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**Roll No : 26**

**Experiment No : 2**

**Title:**

Consider a suitable dataset. For clustering of data instances in different groups, apply different clustering techniques (minimum 2). Visualize the clusters using suitable tool.

**Objective:**

1. Understand the various clustering types and how to implement the same using suitable tool (R Studio)
2. Use R functions to create K-means Clustering models and hierarchical clustering models

**Hardware Requirement**

Any CPU with Pentium Processor or similar, 256 MB RAM or more, 1 GB Hard Disk or more

**Software Requirements:**

32/64-bit Linux/Windows Operating System, latest R Studio

**Theory:**

**What is K-means clustering?**

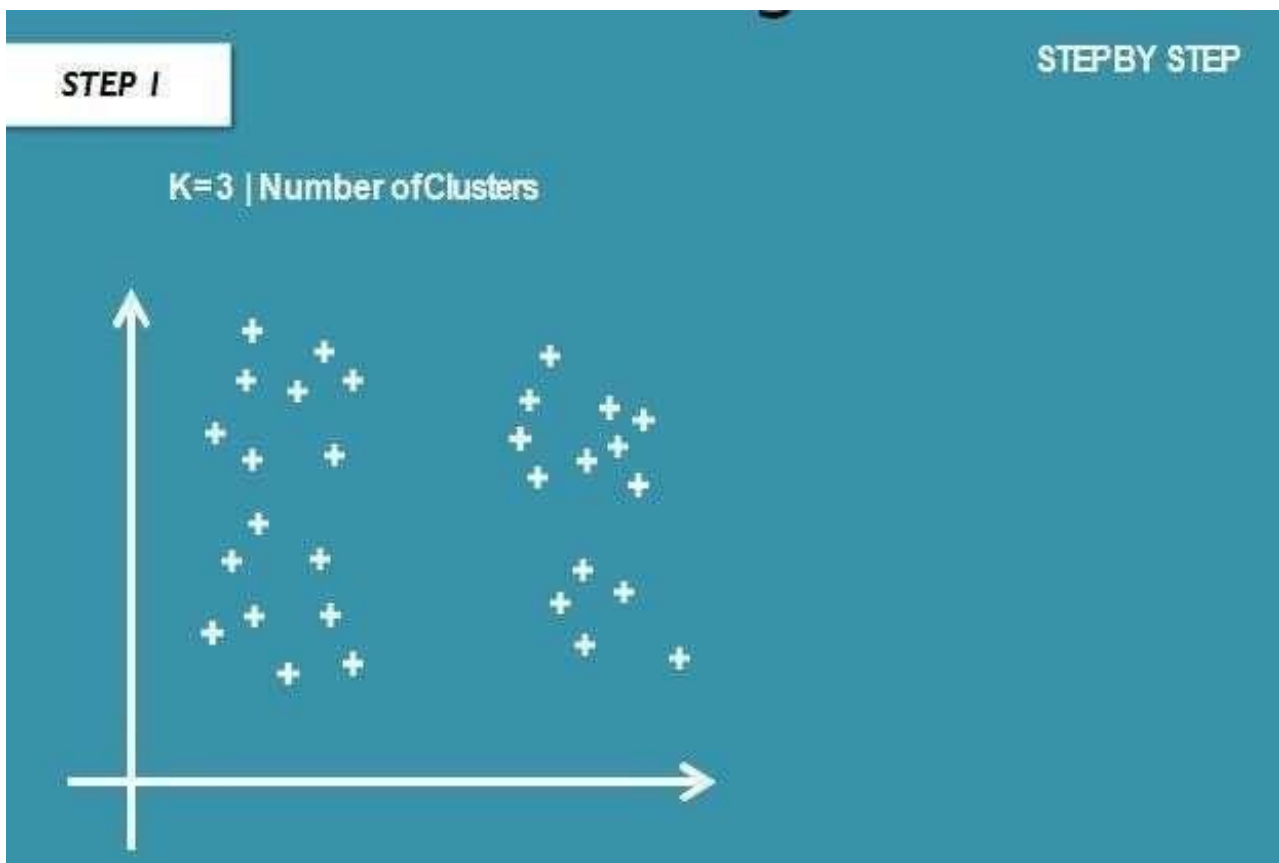
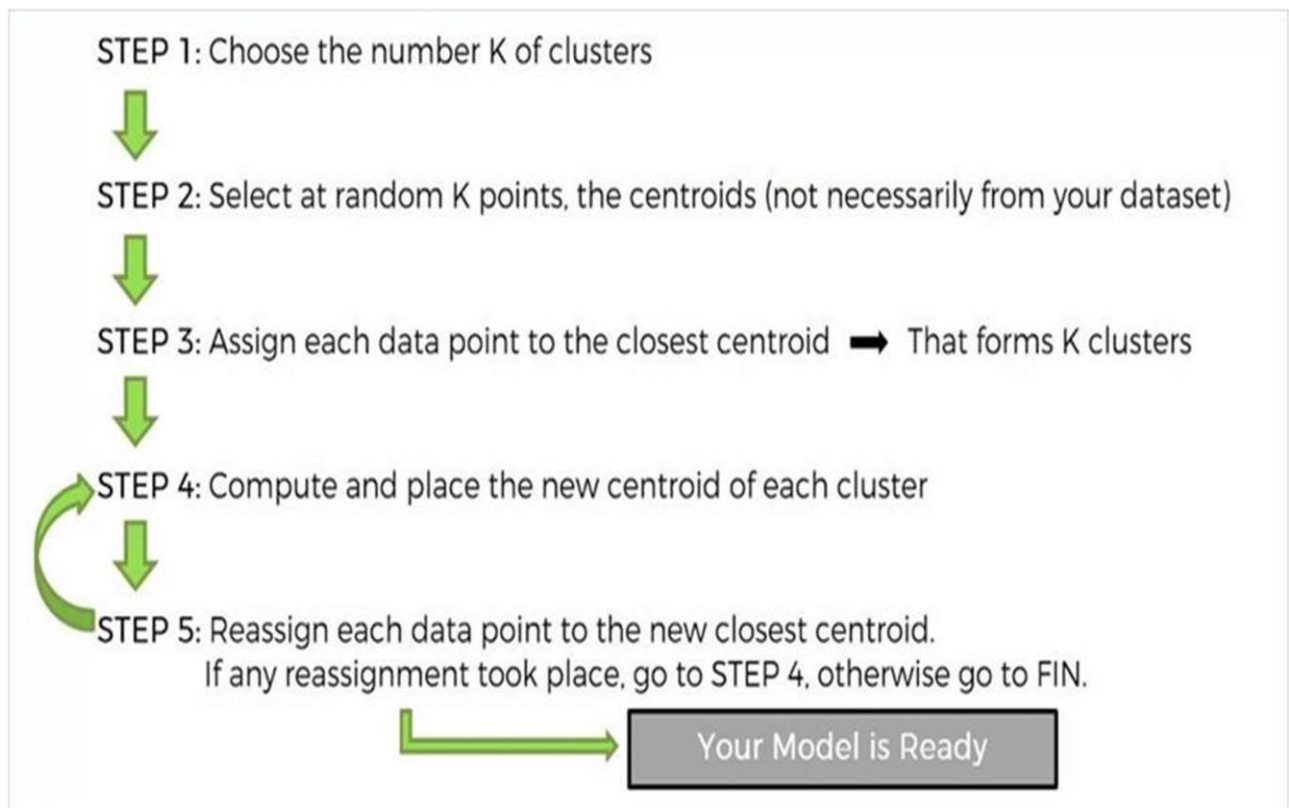
K-means clustering is a type of unsupervised learning, which is used when you have unlabeled data (i.e., data without defined categories or groups). The goal of this algorithm is to find groups in the data, with the number of groups represented by the variable  $K$ . The algorithm works iteratively to assign each data point to one of  $K$  groups based on the features that are provided. Data points are clustered based on feature similarity. The results of the K-means clustering algorithm are:

1. The centroids of the  $K$  clusters, which can be used to label new data
2. Labels for the training data (each data point is assigned to a single cluster)

Rather than defining groups before looking at the data, clustering allows you to find and analyze the groups that have formed organically. The "Choosing K" section below describes how the number of groups can be determined. Each centroid of a cluster is a collection of feature values which define the resulting groups. Examining the centroid

