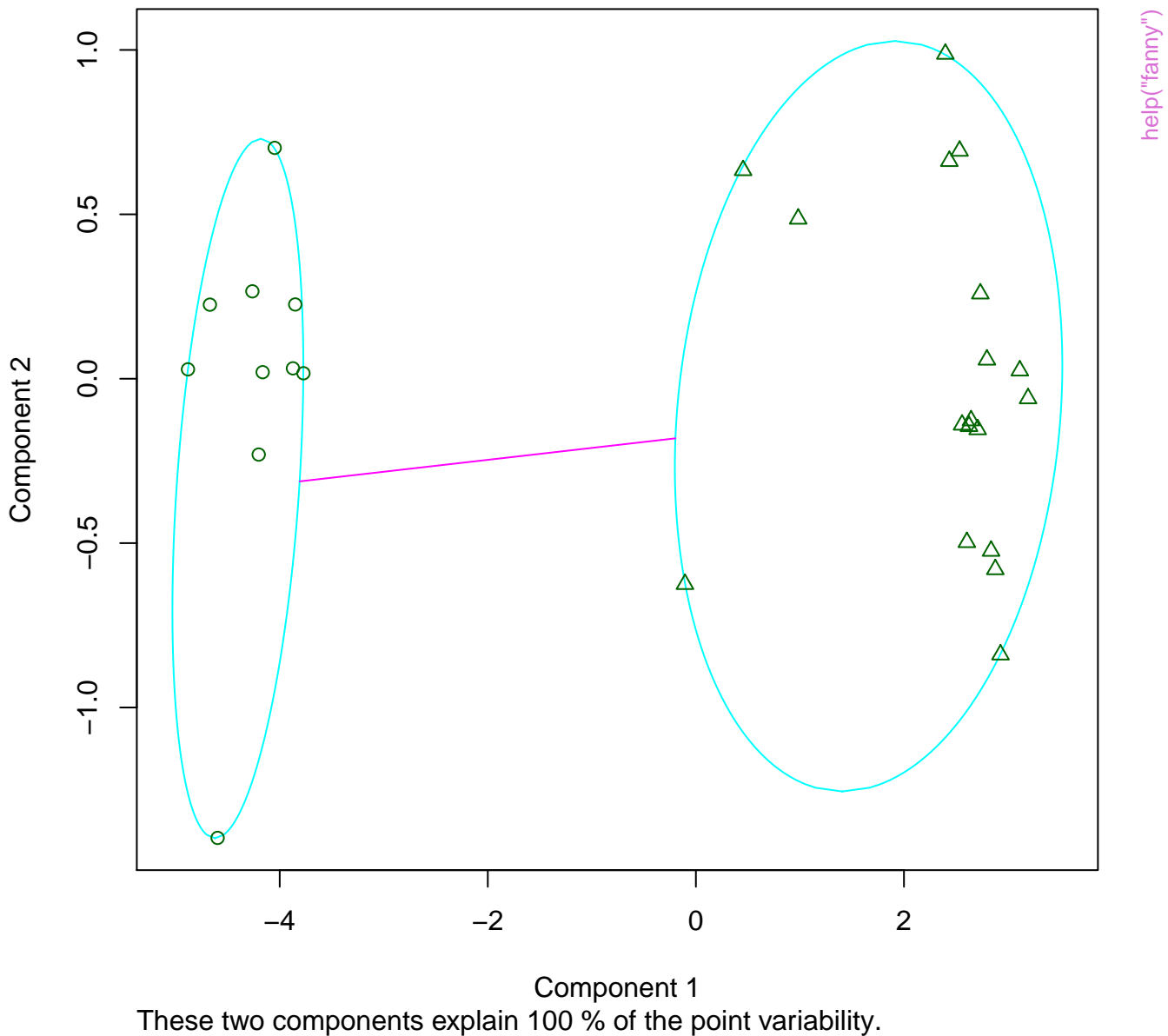
# Dendrogram of diana(x = agriculture)



# ellipsoidhull(<Gauss data>) -- 'spanning points'



**clusplot(fanny(x = x, k = 2))**



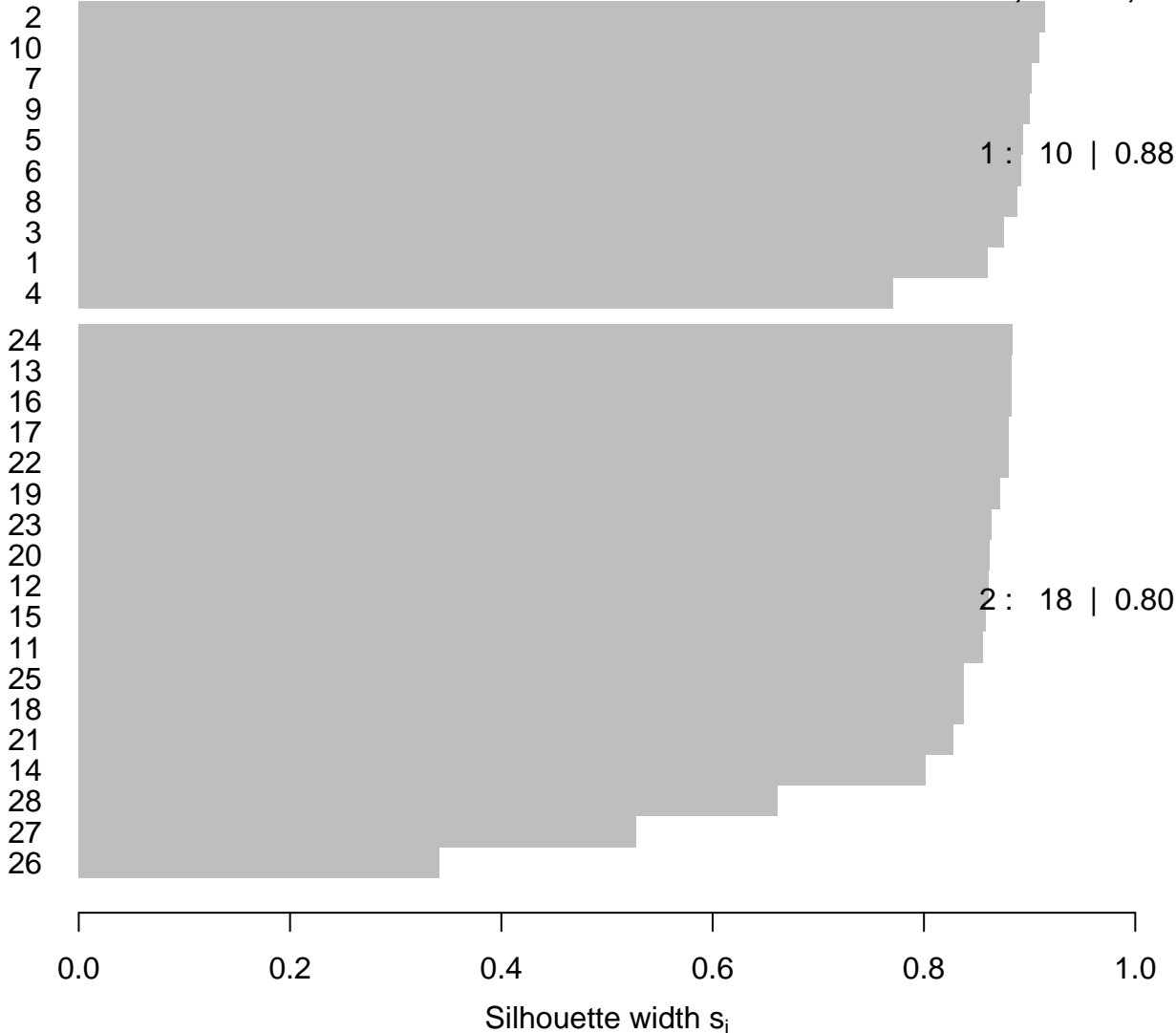
# Silhouette plot of fanny(x = x, k = 2)

n = 28

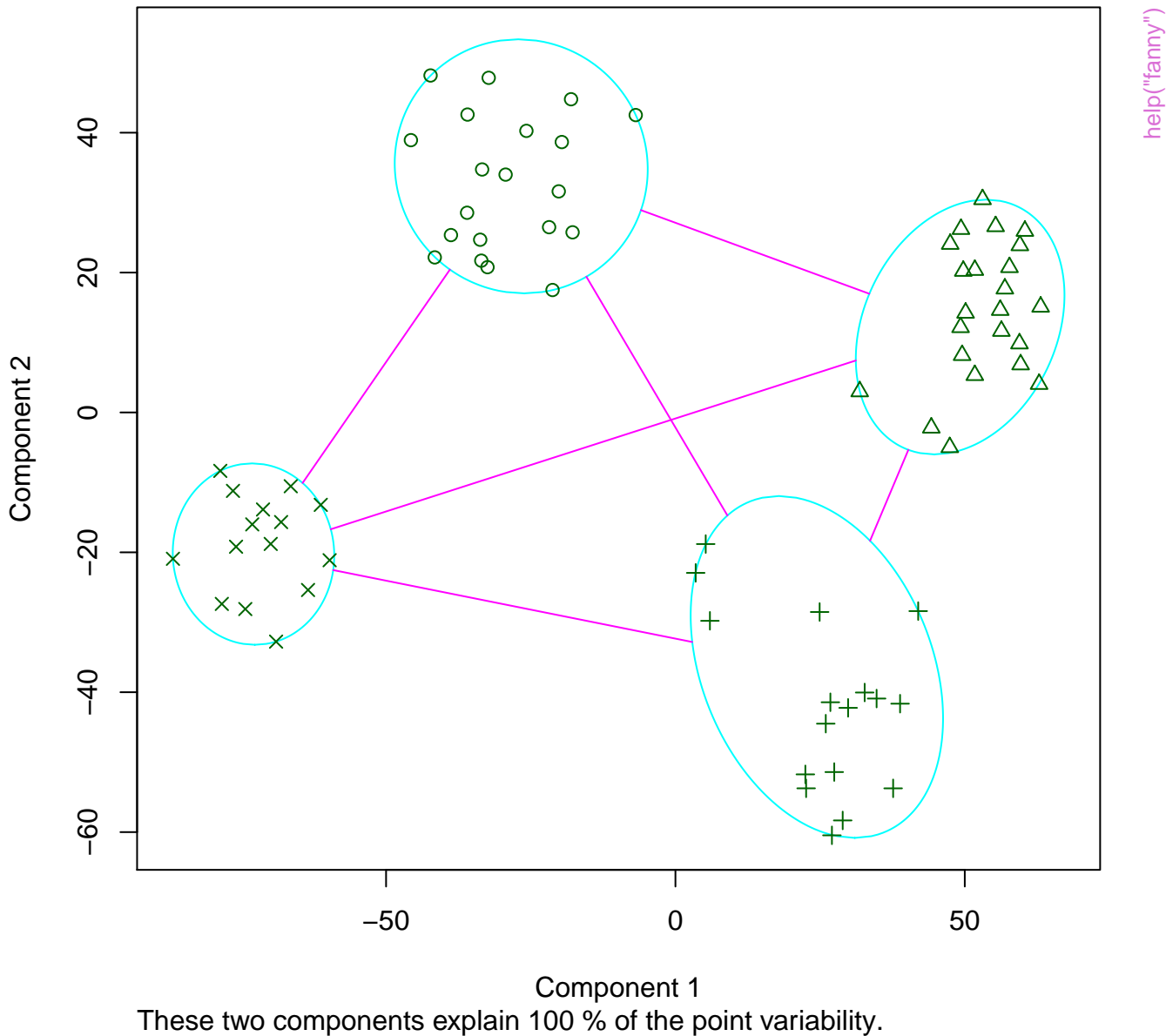
2 clusters  $C_j$

$j : n_j \mid \text{ave}_{i \in C_j} s_i$

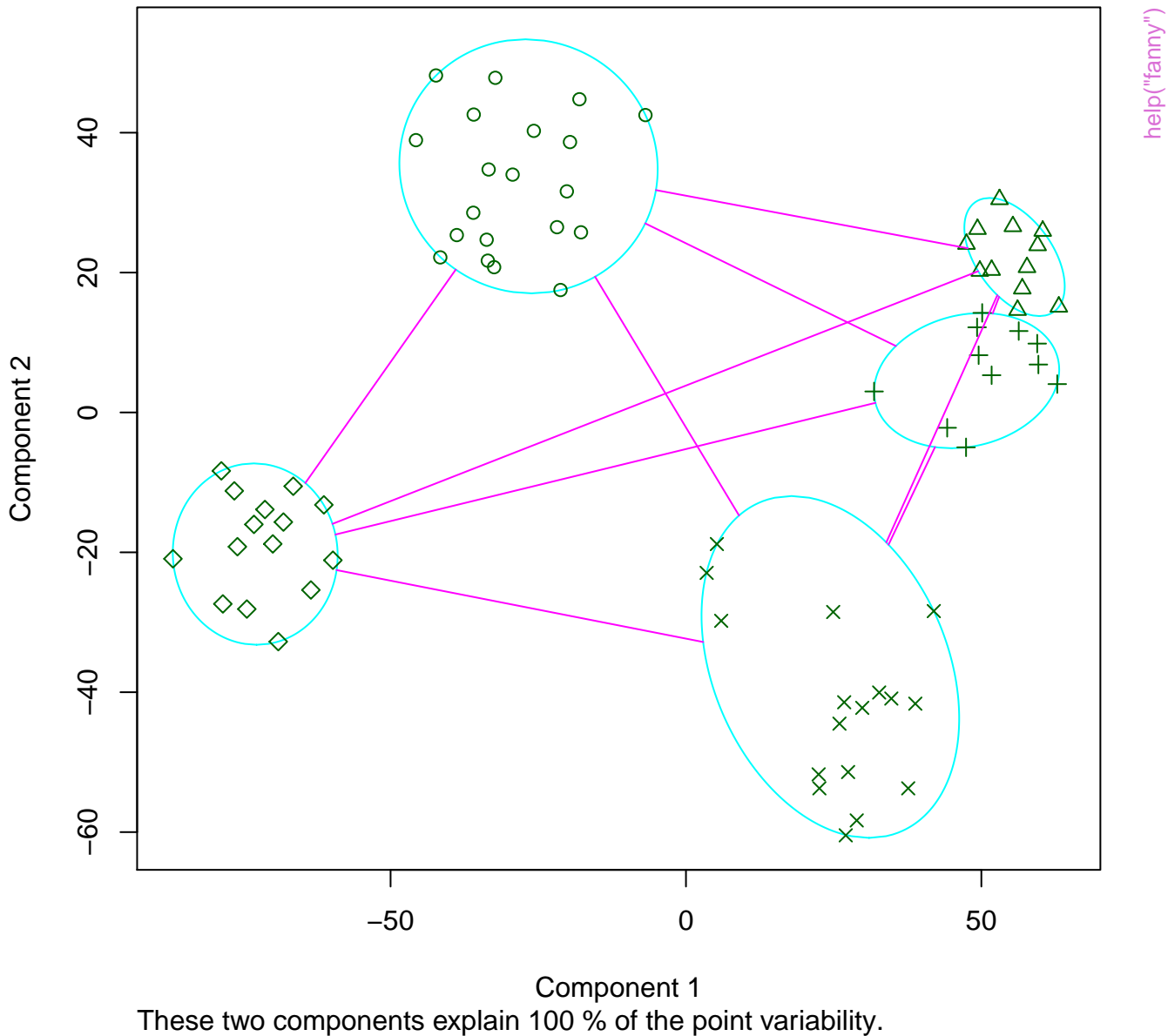
help("fanny")



