tharunte_Homework1

2024-09-12

Q1. Consider the USArrests data. We will now perform hierarchical clustering on the states. (a) Using hierarchical clustering with complete linkage and Euclidean distance, cluster the states. (b) Cut the dendrogram at a height that results in three distinct clusters. Which states belong to which clusters? 12.6 Exercises 551 (c) Hierarchically cluster the states using complete linkage and Euclidean distance, after scaling the variables to have standard deviation one. (d) What effect does scaling the variables have on the hierarchical clustering obtained? In your opinion, should the variables be scaled before the inter-observation dissimilarities are computed? Provide a justification for your answer.

Load and view the dataset

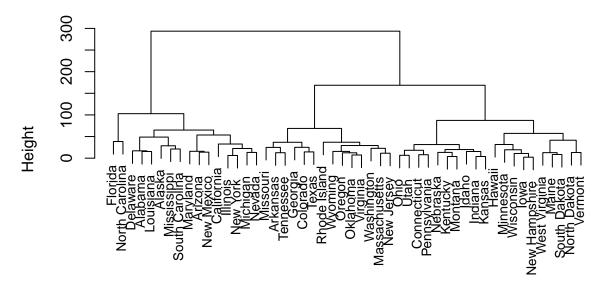
```
data("USArrests")
head(USArrests)
```

```
##
              Murder Assault UrbanPop Rape
## Alabama
                 13.2
                          236
                                     58 21.2
                 10.0
                                     48 44.5
## Alaska
                          263
## Arizona
                  8.1
                          294
                                     80 31.0
## Arkansas
                  8.8
                          190
                                     50 19.5
                                     91 40.6
## California
                  9.0
                          276
## Colorado
                  7.9
                                     78 38.7
                          204
```

Without scaling the data

```
hc.complete <- hclust(dist(USArrests), method = "complete")
plot(hc.complete, main = "Dendrogram using Complete Linkage", xlab ="", sub = "", cex =0.8)
```

Dendrogram using Complete Linkage



Cutting the dendrogram to get 3 clusters

clusters <- cutree(hc.complete,3) # cuts the dendrogram to get 3 clusters
USArrests\$Cluster <- clusters# adds a column to the table
clusters

##	Alabama	Alaska	Arizona	Arkansas	California
##	1	1	1	2	1
##	Colorado	Connecticut	Delaware	Florida	Georgia
##	2	3	1	1	2
##	Hawaii	Idaho	Illinois	Indiana	Iowa
##	3	3	1	3	3
##	Kansas	Kentucky	Louisiana	Maine	Maryland
##	3	3	1	3	1
##	Massachusetts	Michigan	Minnesota	Mississippi	Missouri
##	2	1	3	1	2
##	Montana	Nebraska	Nevada	New Hampshire	New Jersey
##	3	3	1	3	2
##	New Mexico	New York	North Carolina	North Dakota	Ohio
##	1	1	1	3	3
##	Oklahoma	Oregon	Pennsylvania	Rhode Island	South Carolina
##	2	2	3	2	1
##	South Dakota	Tennessee	Texas	Utah	Vermont
##	3	2	2	3	3
##	Virginia	Washington	West Virginia	Wisconsin	Wyoming
##	2	2	3	3	2

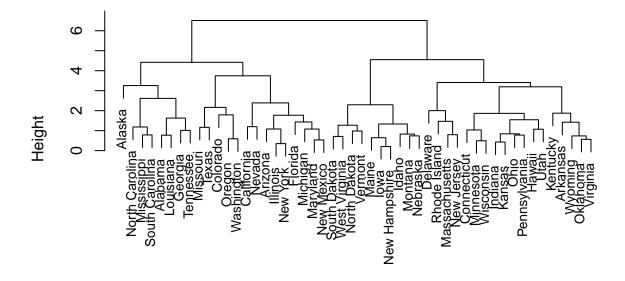
head(USArrests)

```
##
              Murder Assault UrbanPop Rape Cluster
## Alabama
                13.2
                          236
                                    58 21.2
                10.0
                          263
                                    48 44.5
## Alaska
                                                   1
## Arizona
                 8.1
                          294
                                    80 31.0
                                                   1
                 8.8
                          190
                                    50 19.5
                                                   2
## Arkansas
## California
                 9.0
                          276
                                    91 40.6
                                                   1
## Colorado
                 7.9
                          204
                                    78 38.7
```

After Scaling the data

```
# Scaling the data to have mean 0 and standard deviation 1
scaled_USArrests <- scale(USArrests)
hc.complete_sc = hclust(dist(scaled_USArrests), method = "complete")
plot(hc.complete_sc, main = "Dendrogram using Complete Linkage", xlab = "", sub = "", cex = 0.8)</pre>
```