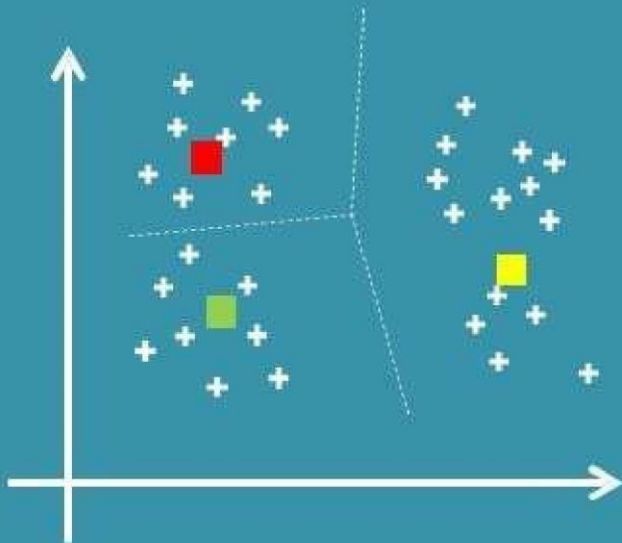
feature weights can be used to qualitatively interpret what kind of group each cluster represents.

**Algorithm:**



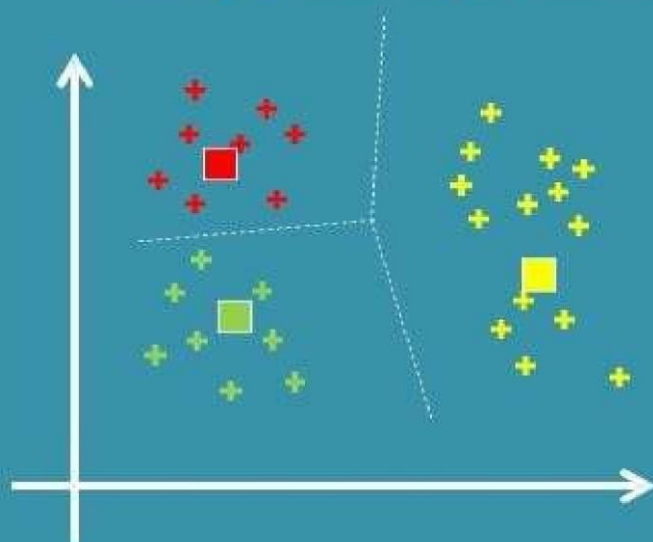
STEP 2

K=3 | Assign the Centroids



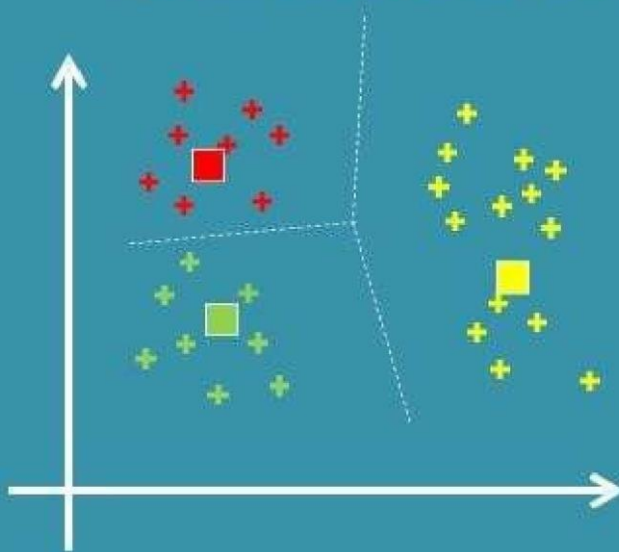
STEP 3