**clusplot(fanny(x = ruspini, k = 4))**



**clusplot(fanny(x = ruspini, k = 5))**



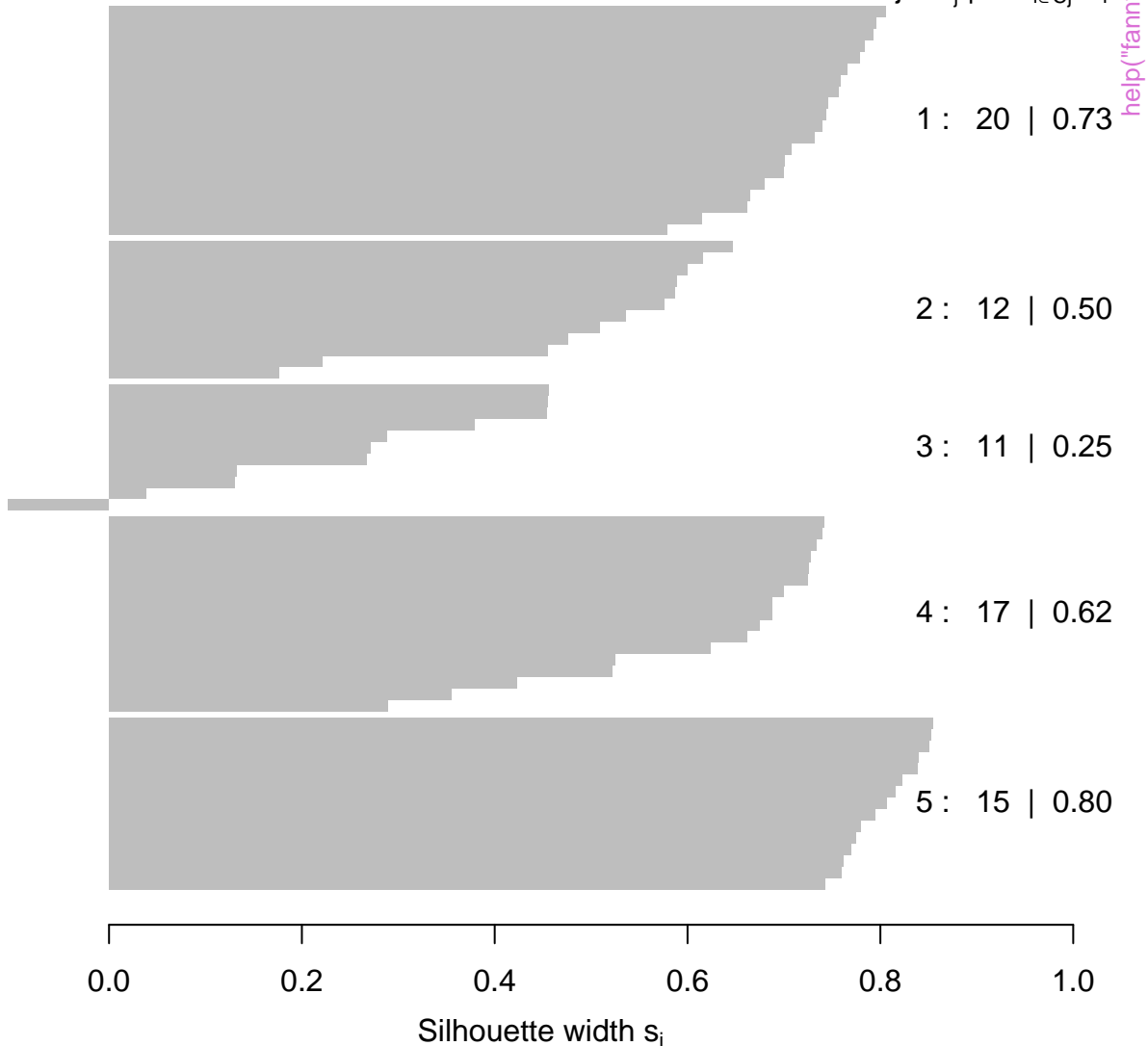


# Silhouette plot of fanny(x = ruspini, k = 5)

n = 75

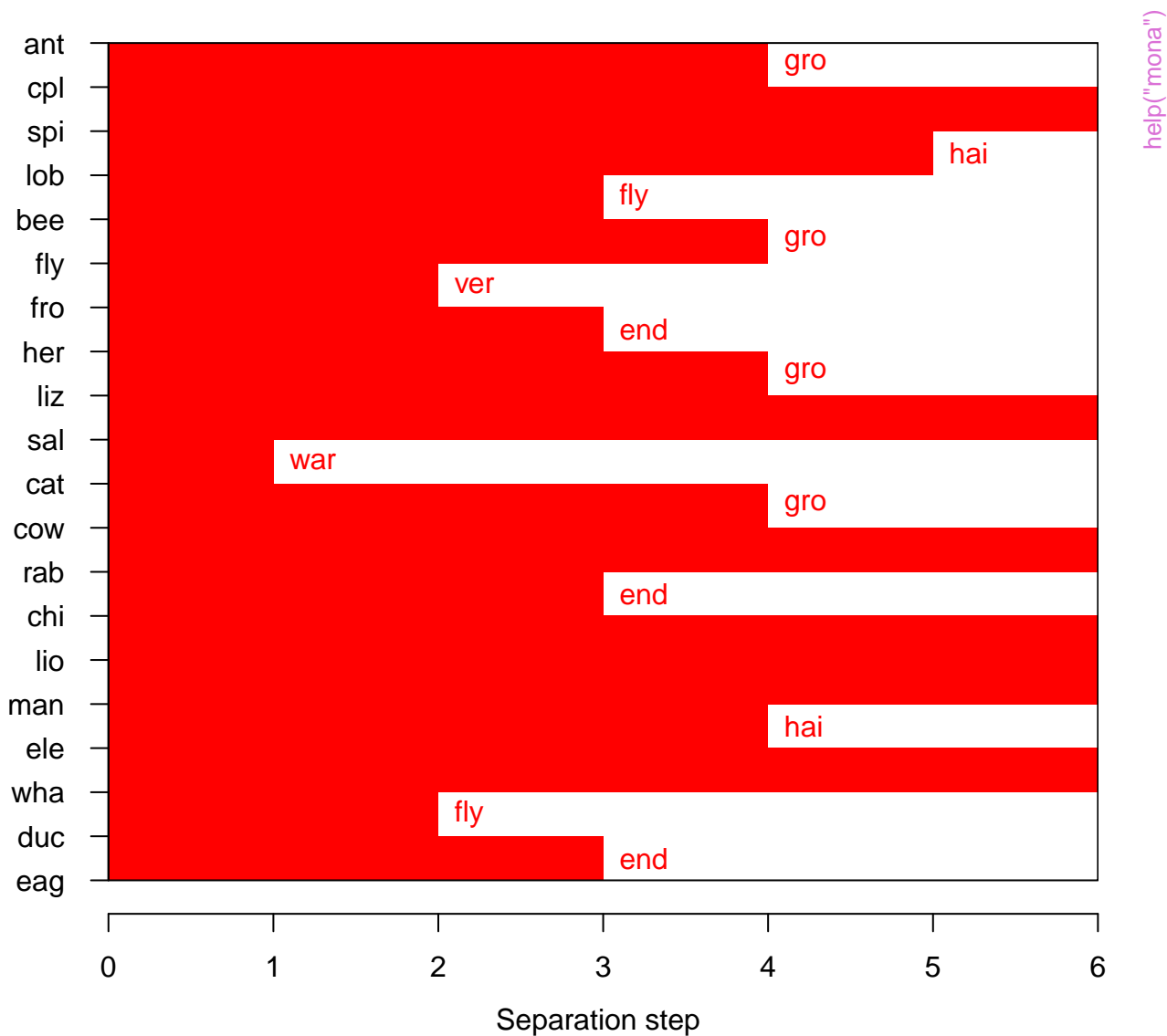
5 clusters  $C_j$

$j : n_j \mid \text{ave}_{i \in C_j} s_i$

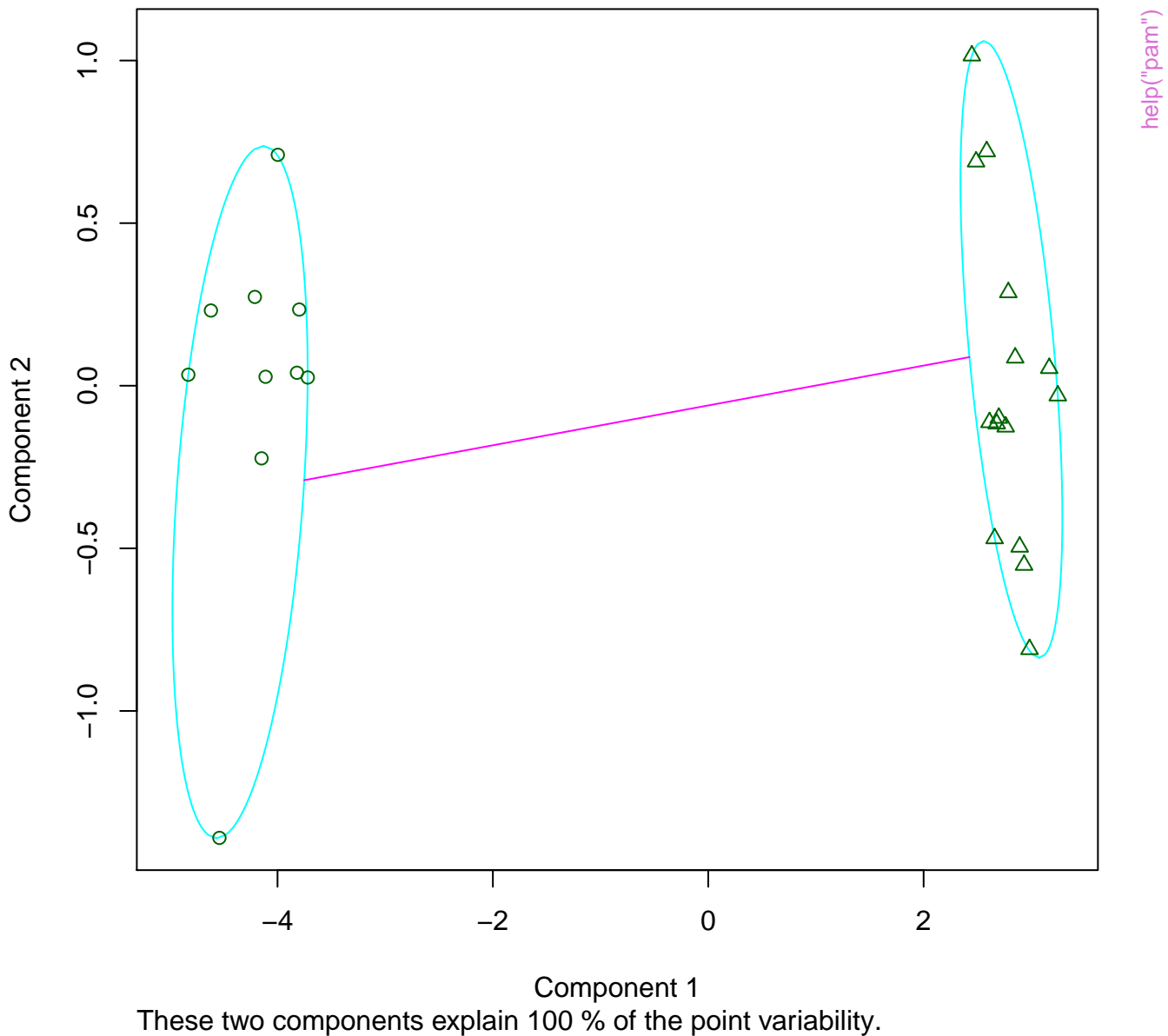


Average silhouette width : 0.61

## Banner of mona(x = animals)



**clusplot(pam(x = x, k = 2))**

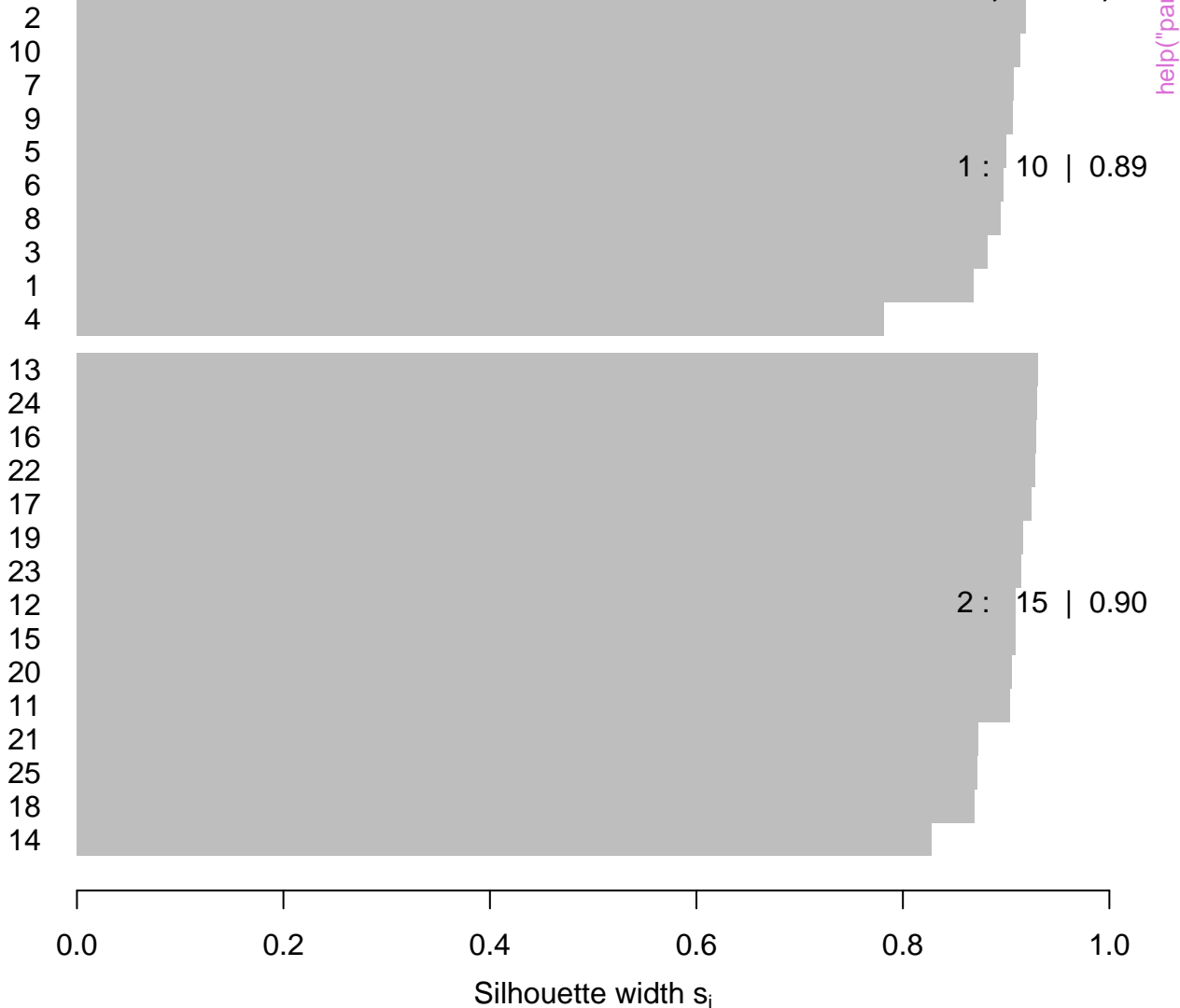


# Silhouette plot of pam(x = x, k = 2)

n = 25

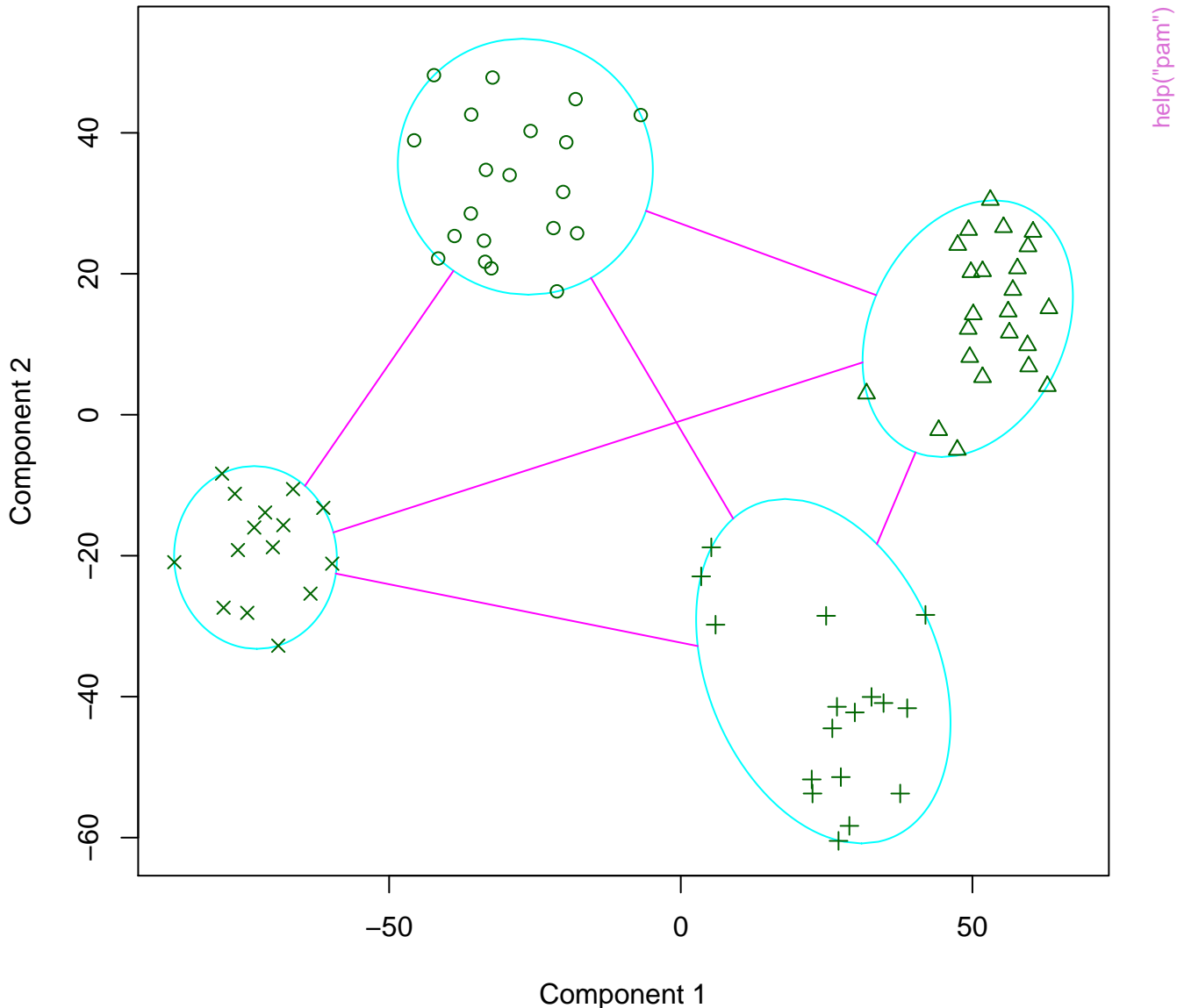
2 clusters  $C_j$

$j : n_j \mid \text{ave}_{i \in C_j} s_i$



Average silhouette width : 0.9

**clusplot(pam(x = ruspini, k = 4))**



These two components explain 100 % of the point variability.

# Silhouette plot of pam(x = ruspini, k = 4)

n = 75

4 clusters  $C_j$

$j : n_j \mid \text{ave}_{i \in C_j} s_i$

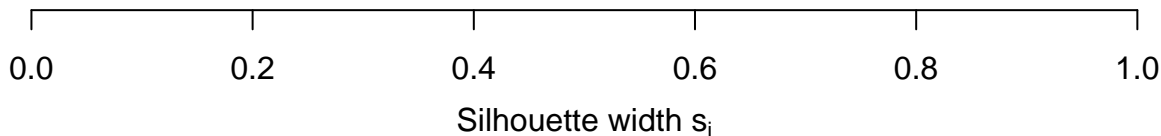
help("pam")