Dendrogram using Complete Linkage



Cutting the dendrogram to get 3 clusters

```
clusters_sc <- cutree(hc.complete_sc,3)
USArrests$Cluster <- clusters_sc
clusters_sc</pre>
```

##	Alabama	Alaska	Arizona	Arkansas	California
##	1	1	1	2	1
##	Colorado	Connecticut	Delaware	Florida	Georgia
##	1	2	2	1	1
##	Hawaii	Idaho	Illinois	Indiana	Iowa
##	2	3	1	2	3
##	Kansas	Kentucky	Louisiana	Maine	Maryland
##	2	2	1	3	1
##	Massachusetts	Michigan	Minnesota	Mississippi	Missouri
##	2	1	2	1	1
##	Montana	Nobnoglio	Nevada	New Hampshire	New Jersey
##	Montana	Nebraska	Nevaua	Mew Hambshire	new Jersey
##	montana 3	Nebraska 3	nevada 1	New Hampshile	New Jersey
	Mew Mexico	3	North Carolina	3	New Jersey 2 Ohio
##	3	3	1	3	2
## ##	3	3	1 North Carolina 1	3 North Dakota 3	2
## ## ##	3 New Mexico 1	3 New York 1	North Carolina 1	3 North Dakota 3	2 Ohio 2
## ## ##	3 New Mexico 1	3 New York 1	North Carolina 1	3 North Dakota 3	2 Ohio 2 South Carolina 1
## ## ## ##	3 New Mexico 1 Oklahoma 2	New York 1 Oregon 1	1 North Carolina 1 Pennsylvania 2	3 North Dakota 3 Rhode Island 2	2 Ohio 2 South Carolina 1
## ## ## ## ##	3 New Mexico 1 Oklahoma 2	New York 1 Oregon 1 Tennessee	1 North Carolina 1 Pennsylvania 2	3 North Dakota 3 Rhode Island 2 Utah	Ohio 2 South Carolina 1 Vermont

head(USArrests)

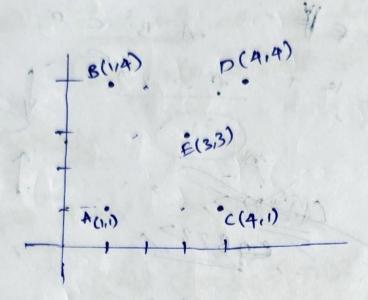
##		Murder	${\tt Assault}$	UrbanPop	Rape	${\tt Cluster}$
##	Alabama	13.2	236	58	21.2	1
##	Alaska	10.0	263	48	44.5	1
##	Arizona	8.1	294	80	31.0	1
##	Arkansas	8.8	190	50	19.5	2
##	${\tt California}$	9.0	276	91	40.6	1
##	Colorado	7.9	204	78	38.7	1

d) Scaling variables before computing hierarchical clustering is crucial because it ensures that all features contribute equally to the distance measurements. Without scaling, variables with larger ranges dominate the distance calculations, which can skew the clustering results. Scaling brings all features to the same scale, so each one has an equal impact on the clustering process. This leads to more meaningful and balanced clusters, reflecting true similarities between observations rather than being biased by the scale of individual features.

Homework:-

data points:- A(1,1), B(1,4), C(4,1), (4,4), E(3,3)

Graph



-) Inital Random Centroids:

Centroid 1: (3,1)

Controld 2: (2,4)

distance of each data point from controids:

Euclidean distance: - d(p,q) = \((x_2-x_1)^2+(y_2-y_1)^2\)

Distance from Centroid 1 (3,1):

$$\rightarrow$$
 Distance $A(1,1) = \sqrt{(3-1)^2+(1-1)^2} = \sqrt{4} = 2$

-> Distance
$$8(1/4) = \sqrt{(3-1)^2 + (1-4)^2} = \sqrt{4+9} = \sqrt{13} = 3.61$$

Distance from centroid 2 (2,4):

-> Distance A(1,1) = \((e-1)^2 + (4-1)^2 = \(\tag{1+9} = \tag{10} = 8.16

T) Distance
$$B(1,4) = \sqrt{(2-1)^2 + (4-4)^2} = \sqrt{1} = 1$$

Mary Con

Clusters 1: - A , C , . Cluster 2: B. D, E

New controid 1:- A(1,1) and ((4,1)

New controld 2: B (1,4) p (4,4) and E (3,3)

$$(\frac{M4+3}{3}, \frac{4+4+3}{3}) = (2.67, 3.67)$$

Irvel cluster one A, C and B, D, E.

Even after 2nd Heration the cluster romanis

we reached the conduction convergence.

a main good direction reduction

o may work or may not work,

rosall votos con.