K=3 | Assign each data the Closest centroid



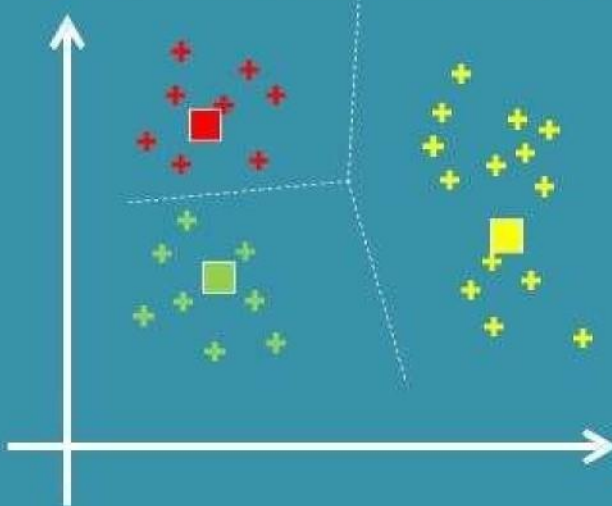
STEP 4

K=3 | Compute and Place the new Centroid of each cluster



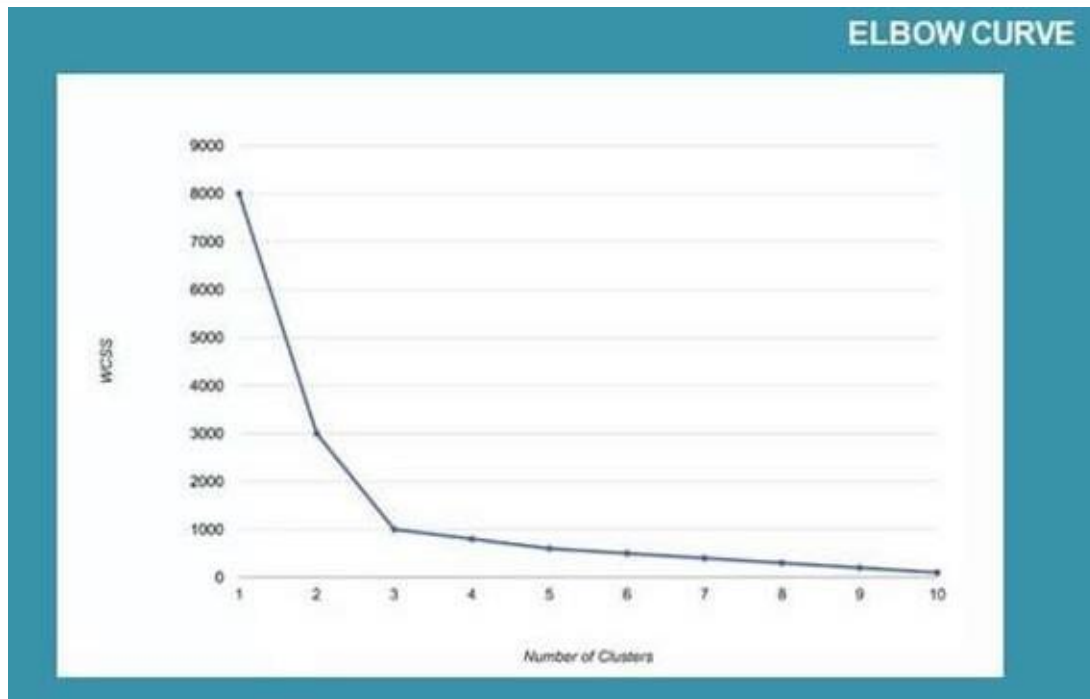
STEP 5

K = 3 | Reassign each datapoint to closest centroid. If any reassignment took place, GO TO Step 4, else FIN