1 : 20 | 0.73

2 : 23 | 0.75

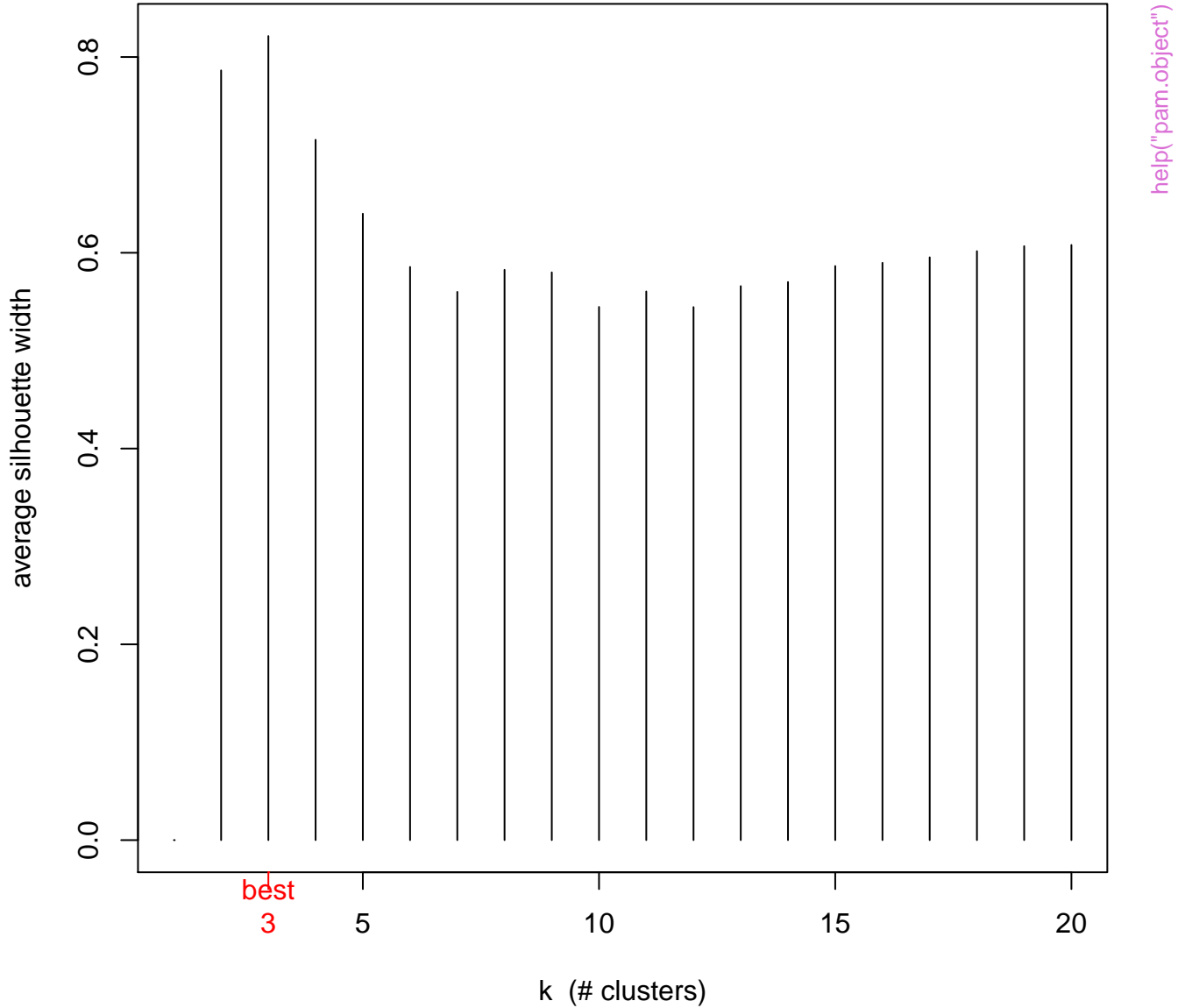
3 : 17 | 0.67

4 : 15 | 0.80

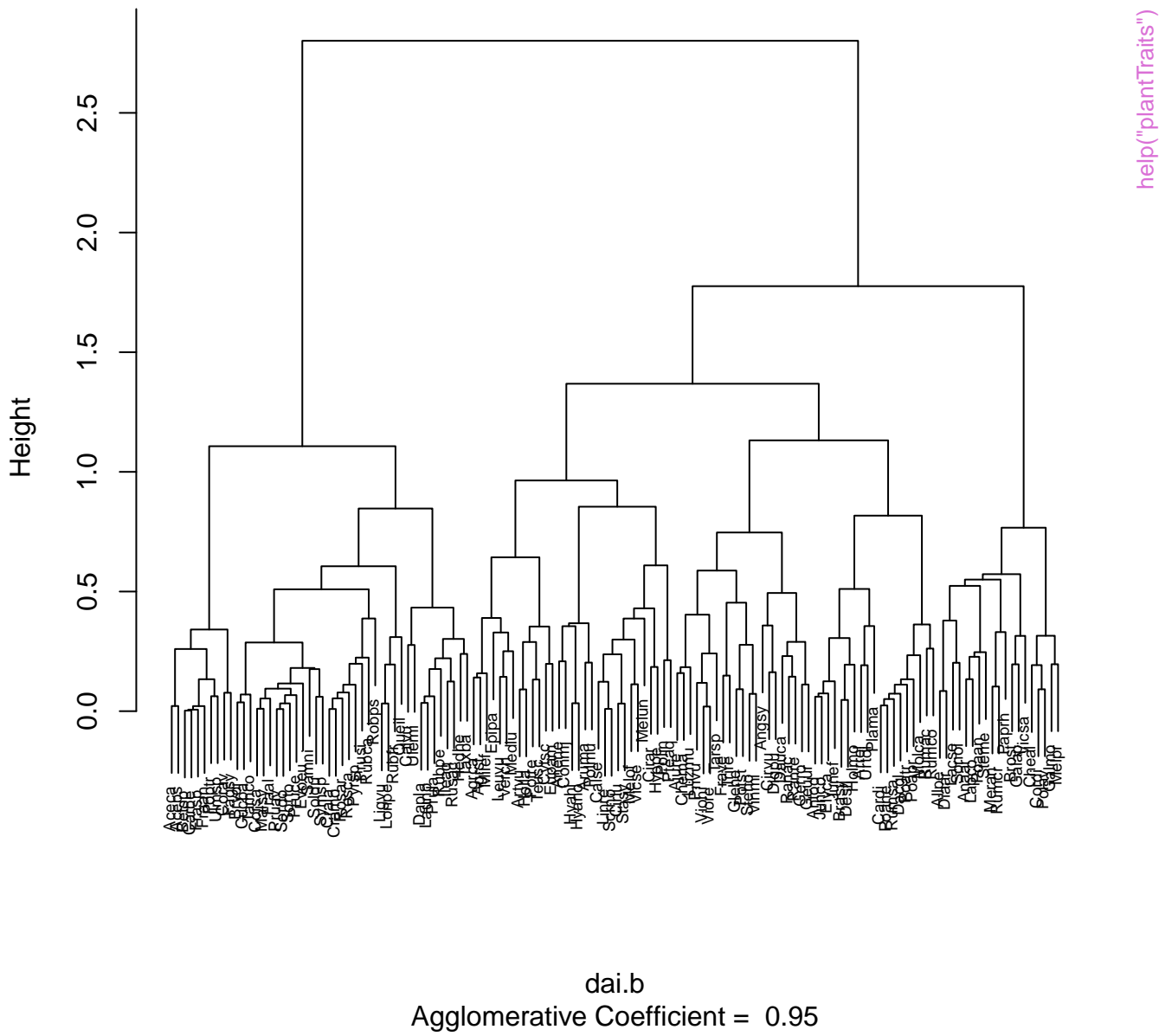


Average silhouette width : 0.74

# pam() clustering assessment

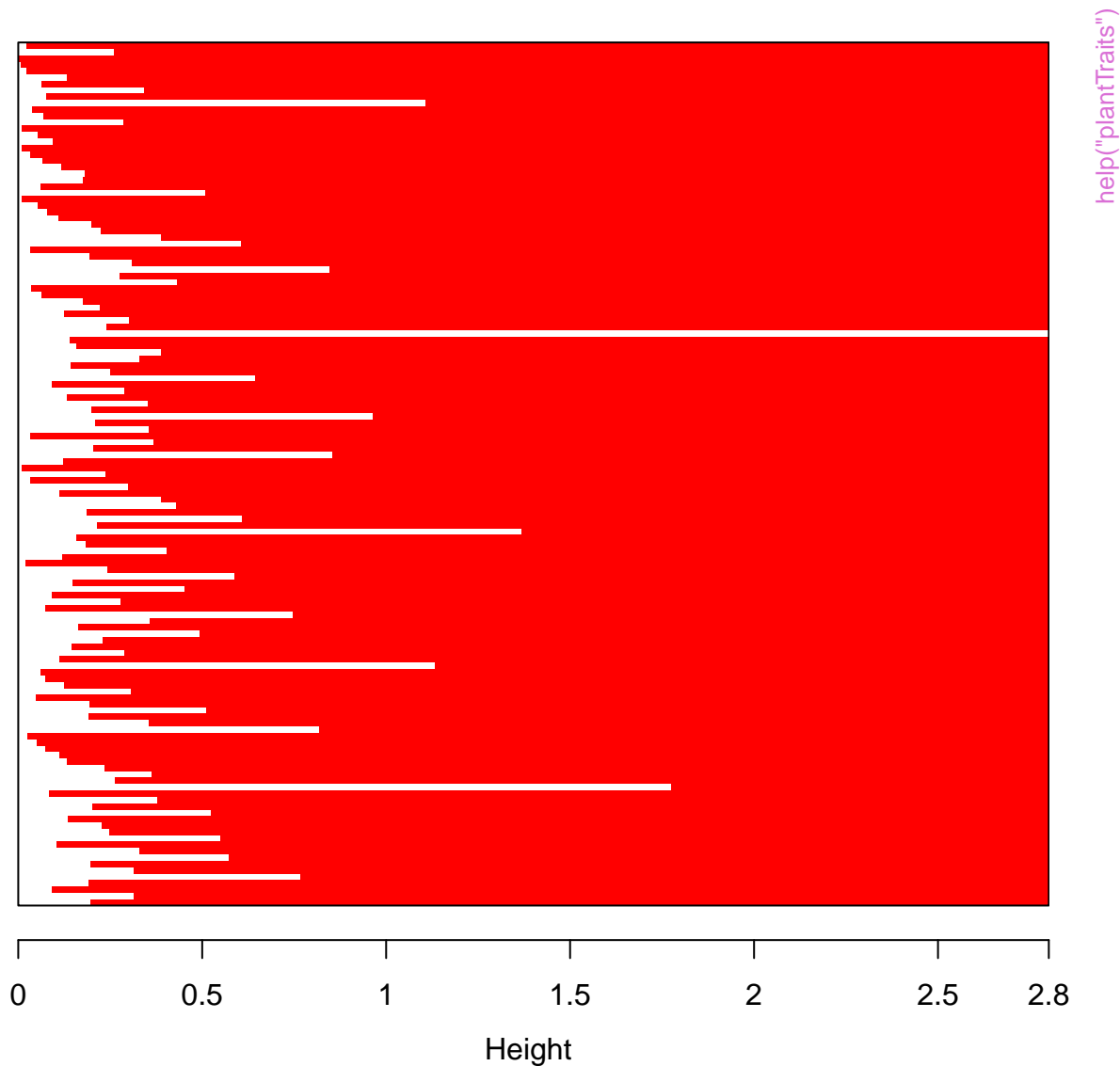


## Dendrogram of `agnes(x = dai.b, method = "ward")`

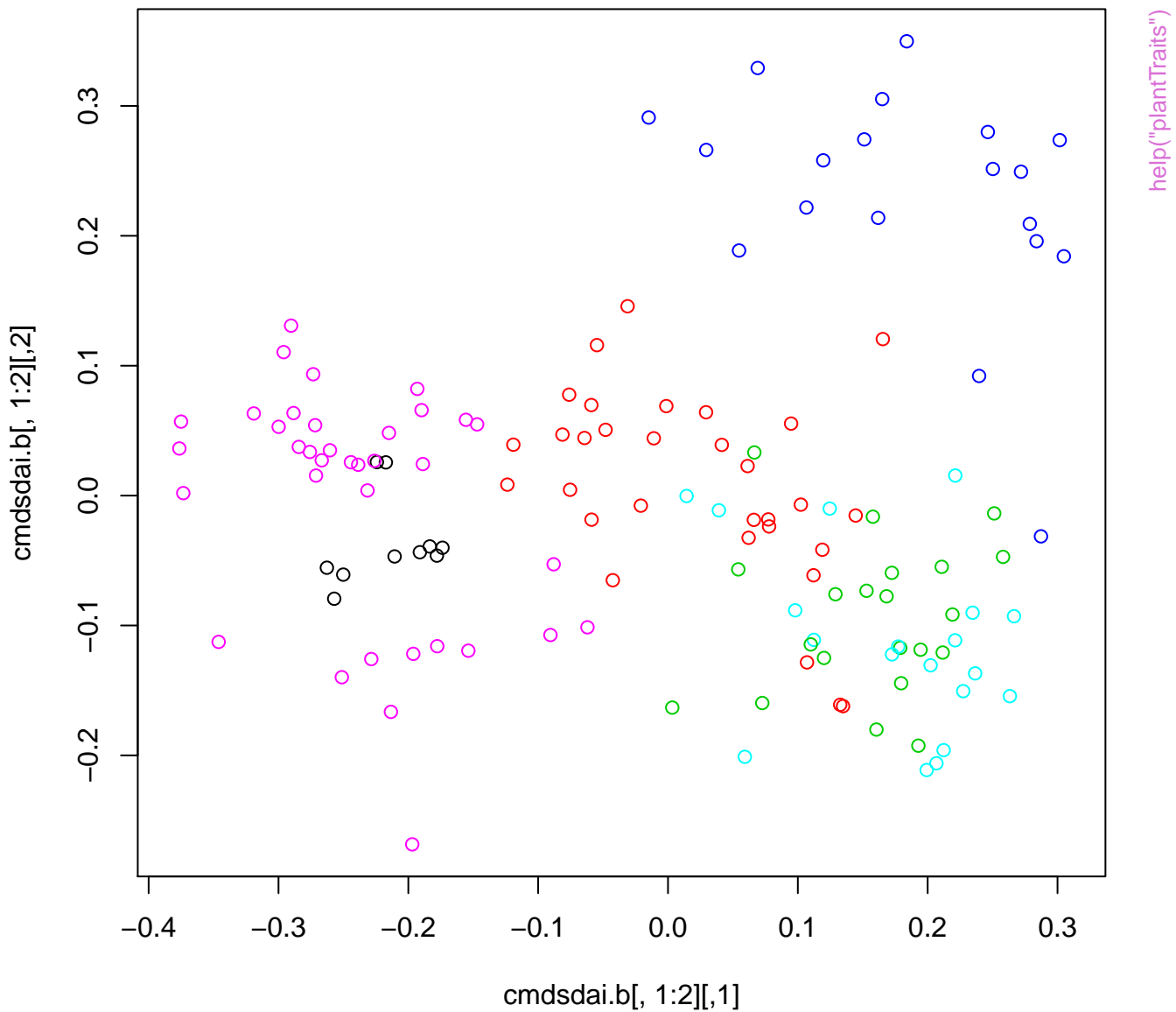




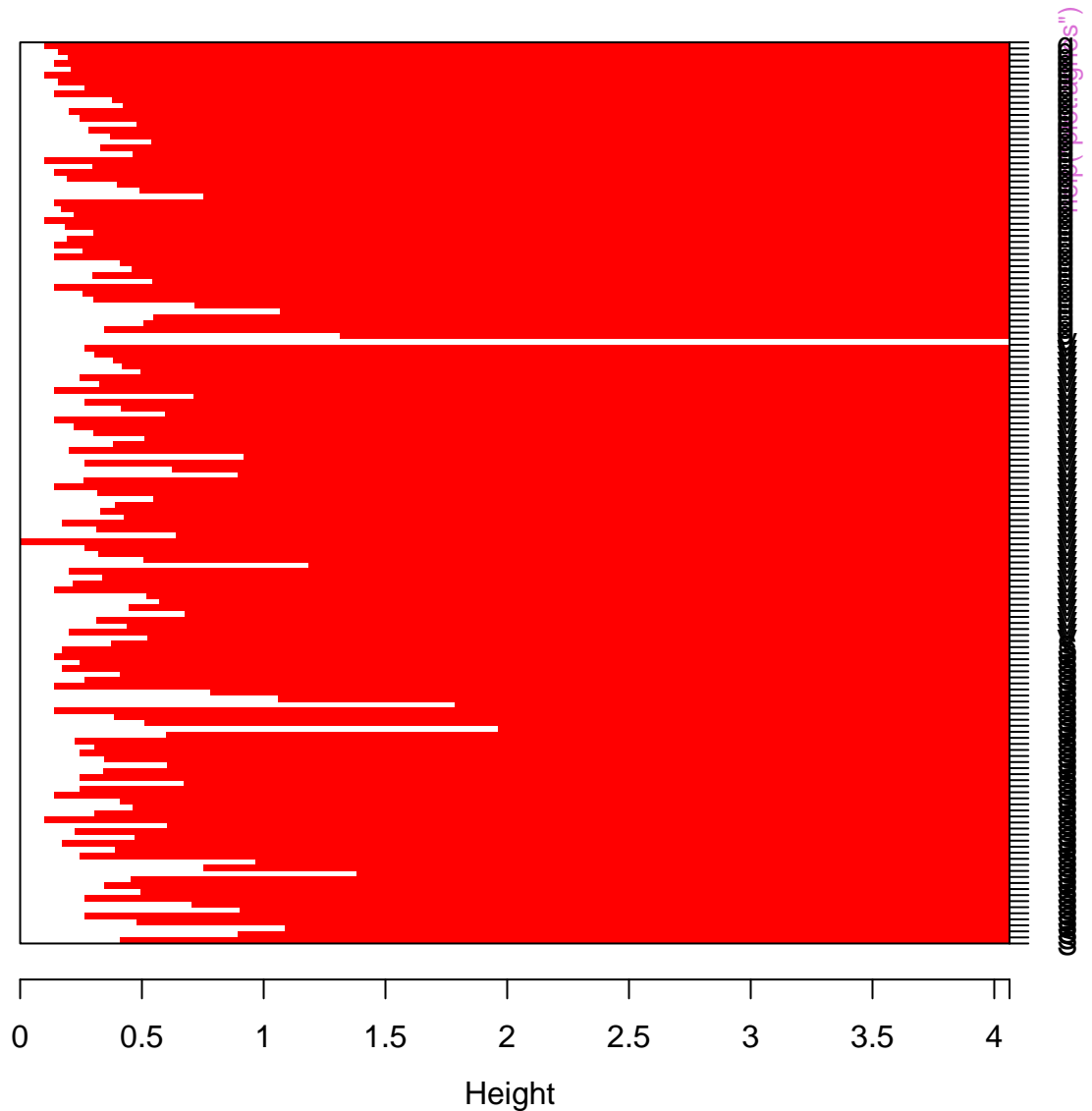
**Banner of `agnes(x = dai.b, method = "ward")`**



Agglomerative Coefficient = 0.95



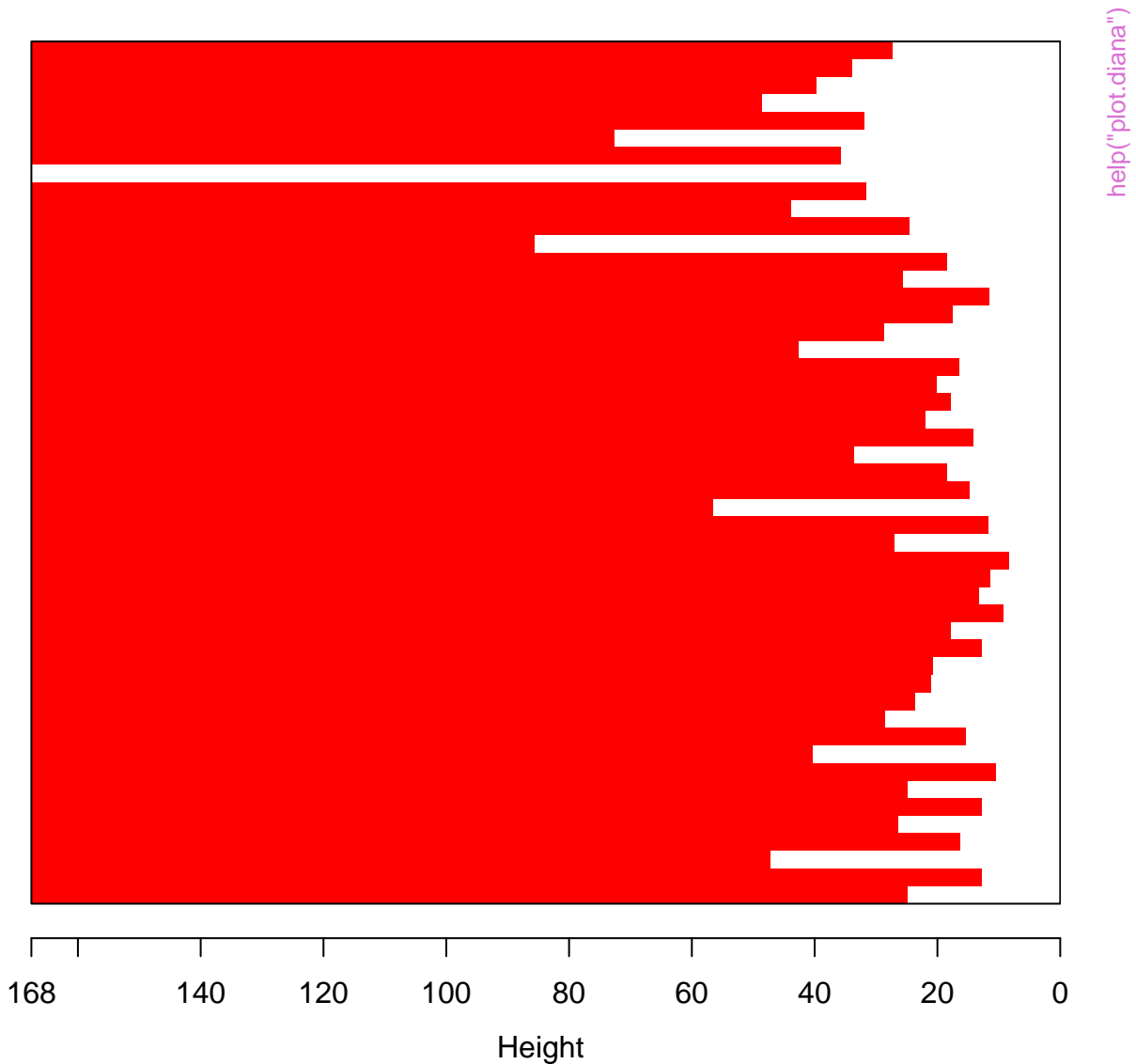
Banner of `agnes(x = iris[, 1:4])`



Agglomerative Coefficient = 0.93

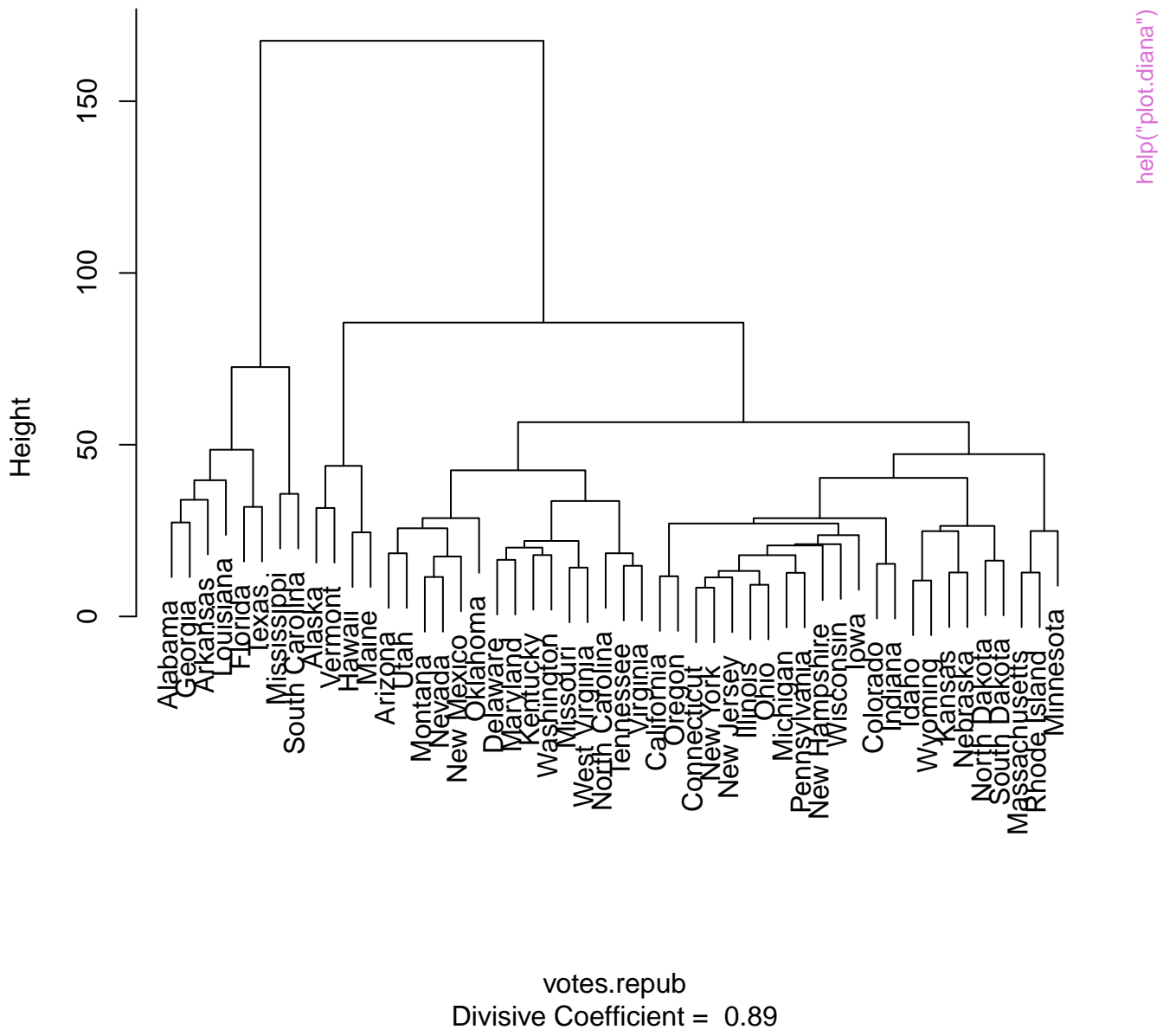
iris[, 1:4]  
Agglomerative Coefficient = 0.93