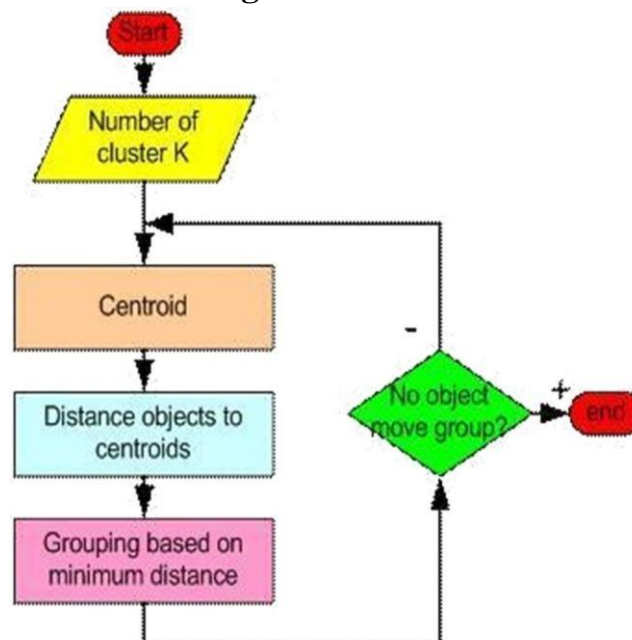
**WITHIN CLUSTER SUM of SQUARES**

$$WCSS = \sum_{P_i \text{ in Cluster 1}} \text{distance}(P_i, C_1)^2 + \sum_{P_i \text{ in Cluster 2}} \text{distance}(P_i, C_2)^2 + \sum_{P_i \text{ in Cluster 3}} \text{distance}(P_i, C_3)^2$$



## Numerical Example

### Steps to Perform K-Means Clustering



As a simple illustration of a k-means algorithm, consider the following data set consisting of the scores of two variables on each of seven individuals:

| Subject | A   | B   |
|---------|-----|-----|
| 1       | 1.0 | 1.0 |
| 2       | 1.5 | 2.0 |
| 3       | 3.0 | 4.0 |
| 4       | 5.0 | 7.0 |
| 5       | 3.5 | 5.0 |
| 6       | 4.5 | 5.0 |
| 7       | 3.5 | 4.5 |

This data set is to be grouped into two clusters. As a first step in finding a sensible initial partition, let the A& B values of the two individuals furthest apart (using the Euclidean distance measure), define the initial cluster means, giving:

|         | Individual | Mean Vector (centroid) |
|---------|------------|------------------------|
| Group 1 | 1          | (1.0, 1.0)             |
| Group 2 | 4          | (5.0, 7.0)             |

The remaining individuals are now examined in sequence and allocated to the cluster to which they are closest, in terms of Euclidean distance to the cluster mean. The mean vector is recalculated each time a new member is added. This leads to the following series of steps:

|  |           |           |
|--|-----------|-----------|
|  | Cluster 1 | Cluster 2 |
|--|-----------|-----------|

| Step | Individual | Mean Vector<br>(centroid) | Individual | Mean Vector<br>(centroid) |
|------|------------|---------------------------|------------|---------------------------|
| 1    | 1          | (1.0, 1.0)                | 4          | (5.0, 7.0)                |
| 2    | 1, 2       | (1.2, 1.5)                | 4          | (5.0,                     |

|   |         |            |            |            |
|---|---------|------------|------------|------------|
|   |         |            |            | 7.0)       |
| 3 | 1, 2, 3 | (1.8, 2.3) | 4          | (5.0, 7.0) |
| 4 | 1, 2, 3 | (1.8, 2.3) | 4, 5       | (4.2, 6.0) |
| 5 | 1, 2, 3 | (1.8, 2.3) | 4, 5, 6    | (4.3, 5.7) |
| 6 | 1, 2, 3 | (1.8, 2.3) | 4, 5, 6, 7 | (4.1, 5.4) |

Now the initial partition has changed, and the two clusters at this stage having the following characteristics:

|           | Individual | Mean Vector<br>(centroid) |
|-----------|------------|---------------------------|
| Cluster 1 | 1, 2, 3    | (1.8, 2.3)                |
| Cluster 2 | 4, 5, 6, 7 | (4.1, 5.4)                |

But we cannot yet be sure that each individual has been assigned to the right cluster. So, we compare each individual's distance to its own cluster mean and to that of the opposite cluster. And we find:

| Individual | Distance to mean (centroid) of Cluster 1 | Distance to mean (centroid) of Cluster 2 |
|------------|------------------------------------------|------------------------------------------|
| 1          | 1.5                                      | 5.4                                      |
| 2          | 0.4                                      | 4.3                                      |
| 3          | 2.1                                      | 1.8                                      |
| 4          | 5.7                                      | 1.8                                      |
| 5          | 3.2                                      | 0.7                                      |
| 6          | 3.8                                      | 0.6                                      |
| 7          | 2.8                                      | 1.1                                      |

Only individual 3 is nearer to the mean of the opposite cluster (Cluster 2) than its own (Cluster 1). In other words, each individual's distance to its own cluster mean should be smaller than the distance to the other cluster's mean (which is not the case with individual 3). Thus, individual 3 is relocated to Cluster 2 resulting in the new partition:

|           | Individuals   | Mean Vector (centroid) |
|-----------|---------------|------------------------|
| Cluster 1 | 1, 2          | (1.3, 1.5)             |
| Cluster 2 | 3, 4, 5, 6, 7 | (3.9, 5.1)             |

The iterative relocation would now continue from this new partition until no more relocations occur. However, in this example each individual is now nearer its own cluster mean than that of the other cluster and the iteration stops, choosing the latest partitioning as the final cluster solution.