Banner of `diana(x = votes.repub, metric = "manhattan", stand = TR`

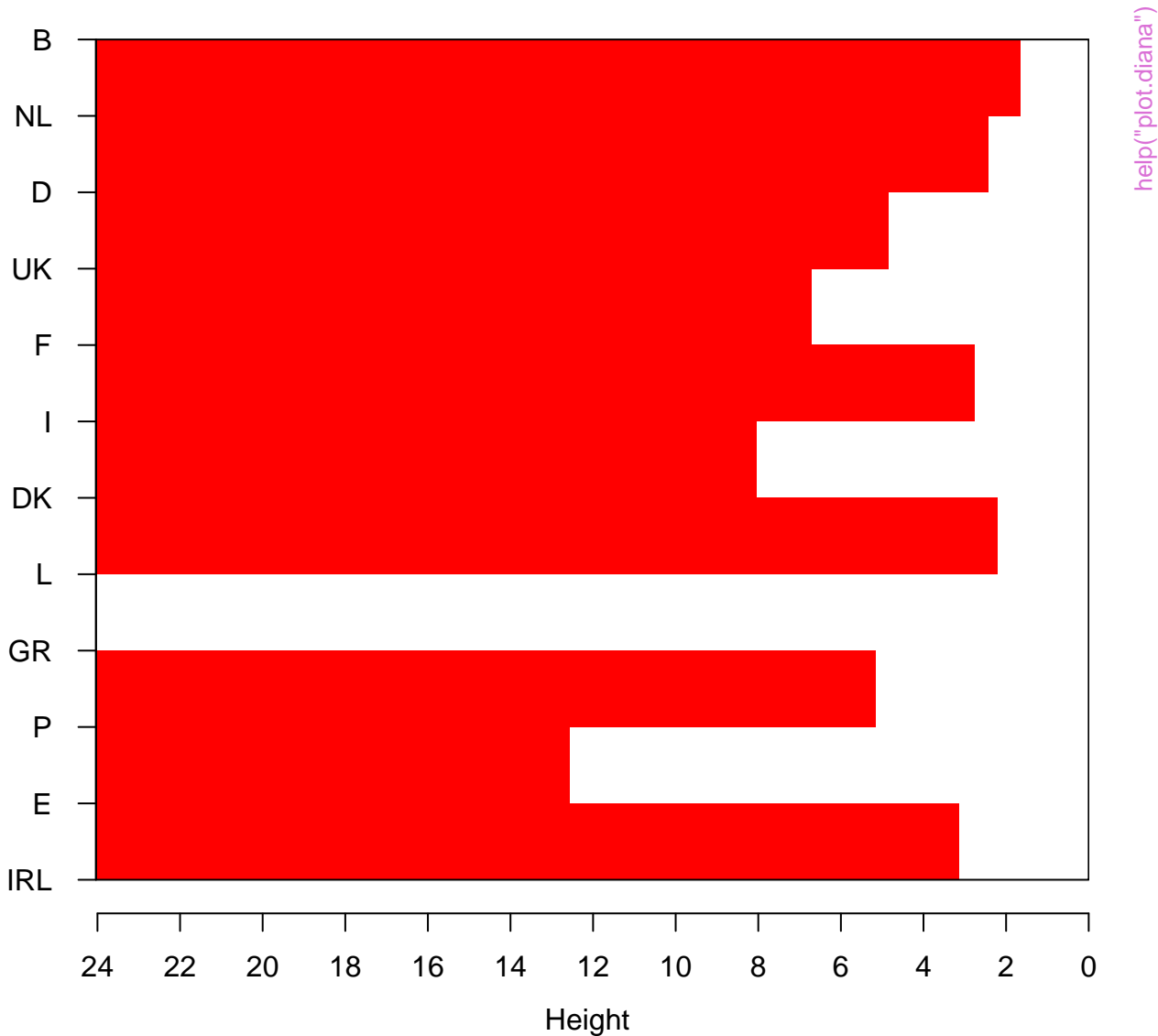


Divisive Coefficient = 0.89

Dendrogram of `diana(x = votes.repub, metric = "manhattan", stand = TRUE)`

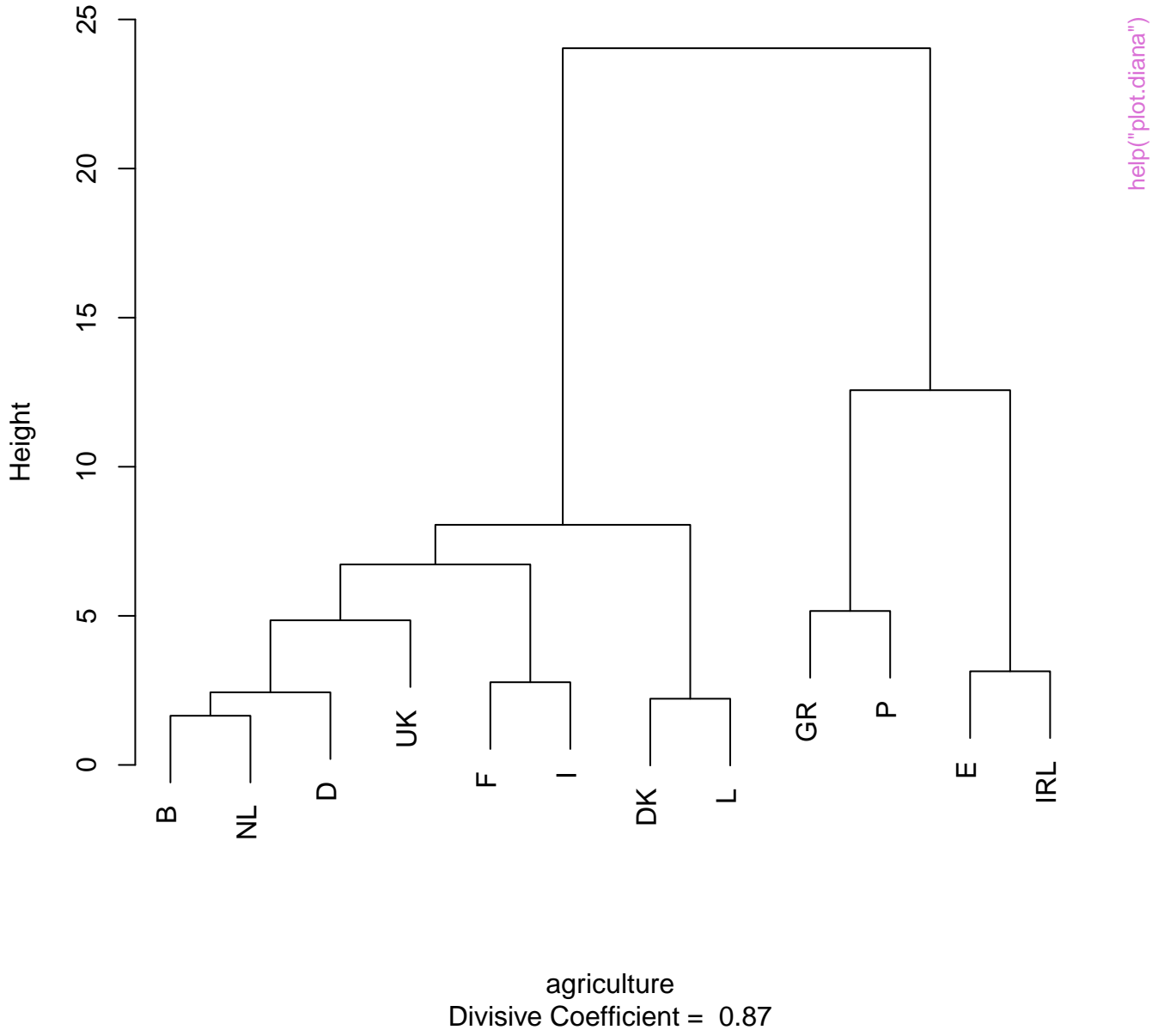


# Banner of diana(x = agriculture)



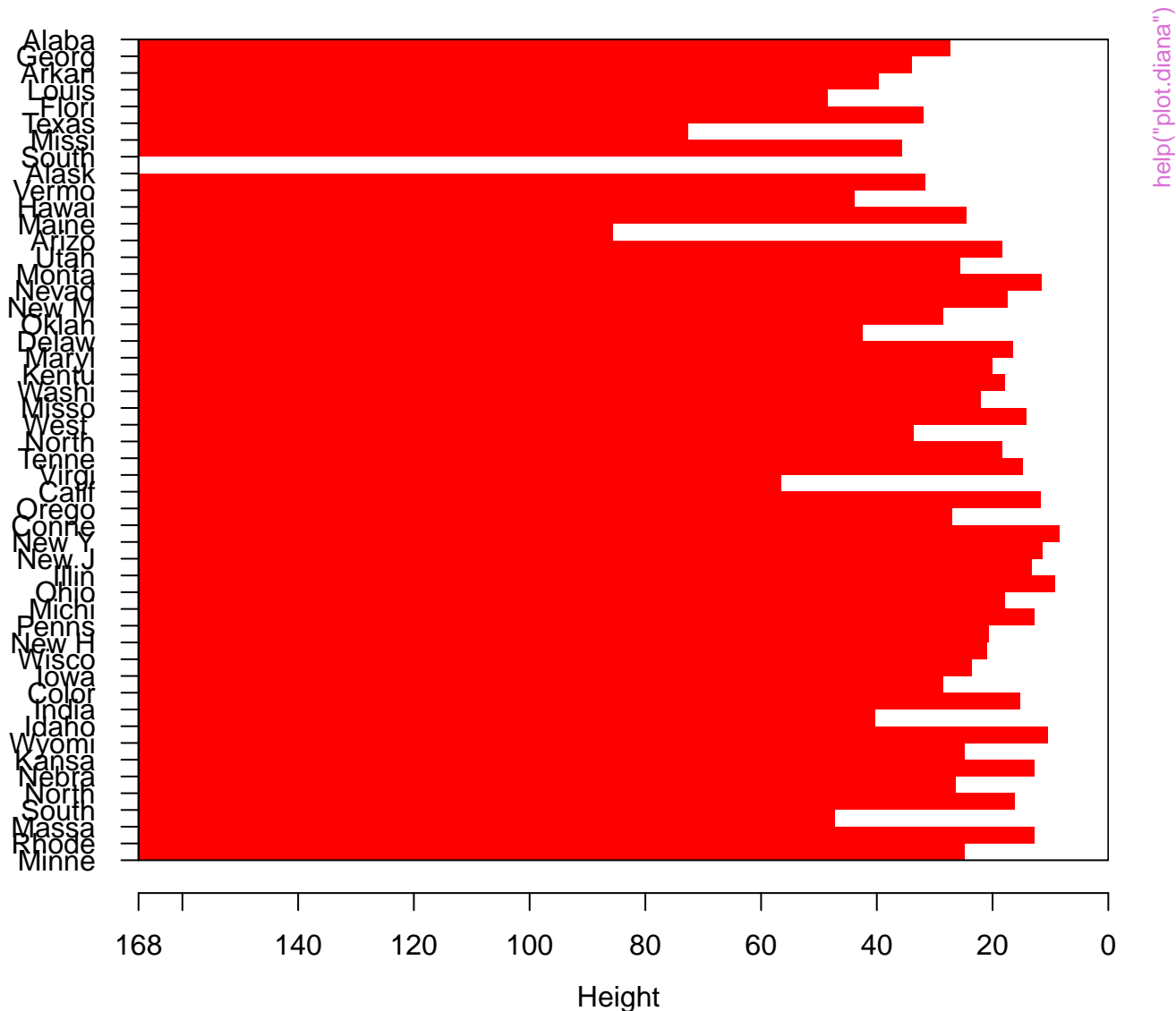
Divisive Coefficient = 0.87

# Dendrogram of diana(x = agriculture)



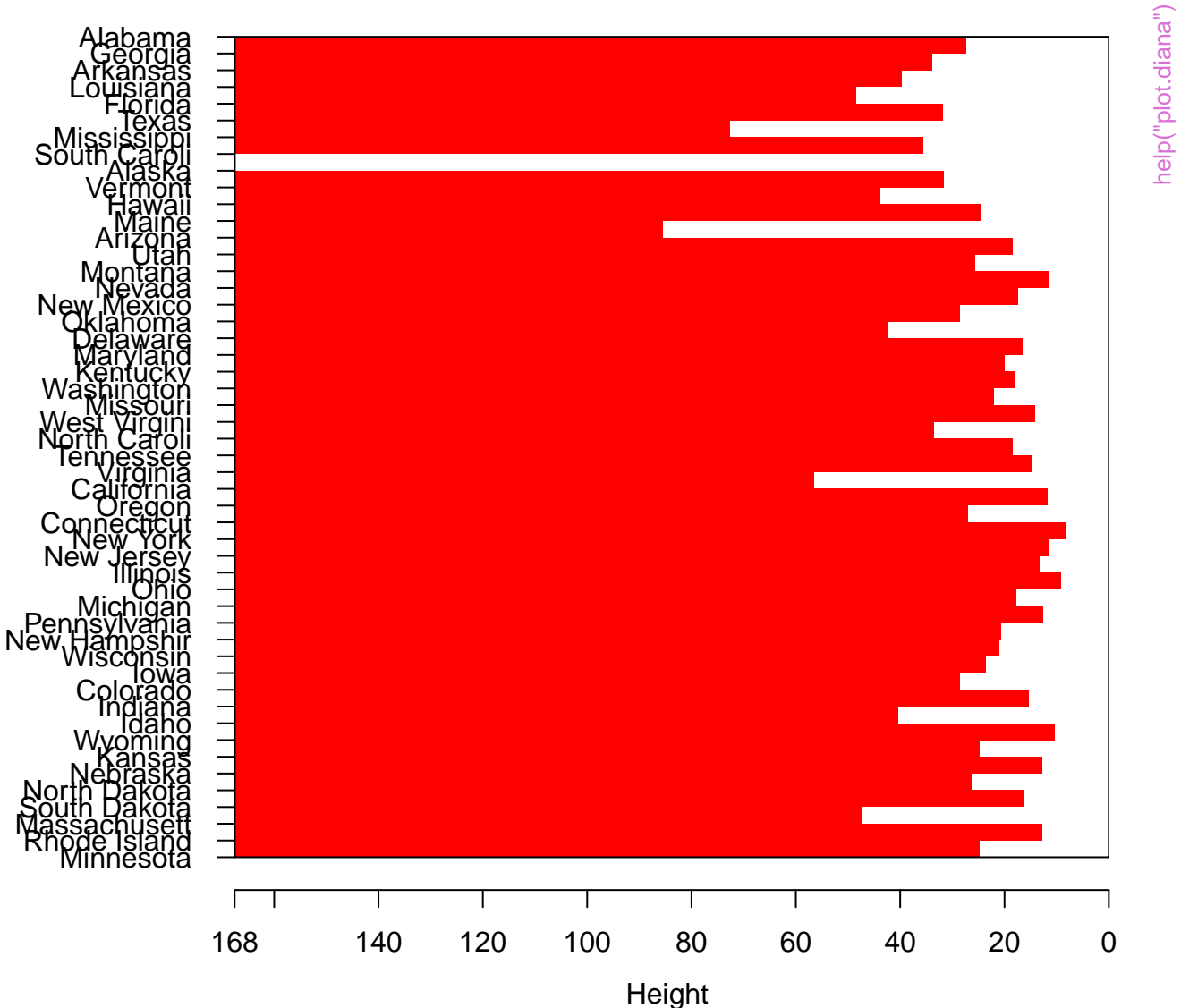


Banner of `diana(x = votes.repub, metric = "manhattan", stand = T`



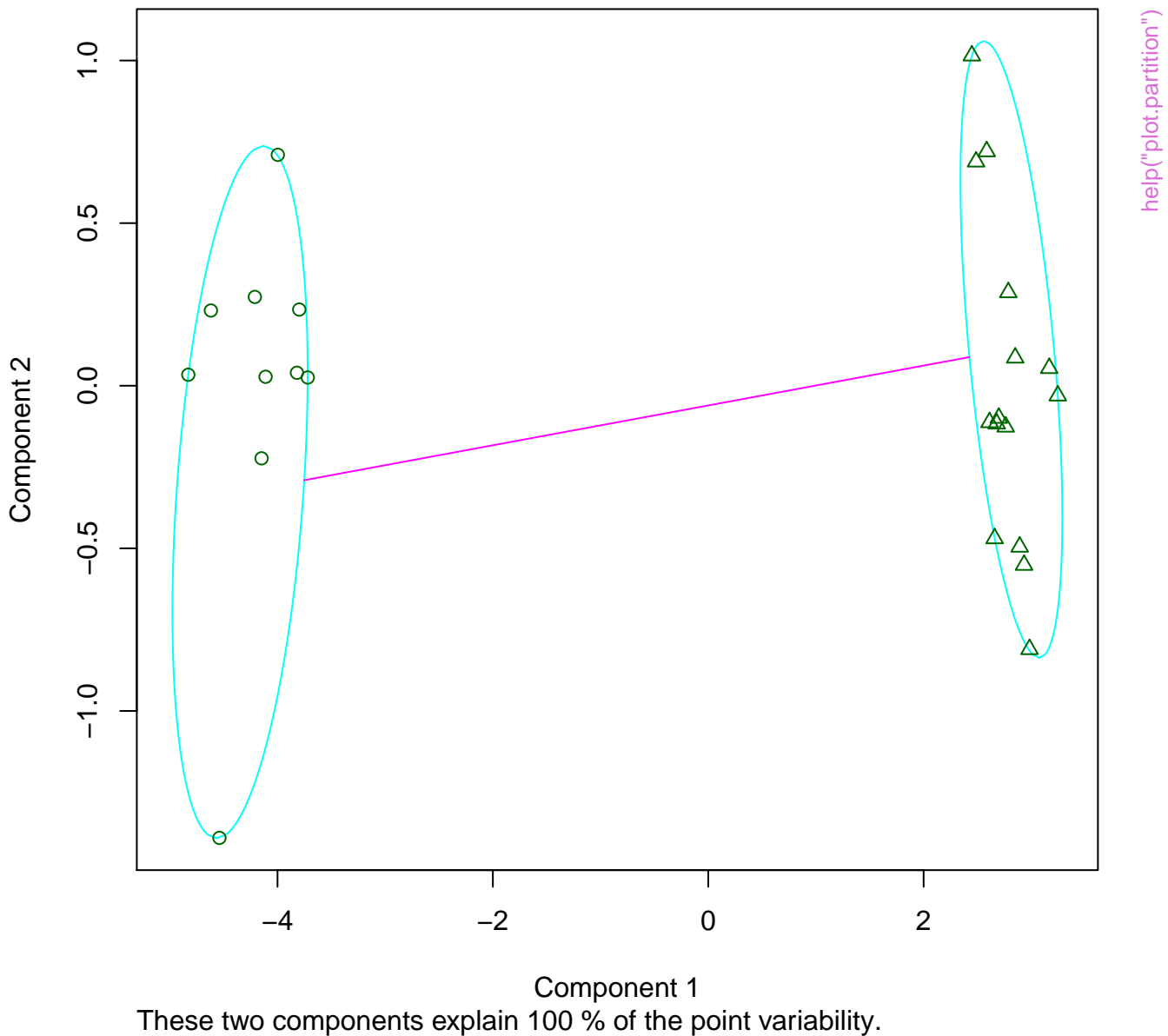
Divisive Coefficient = 0.89

Banner of `diana(x = votes.repub, metric = "manhattan", star`



Divisive Coefficient = 0.89

**clusplot(pam(x = x, k = 2))**

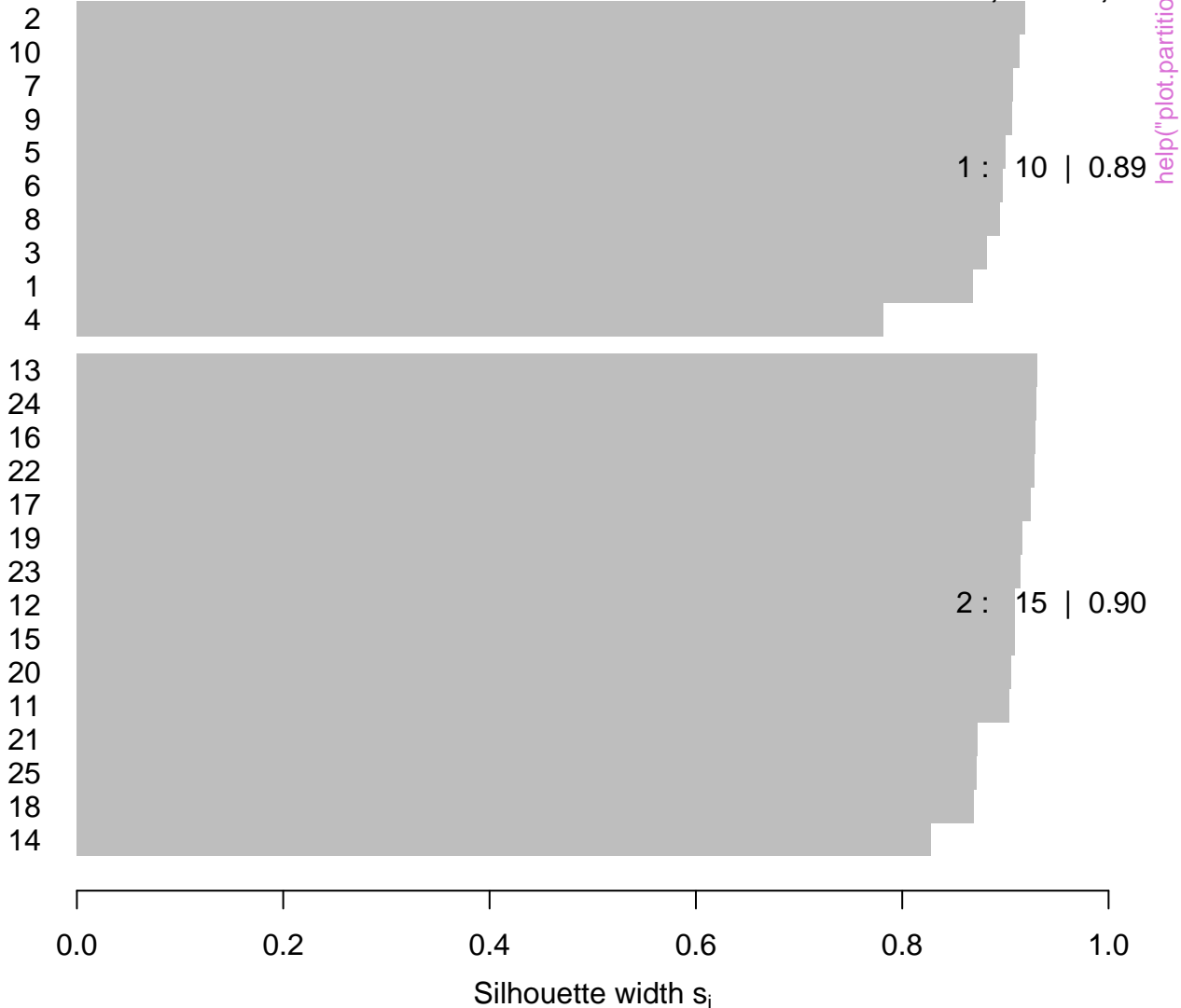


# Silhouette plot of pam(x = x, k = 2)

n = 25

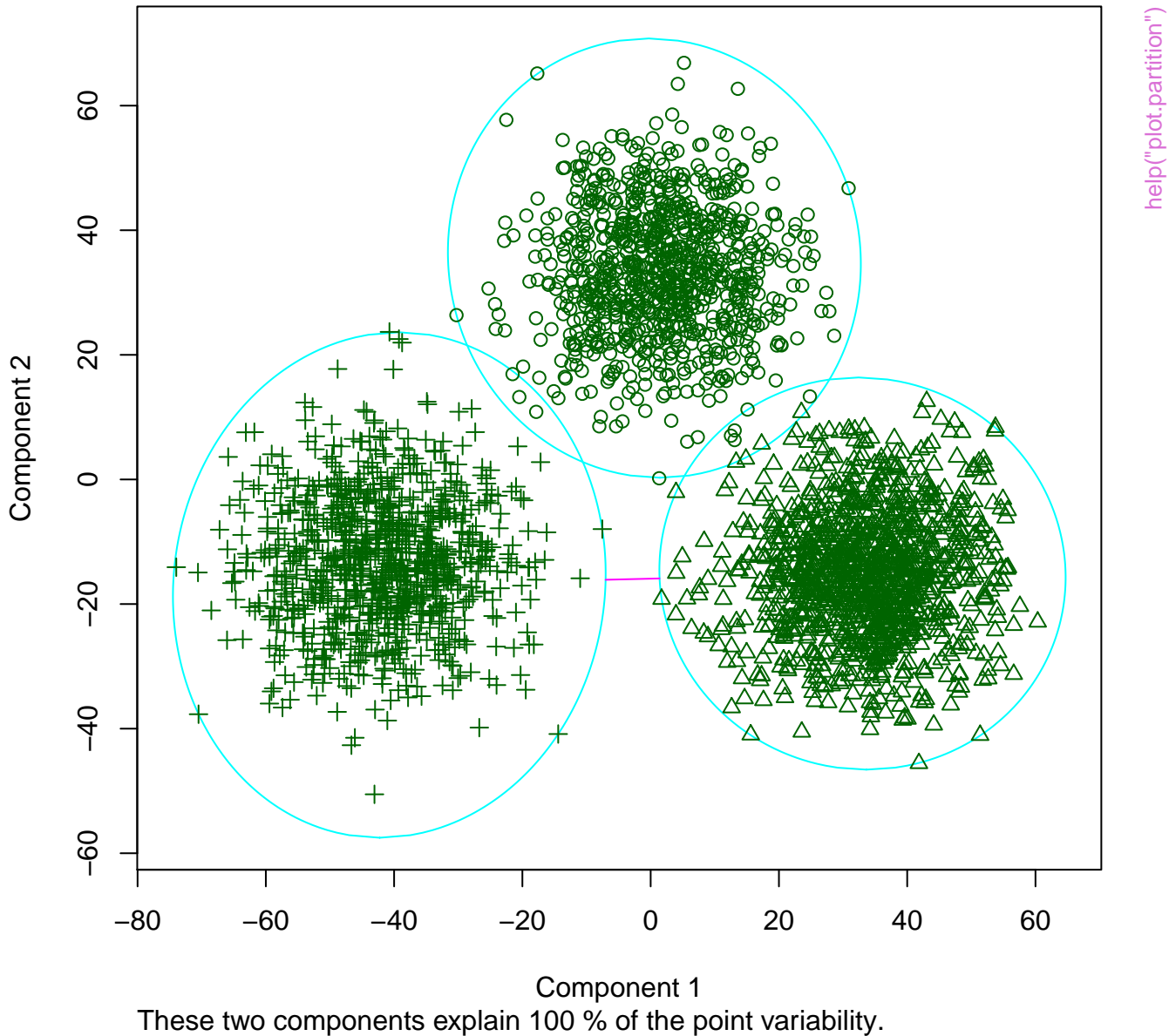
2 clusters  $C_j$

j :  $n_j$  |  $\text{ave}_{i \in C_j} s_i$



Average silhouette width : 0.9

**clusplot(clara(x = xclara, k = 3, keep.data = FALSE))**

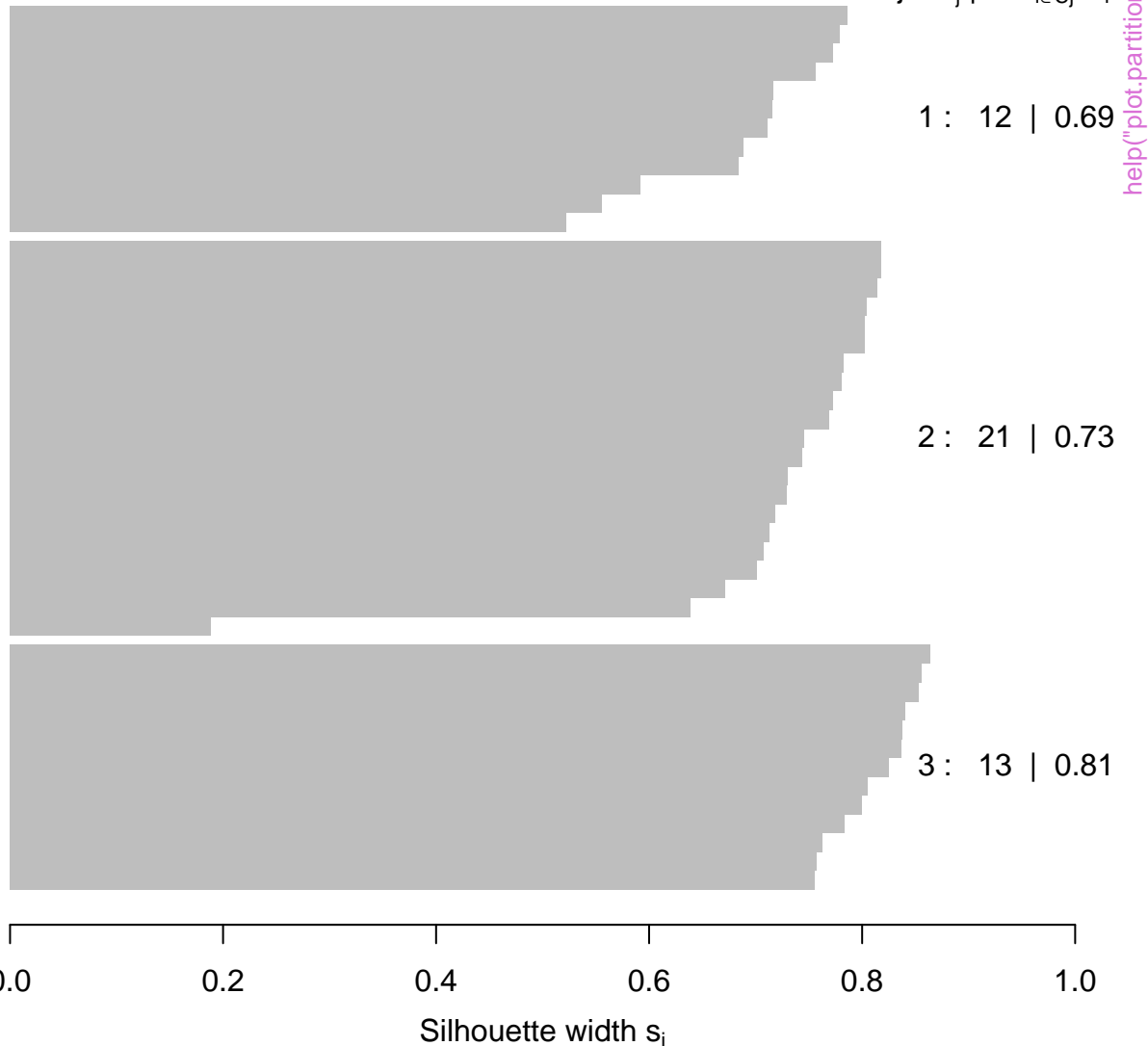


# Silhouette plot of clara(x = xclara, k = 3, keep.data = FALSE)

n = 46

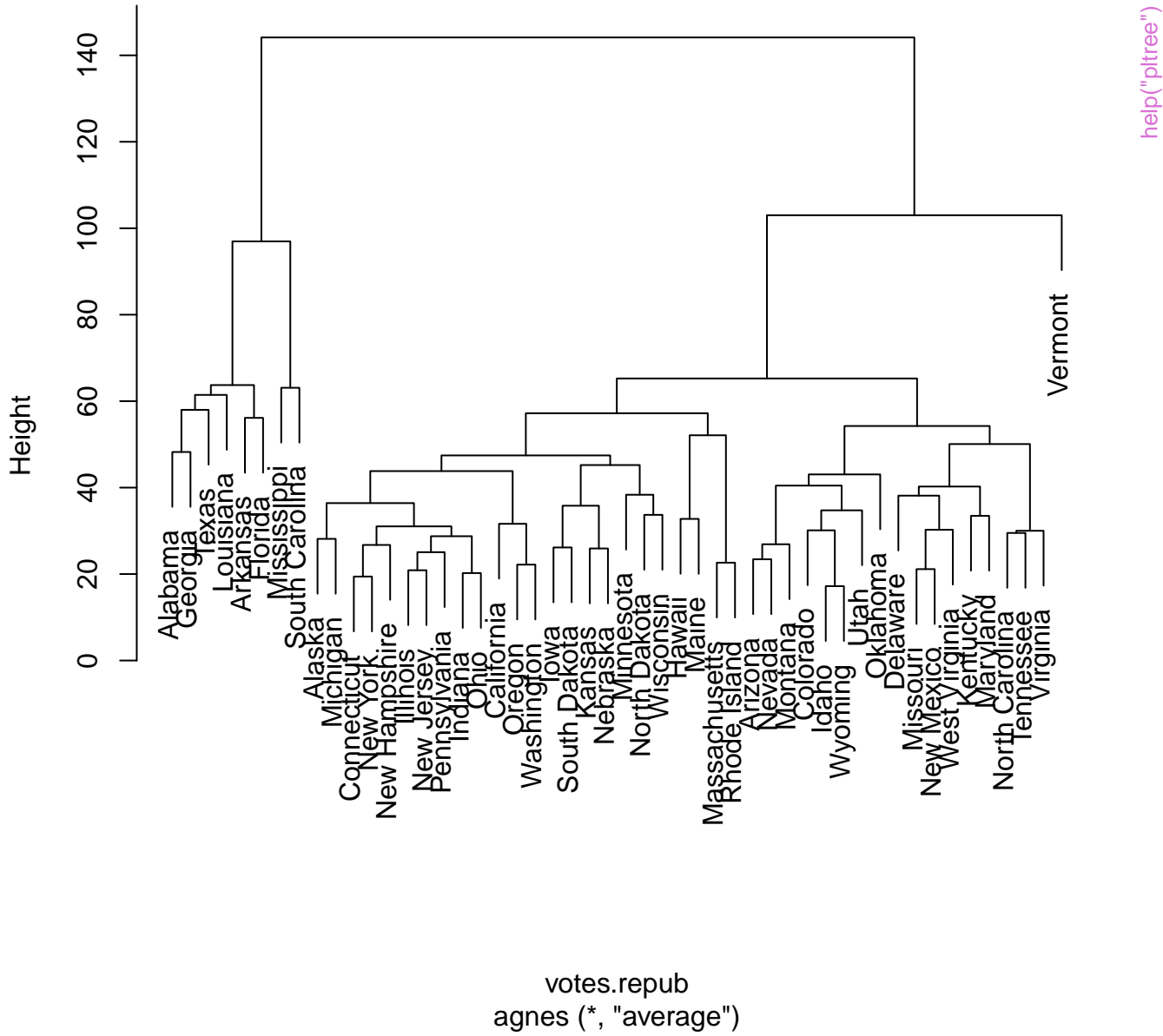
3 clusters  $C_j$

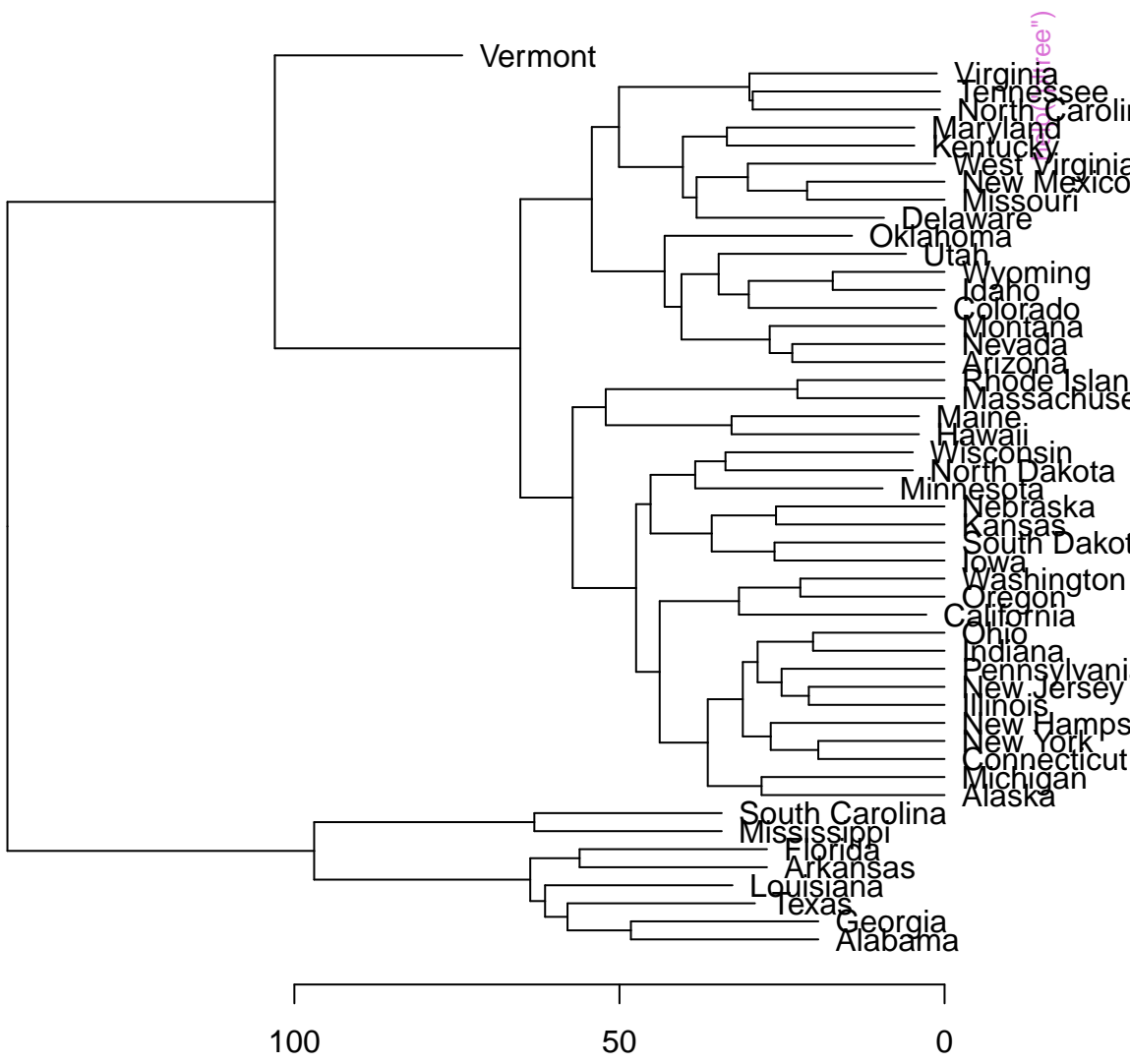
$j : n_j \mid \text{ave}_{i \in C_j} s_i$