## R implementation

The K-Means function, provided by the *clustep* package, is used as follows:

**kmeans (x, centers, iter.max = 10, nstart = 1)**

– Where,

–  $x$

numeric matrix of data, or an object that can be coerced to such a matrix (such as a numeric vector or a dataframe with all numeric columns).



- *centers*

either the number of clusters, say  $k$ , or a set of initial (distinct) cluster centers. If a number, a random set of (distinct) rows in  $x$  is chosen as the initial centers.

- *iter.max*

the maximum number of iterations allowed.

- *nstart*

if centers are a number, how many random sets should be chosen?

## **IRIS dataset**

This is perhaps the best-known database to be found in the pattern recognition literature. The data set contains 3 classes of 50 instances each, where each class refers to a type of iris plant.

### **Attribute Information:**

- sepal length in cm
- sepal width in cm
- petal length in cm • petal width in cm
- class:

1 Iris Setosa

2 Iris Versicolour

**Steps**                    3 Iris Virginica

1. Set working directory
2. Get data from datasets
3. Execute the model
4. View the output
5. Plot the results

### **CODE:**

```
library(ggplot2)
ggplot(iris, aes(Petal.Length, Petal.Width, color
= Species)) +
geom_point()
set.seed(20)
irisCluster <- kmeans(iris[, 3:4], 3, nstart = 20) irisCluster
```

### **Output:**



- Compute distances (similarities) between the new cluster and each of the old clusters.
- Repeat steps 2 and 3 until all items are clustered into a single cluster of size  $N$ .

## **R Implementation**

```
hclust(d, method = "complete", members = NULL)
```

```
## S3 method for class 'hclust'
```

```
plot(x, labels = NULL, hang = 0.1, check =  
  TRUE, axes = TRUE, frame.plot =  
  FALSE, ann = TRUE, main = "Cluster  
  Dendrogram",  
  sub = NULL, xlab = NULL, ylab = "Height", ...)
```

## Arguments

|                                |                                                                                                                                                                                                                                                                                                |
|--------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| d                              | a dissimilarity structure as produced by dist.                                                                                                                                                                                                                                                 |
| method                         | the agglomeration method to be used. This should be (an unambiguous abbreviation of) one of "ward.D", "ward.D2", "single", "complete", "average" (= UPGMA), "mcquitty" (=WPGMA), "median" (= WPGMC) or "centroid" (= UPGMC).                                                                   |
| members                        | NULL or a vector with length size of d. See the 'Details' section.                                                                                                                                                                                                                             |
| x                              | an object of the type produced by hclust.                                                                                                                                                                                                                                                      |
| hang                           | The fraction of the plot height by which labels should hang below the rest of the plot. A negative value will cause the labels to hang down from 0.                                                                                                                                            |
| check                          | logical indicating if the x object should be checked for validity. This check is not necessary when x is known to be valid such as when it is the direct result of hclust(). The default is check=TRUE, as invalid inputs may crash R due to memory violation in the internal C plotting code. |
| labels                         | A character vector of labels for the leaves of the tree. By default the row names or rownumbers of the original data are used. If labels = FALSE no labels at all are plotted.                                                                                                                 |
| axes,                          | logical flags as in                                                                                                                                                                                                                                                                            |
| <a href="#">plot.default</a> , | frame.plot, ann main, sub, character strings for <a href="#">title</a> , sub and xlab                                                                                                                                                                                                          |
|                                | have a non-NULL default when there's axlab, ylab tree\$call.                                                                                                                                                                                                                                   |
| ...                            | Further graphical arguments. E.g., cex controls the size of the labels (if plotted) in the same way as <a href="#">text</a> .                                                                                                                                                                  |

Step 3 can be done in different ways, which is what distinguishes *single-link* from *complete-link* and *average-link* clustering

## Mtcars dataset

The data was extracted from the 1974 *Motor Trend* magazine, and comprises fuel consumption and 10 aspects of automobile design and performance for 32 automobiles (1973–74 models)

A data frame with 32 observations on 11 variables.