Average silhouette width : 0.74

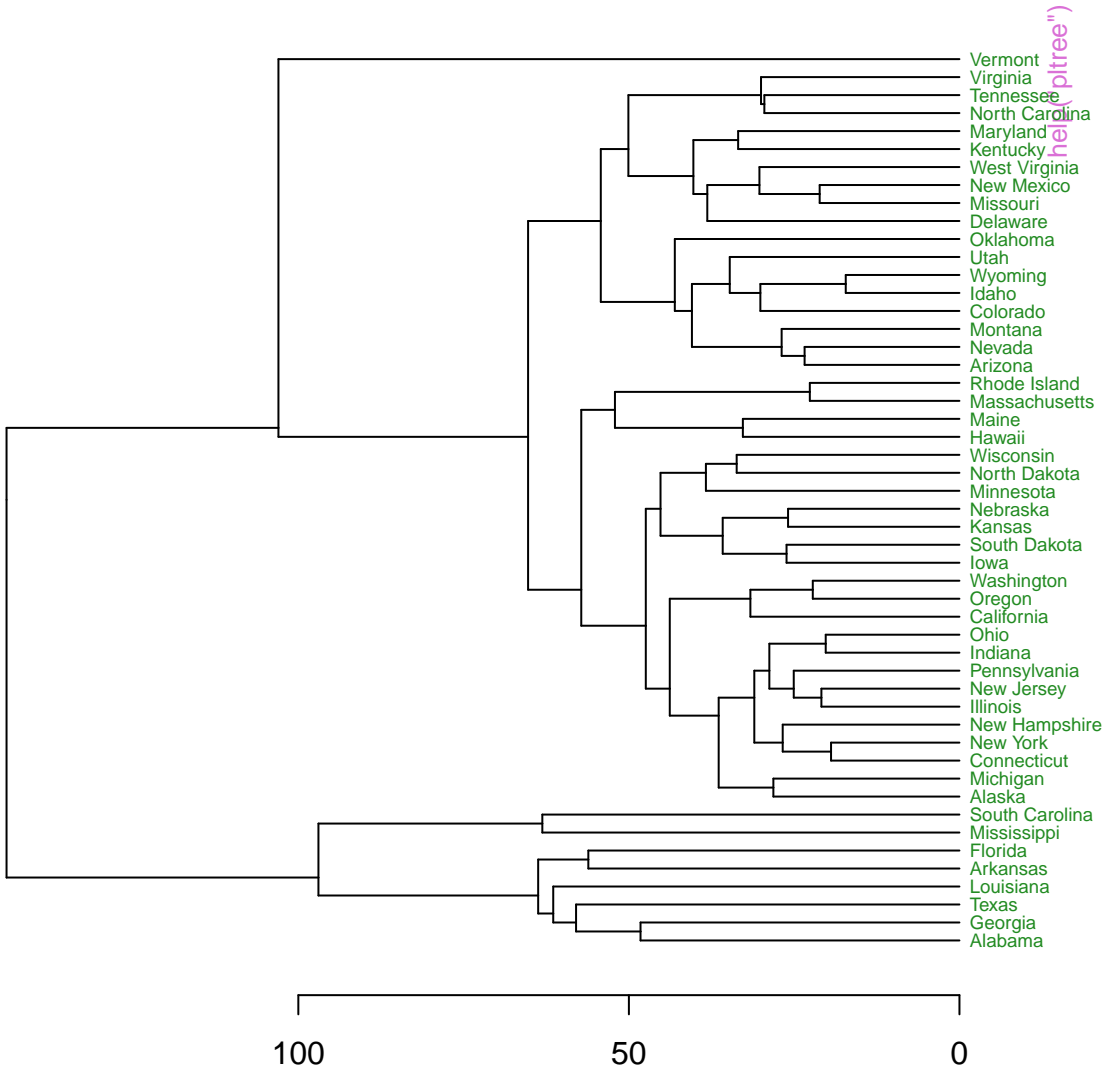
Dendrogram of agnes(x = votes.repub)



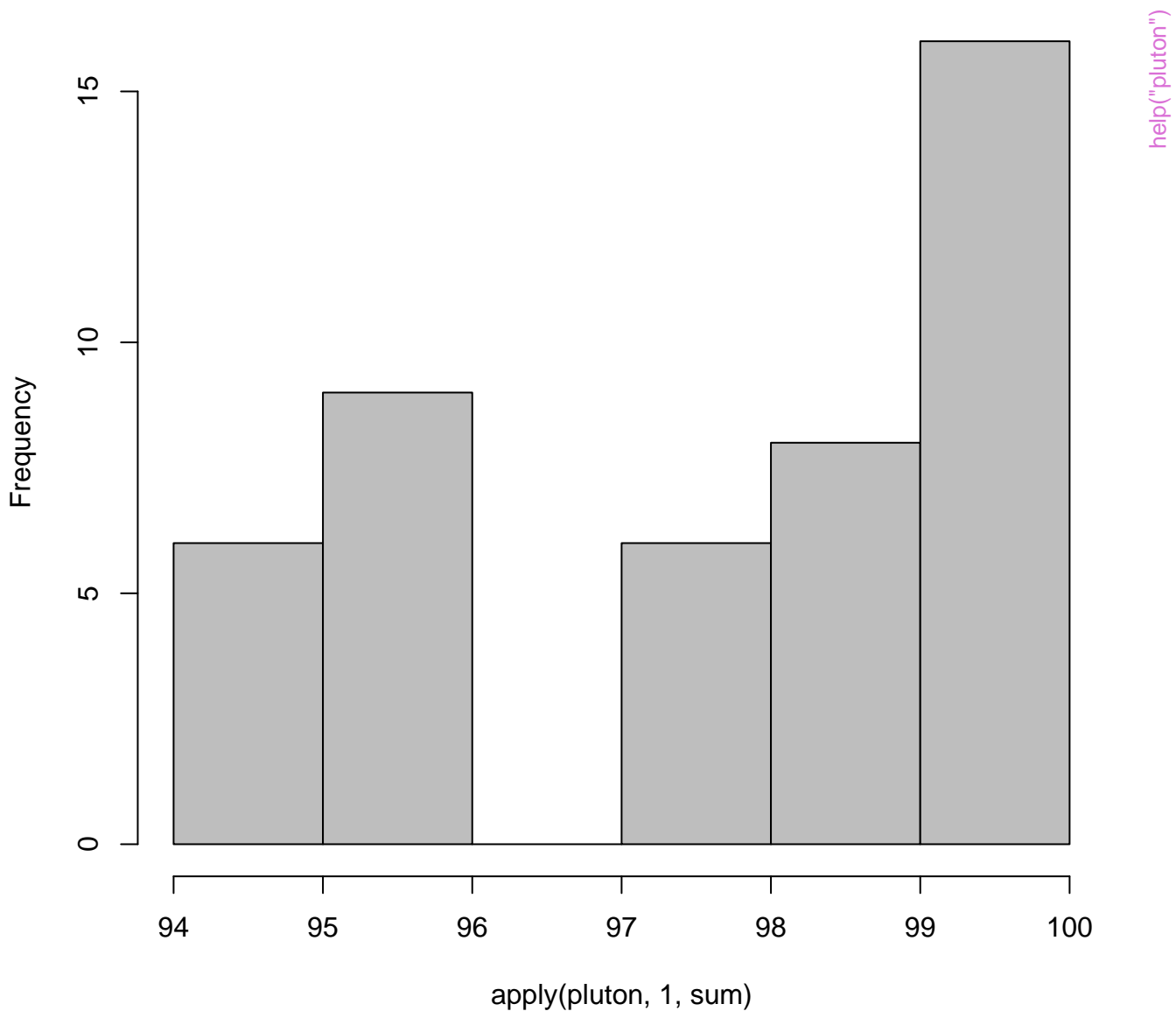


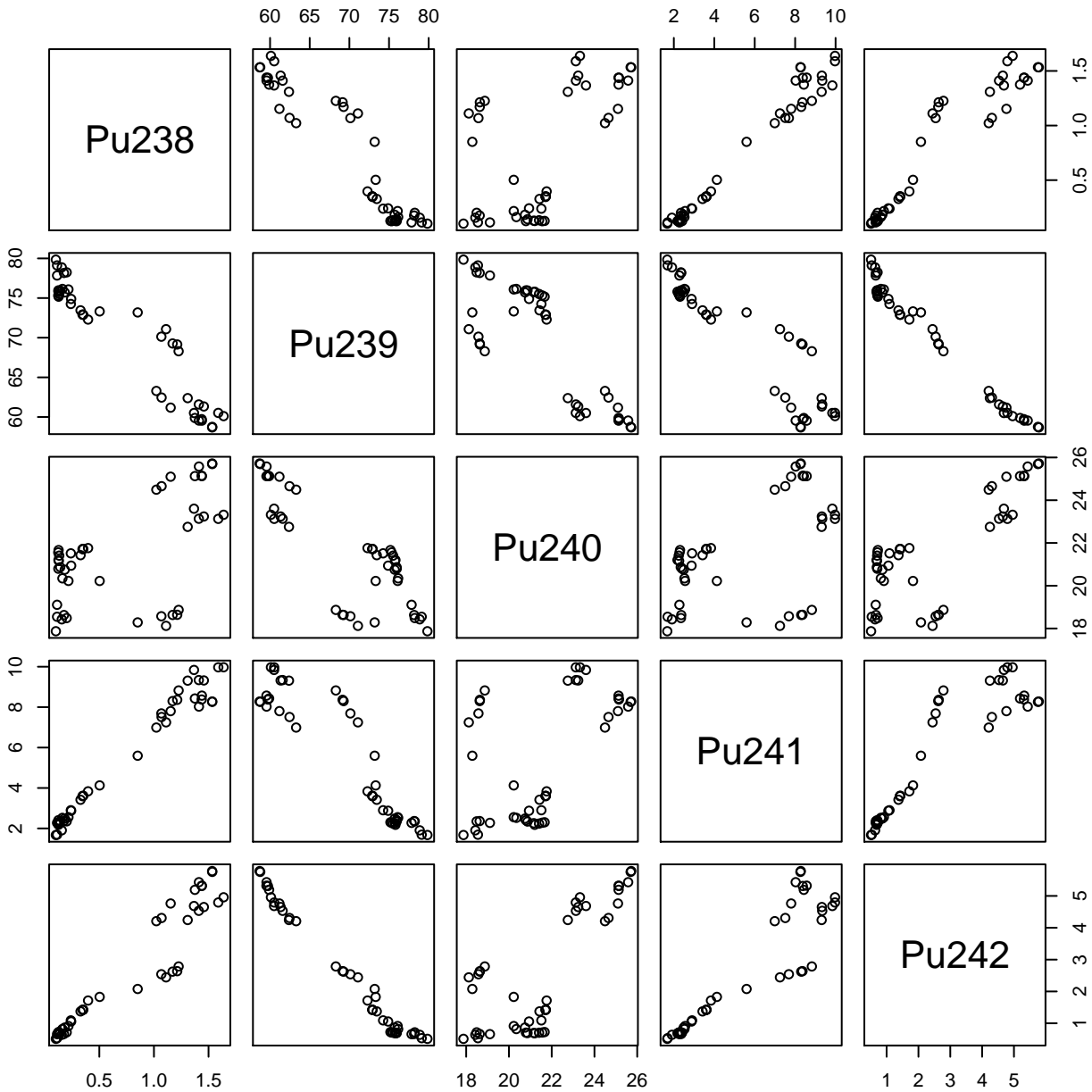


**agnes(x = votes.repub)**



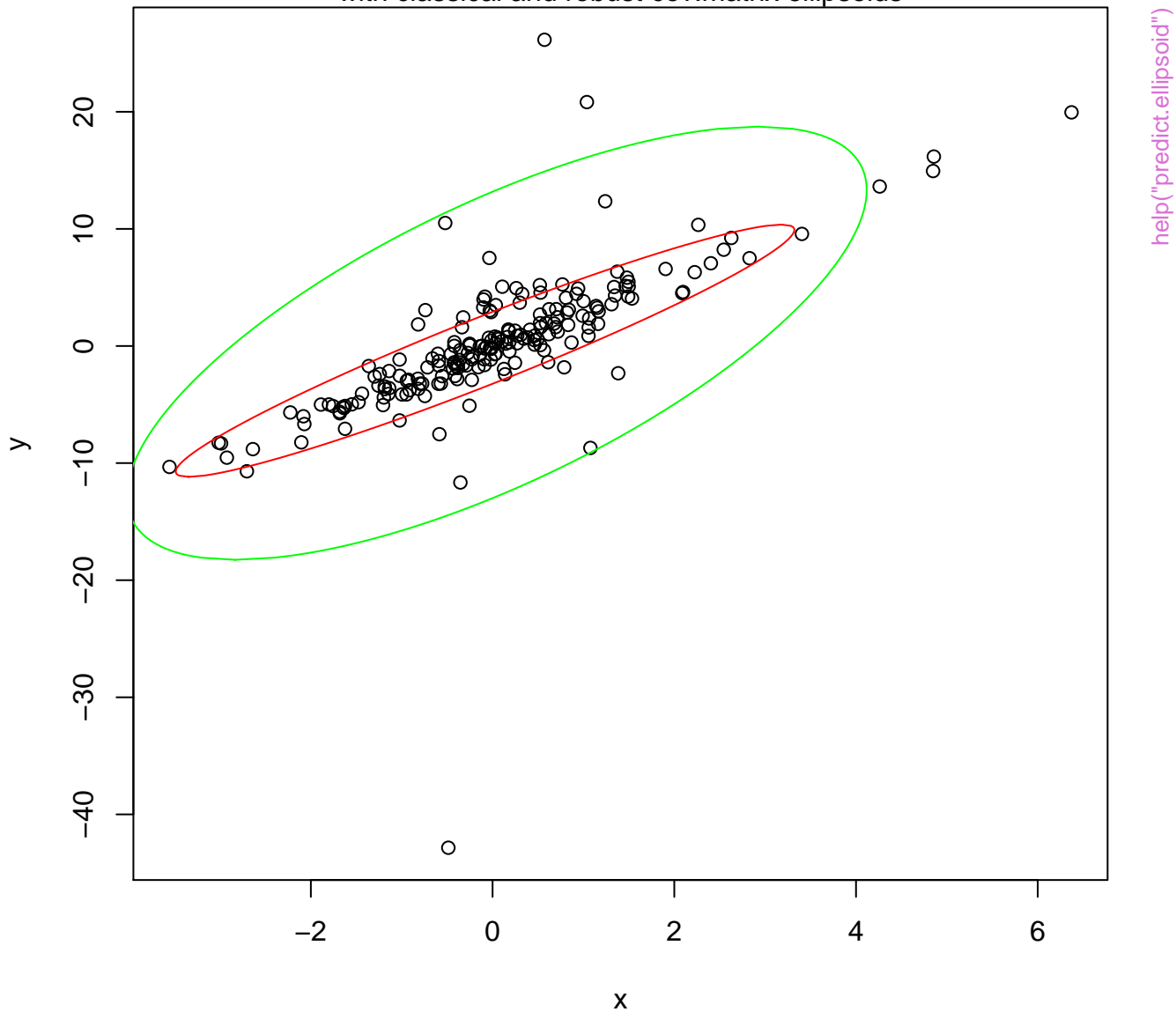
**Histogram of `apply(pluton, 1, sum)`**



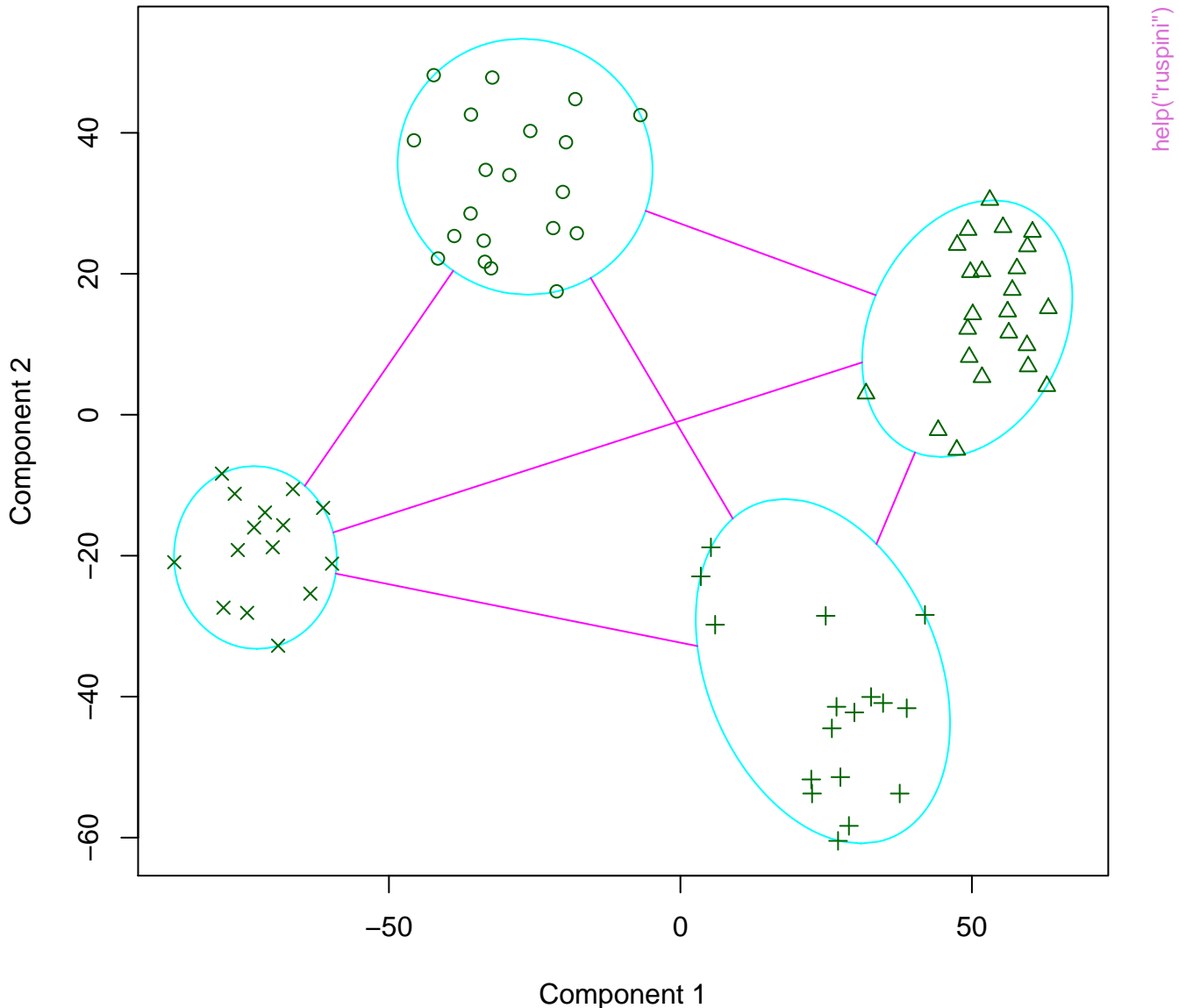


# non-normal data (N=200)

with classical and robust cov.matrix ellipsoids



**clusplot(pam(x = ruspini, k = 4))**



These two components explain 100 % of the point variability.