[, 1] mpg Miles/(US)  
gallon [, 2] cyl Number  
of cylinders [, 3] disp  
Displacement (cu.in.)[,  
4] hp Gross horsepower  
[, 5] drat Rear axle ratio  
[, 6] wt Weight (lb/1000)

[, 7] qsec 1/4-mile time[,  
8] vs

V/S

[, 9] am Transmission (0 = automatic, 1 = manual)

[,10] gear Number of forward  
gearsNumber of  
carburetors

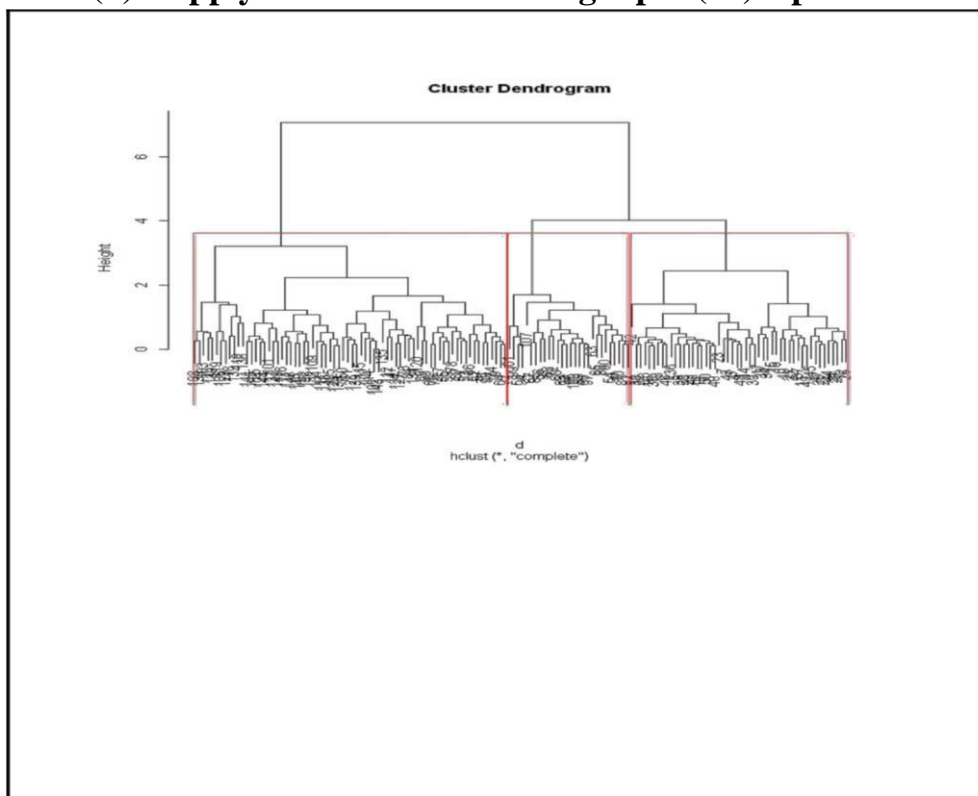
[,11] carb

In general, there are many choices of cluster analysis methodology. The `hclust` function in R uses the complete linkage method for hierarchical clustering by default. This particular clustering method defines the cluster distance between two clusters to be the maximum distance between their individual components. At every stage of the clustering process, the two nearest clusters are merged into a new cluster.

With the **distance matrix** in previous tutorial, we can use various techniques of cluster analysis for relationship discovery. For example, in the data set `mtcars`, we can run the distance matrix with `hclust`, and plot a dendrogram that displays a hierarchical relationship among the vehicles.

```
> d <- dist(as.matrix(mtcars)) # find distance matrix
```

```
> hc <- hclust(d) # apply hierarchical clustering > plot(hc) # plot the
```



**dendrogram**

**Conclusion:** Hence we are able to demonstrate various clustering method using R Tool.