# Silhouette plot of pam(x = ruspini, k = 4)

n = 75

4 clusters  $C_j$

$j : n_j \mid \text{ave}_{i \in C_j} s_i$

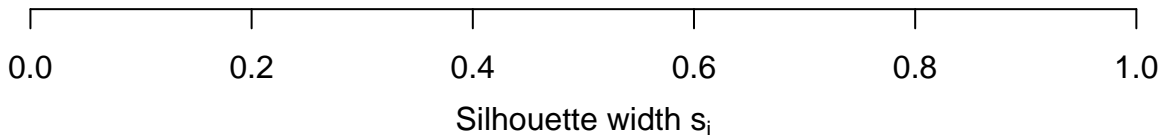
[help\("ruspini"\)](#)

1 : 20 | 0.73

2 : 23 | 0.75

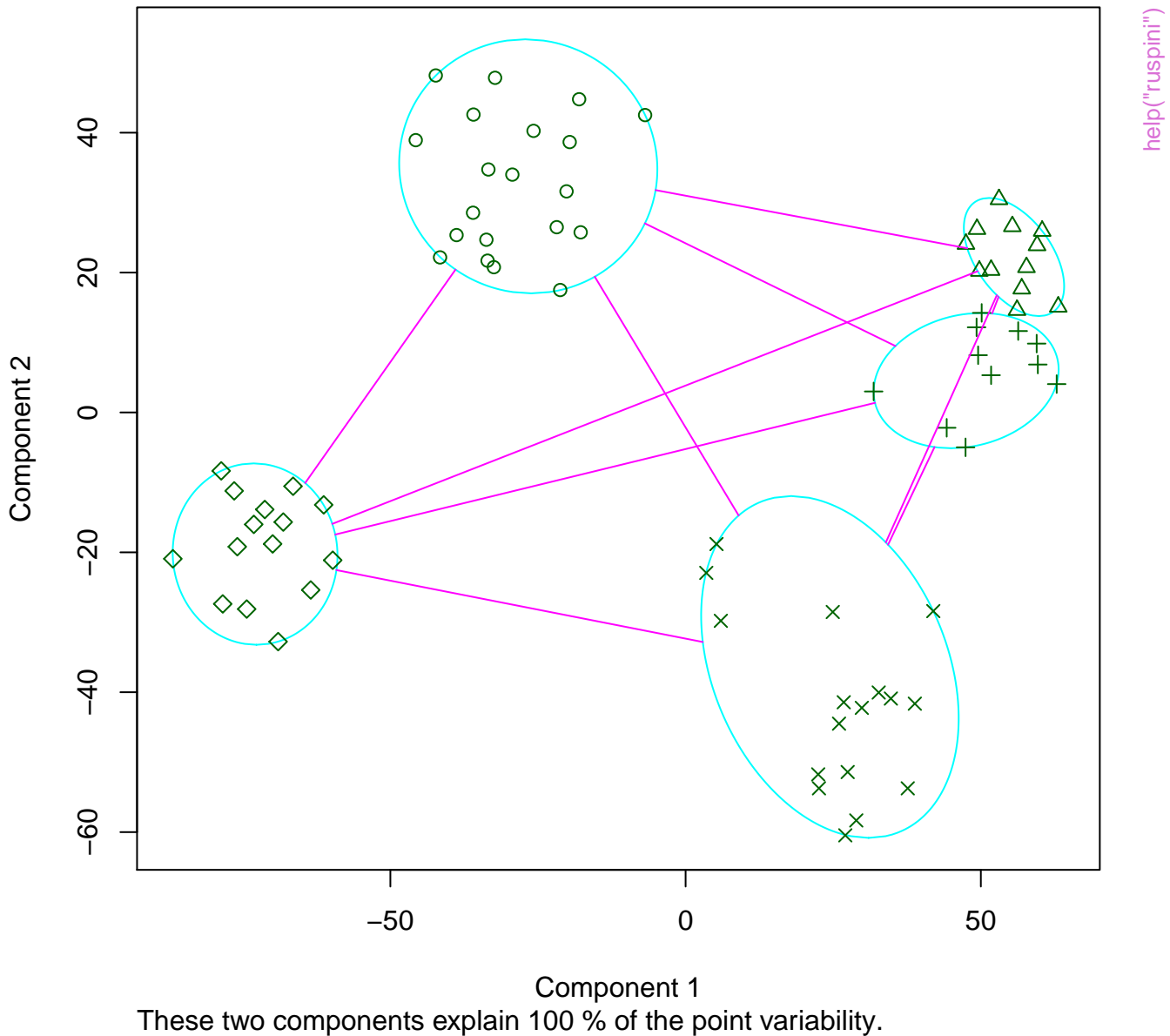
3 : 17 | 0.67

4 : 15 | 0.80



Average silhouette width : 0.74

**clusplot(fanny(x = ruspini, k = 5))**

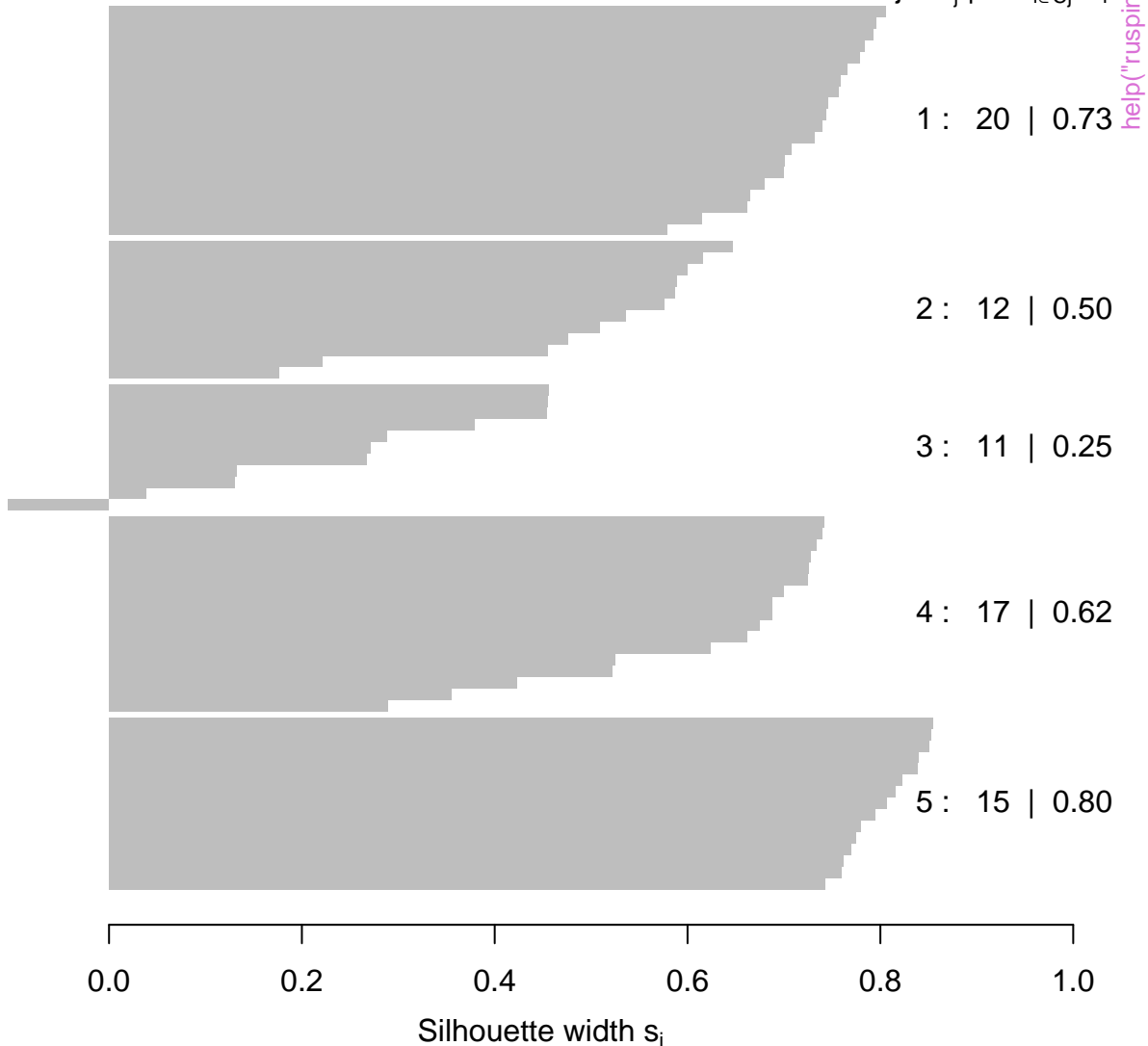


# Silhouette plot of fanny(x = ruspini, k = 5)

n = 75

5 clusters  $C_j$

$j : n_j \mid \text{ave}_{i \in C_j} s_i$



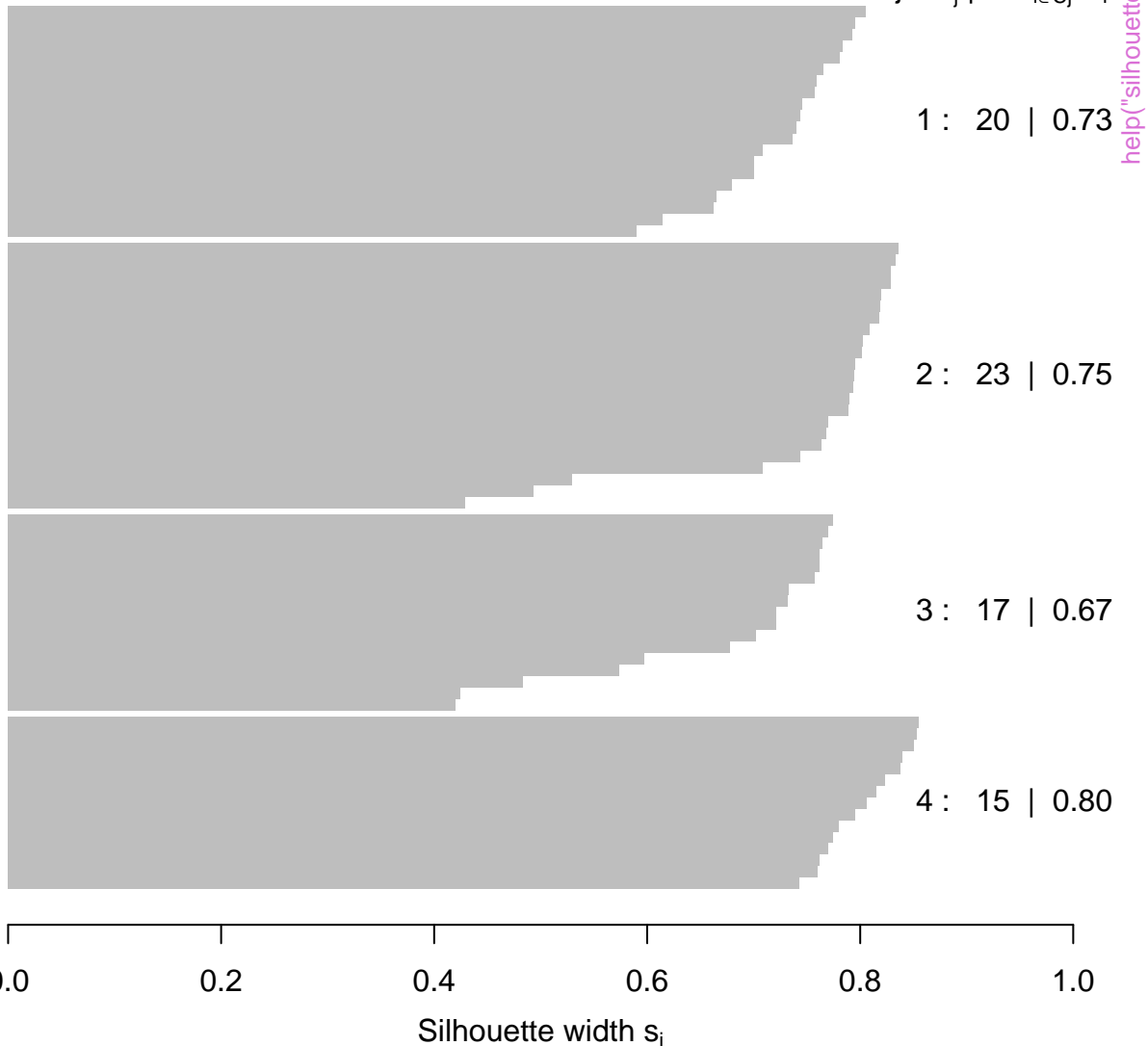


# Silhouette plot of pam(x = ruspini, k = 4)

n = 75

4 clusters  $C_j$

$j : n_j \mid \text{ave}_{i \in C_j} s_i$

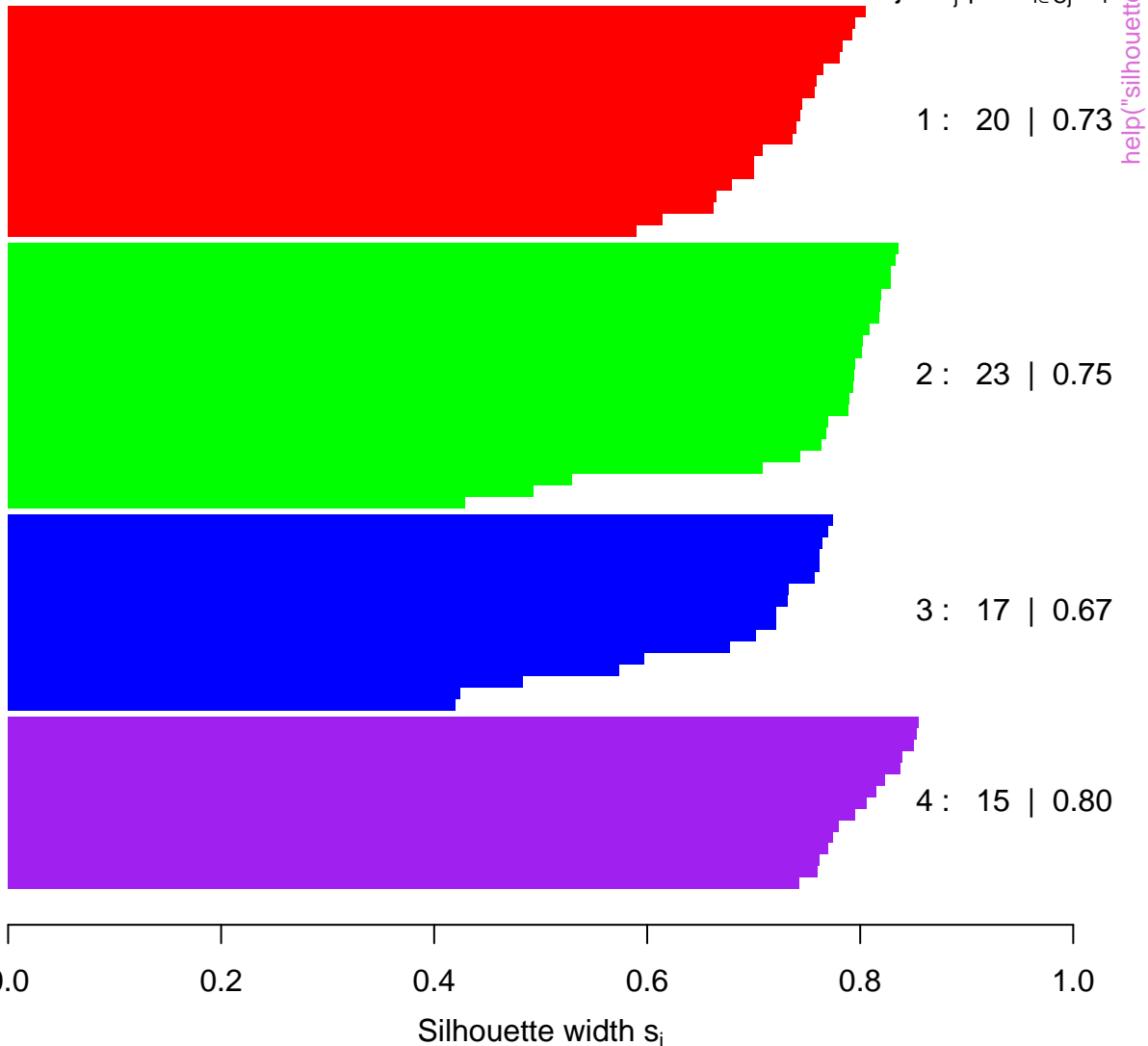


# Silhouette plot of pam(x = ruspini, k = 4)

n = 75

4 clusters  $C_j$

$j : n_j \mid \text{ave}_{i \in C_j} s_i$



### Silhouette plot of (x = pr4\$clustering, dist = dist(ruspini, "canberra"))

n = 75

4 clusters  $C_j$

$$j : n_j \mid \text{ave}_{i \in C_j} s_i$$

1 : 20 | 0.47

2 : 23 | 0.67

3 : 17 | 0.73

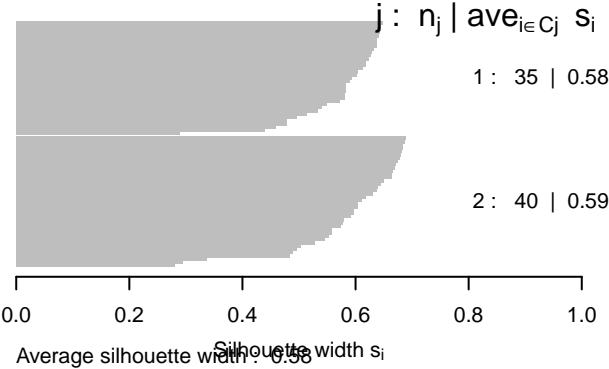
4 : 15 | 0.66

Average silhouette width : 0.63

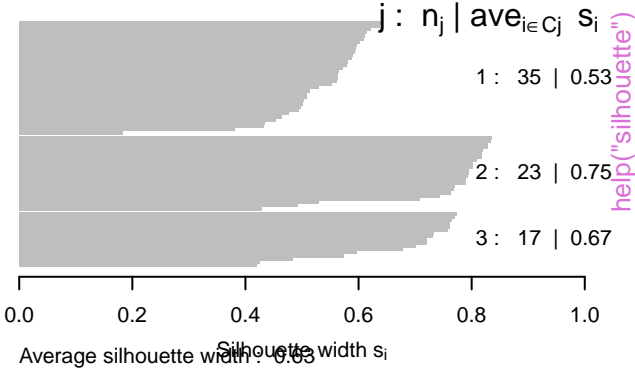
```
help("silhouette")
```

# PAM(Ruspini) as in Kaufman & Rousseeuw, p.101

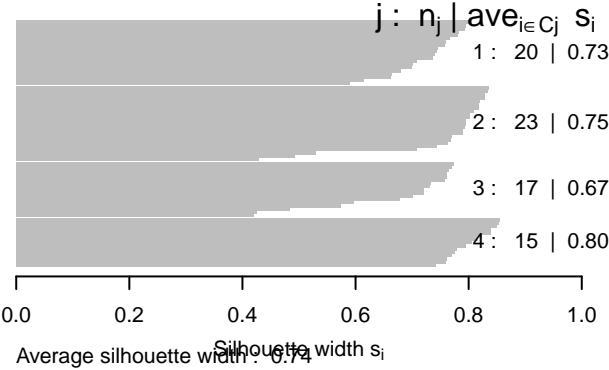
**k = 2**



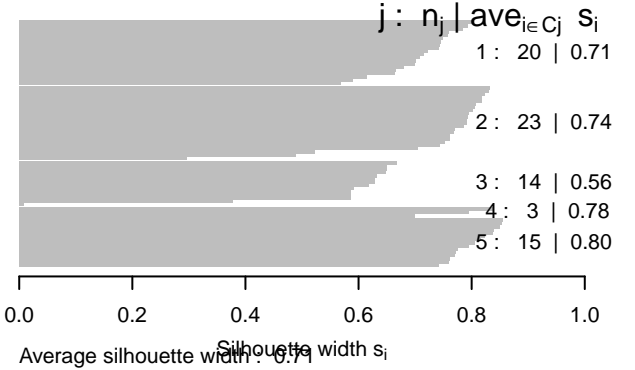
**k = 3**



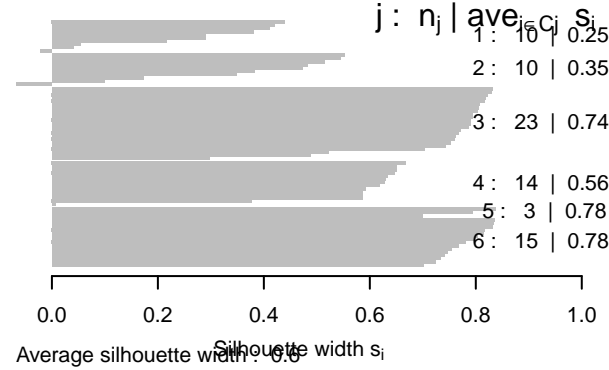
**k = 4**



**k = 5**

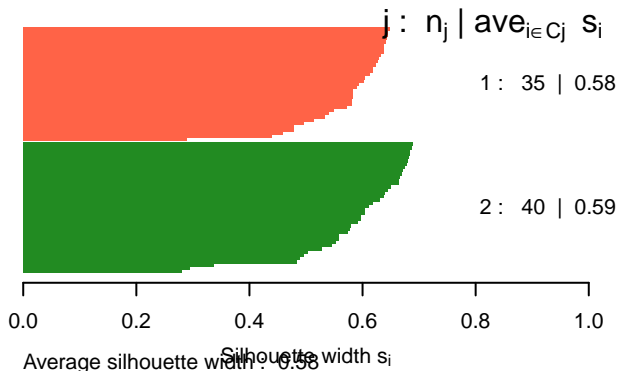


**k = 6**

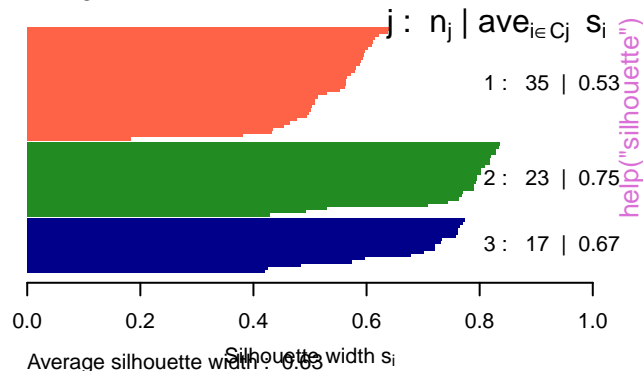


help("silhouette")

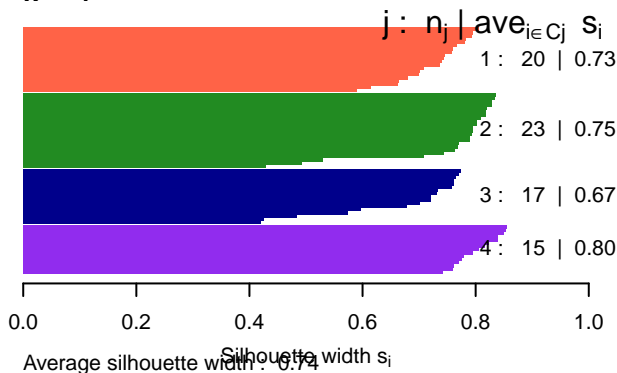
**k = 2**



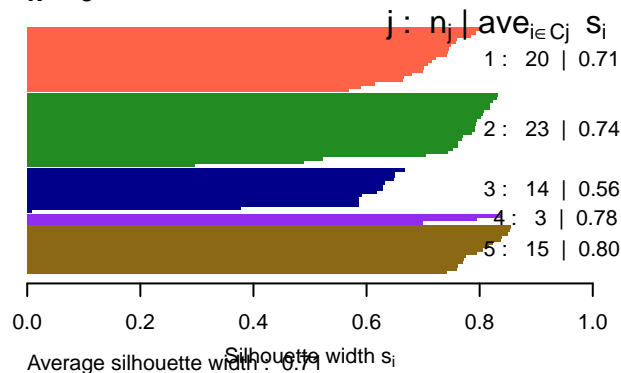
**k = 3**



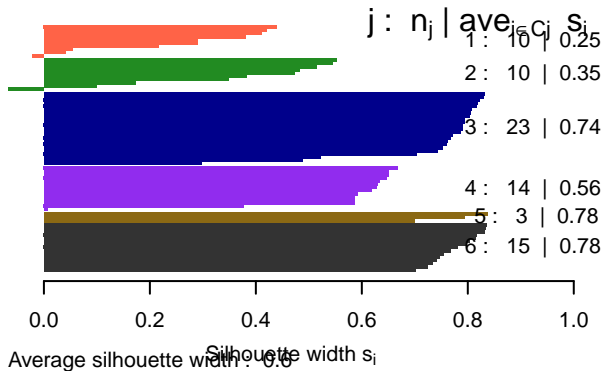
**k = 4**



**k = 5**



**k = 6**



# Silhouette plot of clara(x = xc1k, k = 3)

n = 46

3 clusters  $C_j$

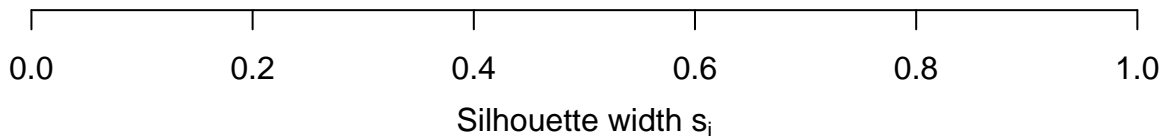
$j : n_j \mid \text{ave}_{i \in C_j} s_i$

1 : 8 | 0.72

2 : 20 | 0.75

3 : 18 | 0.65

help("silhouette")



**plot(silhouette(clara(.), full = TRUE))**

n = 1000

3 clusters  $C_j$

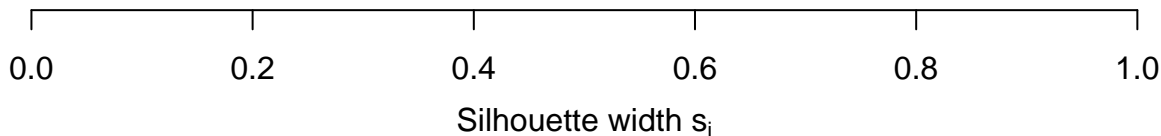
$j : n_j \mid \text{ave}_{i \in C_j} s_i$

help("silhouette")

1 : 322 | 0.69

2 : 399 | 0.70

3 : 279 | 0.68



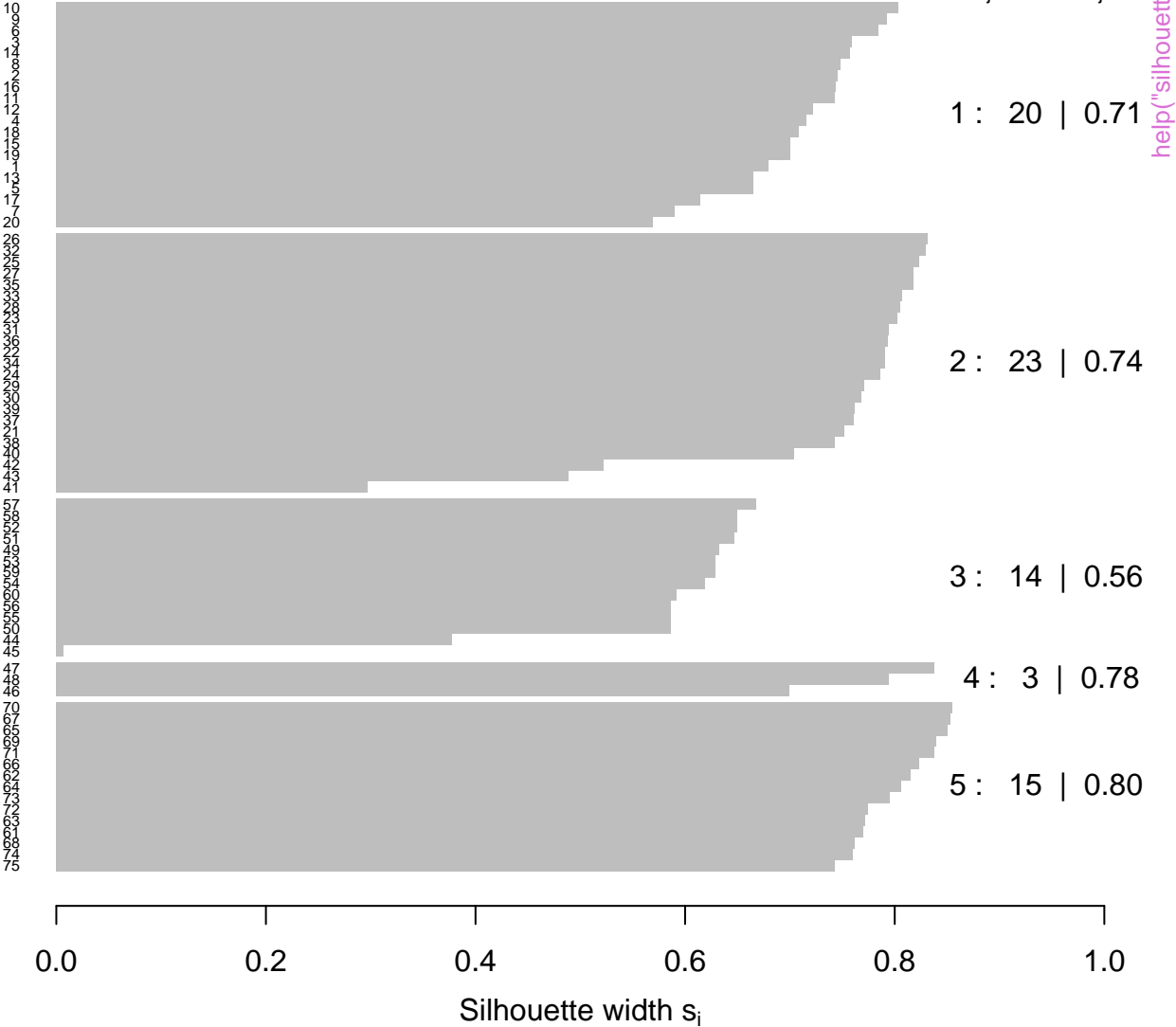
Average silhouette width : 0.69

Silhouette plot of (x = cutree(ar, k = 5), dist = daisy(ruspini))

n = 75

5 clusters  $C_j$

$j : n_j \mid \text{ave}_{i \in C_j} s_i$



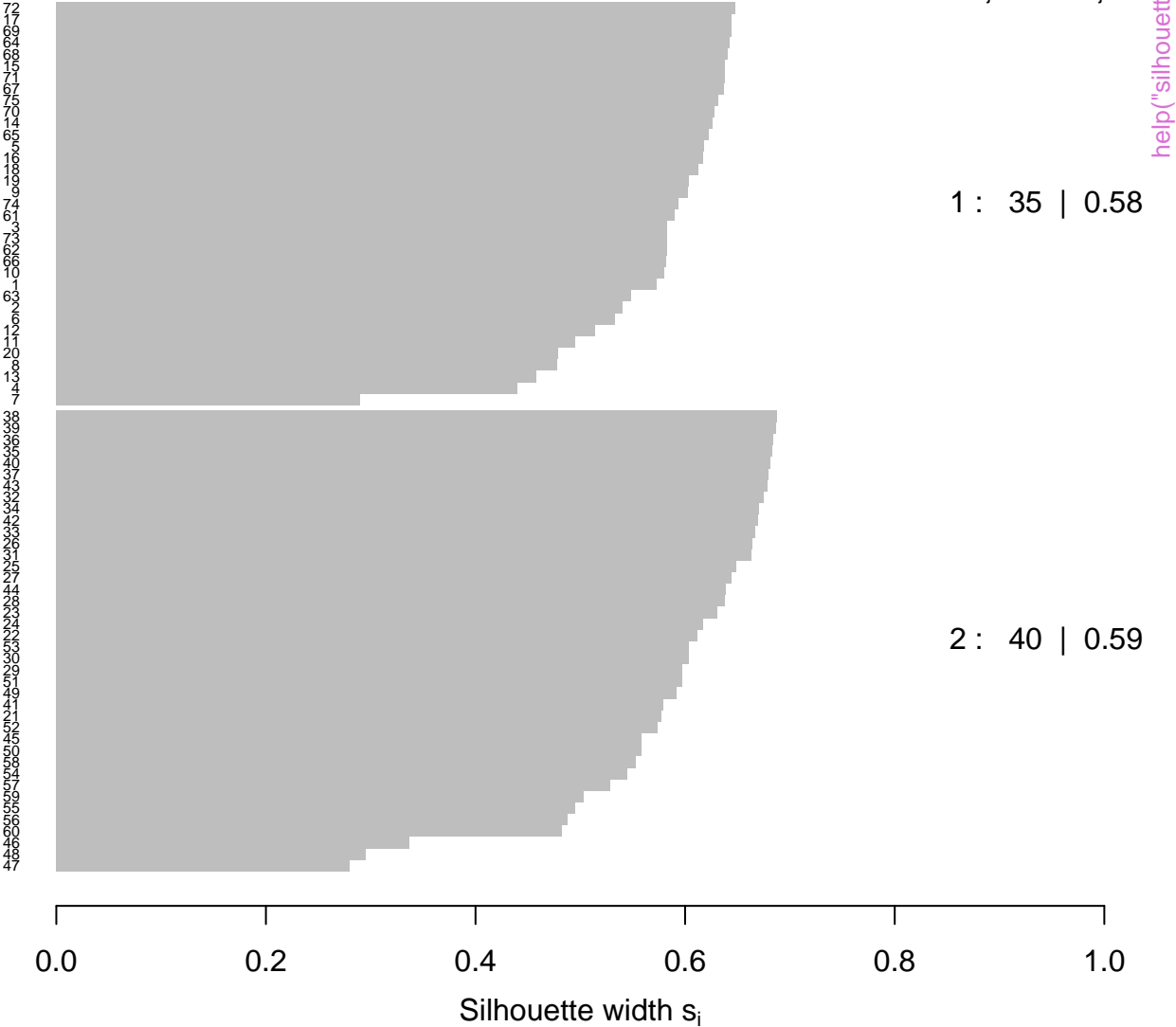


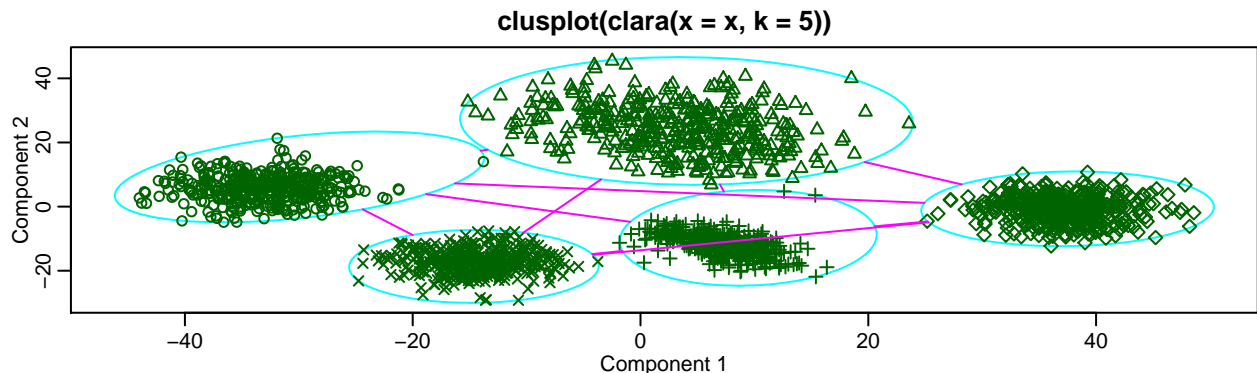
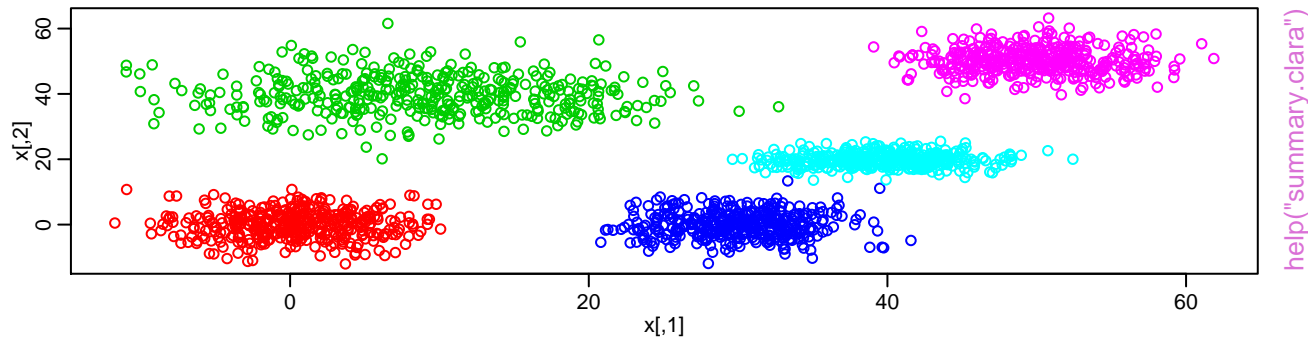
Silhouette plot of (x = cutree(ar, k = 2), dist = daisy(ruspini))

n = 75

2 clusters  $C_j$

$j : n_j \mid \text{ave}_{i \in C_j} s_i$





These two components explain 100 % of the point variability.

### Silhouette plot of clara(x = x, k = 5)

