

Assignment_5

2025-11-11

Loading packages

```
library(readr)
library(dplyr)

## 
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
## 
##     filter, lag

## The following objects are masked from 'package:base':
## 
##     intersect, setdiff, setequal, union

library(class)
library(gmodels)
library(tidyverse)

## — Attaching core tidyverse packages ————— tidyverse
2.0.0 —
## ✓forcats    1.0.1      ✓stringr    1.5.2
## ✓ggplot2    4.0.0      ✓tibble      3.3.0
## ✓lubridate  1.9.4      ✓tidyrm    1.3.1
## ✓purrr     1.1.0

## — Conflicts —————
tidyverse_conflicts() —
## ✗ dplyr::filter() masks stats::filter()
## ✗ dplyr::lag()   masks stats::lag()
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all
conflicts to become errors

library(factoextra)

## Welcome! Want to learn more? See two factoextra-related books at
## https://goo.gl/ve3WBa

library(flexclust)
library(stats)
library(cluster)
library(caret)

## Loading required package: lattice
## 
## Attaching package: 'lattice'
```

```

## 
## The following objects are masked from 'package:flexclust':
## 
##     barchart, bwplot, densityplot, histogram
## 
## 
## Attaching package: 'caret'
## 
## The following object is masked from 'package:purrr':
## 
##     lift

```

Importing the dataset

```

cereals <- read_csv("./Cereals.csv")

## Rows: 77 Columns: 16
## — Column specification


---


## Delimiter: ","
## chr (3): name, mfr, type
## dbl (13): calories, protein, fat, sodium, fiber, carbo, sugars, potass,
## vita...
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this
## message.

summary(cereals)      #77 observations

##      name          mfr        type      calories
##  Length:77      Length:77      Length:77      Min.   : 50.0
##  Class :character Class :character Class :character 1st Qu.:100.0
##  Mode  :character Mode  :character Mode  :character Median  :110.0
##                                         Mean   :106.9
##                                         3rd Qu.:110.0
##                                         Max.   :160.0
##
##      protein        fat       sodium       fiber
##  Min.   :1.000  Min.   :0.000  Min.   : 0.0  Min.   : 0.000
##  1st Qu.:2.000  1st Qu.:0.000  1st Qu.:130.0  1st Qu.: 1.000
##  Median :3.000  Median :1.000  Median :180.0  Median : 2.000
##  Mean   :2.545  Mean   :1.013  Mean   :159.7  Mean   : 2.152
##  3rd Qu.:3.000  3rd Qu.:2.000  3rd Qu.:210.0  3rd Qu.: 3.000
##  Max.   :6.000  Max.   :5.000  Max.   :320.0  Max.   :14.000
##
##      carbo        sugars      potass      vitamins
##  Min.   : 5.0  Min.   :0.000  Min.   :15.00  Min.   : 0.00
##  1st Qu.:12.0  1st Qu.:3.000  1st Qu.:42.50  1st Qu.:25.00
##  Median :14.5  Median :7.000  Median :90.00  Median :25.00
##  Mean   :14.8  Mean   :7.026  Mean   :98.67  Mean   :28.25

```

```

## 3rd Qu.:17.0   3rd Qu.:11.000   3rd Qu.:120.00   3rd Qu.: 25.00
## Max.    :23.0   Max.    :15.000   Max.    :330.00   Max.    :100.00
## NA's     :1      NA's     :1      NA's     :2
## shelf           weight          cups          rating
## Min.   :1.000   Min.   :0.50    Min.   :0.250   Min.   :18.04
## 1st Qu.:1.000   1st Qu.:1.00    1st Qu.:0.670   1st Qu.:33.17
## Median  :2.000   Median  :1.00    Median  :0.750   Median  :40.40
## Mean    :2.208   Mean    :1.03    Mean    :0.821   Mean    :42.67
## 3rd Qu.:3.000   3rd Qu.:1.00    3rd Qu.:1.000   3rd Qu.:50.83
## Max.    :3.000   Max.    :1.50    Max.    :1.500   Max.    :93.70
##

```

Data procesing

```

cereals <- na.omit(cereals) #removing the observation with null values
summary(cereals)           #3 observations have been removed, now the total
is 74

##      name            mfr            type            calories
##  Length:74          Length:74          Length:74          Min.   : 50
##  Class :character   Class :character   Class :character  1st Qu.:100
##  Mode  :character   Mode  :character   Mode  :character  Median  :110
##                                         Mean   :107
##                                         3rd Qu.:110
##                                         Max.   :160
##      protein          fat            sodium          fiber            carbo
##  Min.   :1.000   Min.   :0       Min.   :  0.0  Min.   : 0.000   Min.   :
##  1st Qu.:2.000   1st Qu.:0       1st Qu.:135.0  1st Qu.: 0.250   1st
##  Qu.:12.00
##  Median  :2.500   Median  :1       Median  :180.0  Median  : 2.000   Median
##  :14.50
##  Mean    :2.514   Mean    :1       Mean    :162.4  Mean    : 2.176   Mean
##  :14.73
##  3rd Qu.:3.000   3rd Qu.:1       3rd Qu.:217.5  3rd Qu.: 3.000   3rd
##  Qu.:17.00
##  Max.    :6.000   Max.    :5       Max.    :320.0  Max.    :14.000   Max.
##  :23.00
##      sugars          potass          vitamins        shelf
##  Min.   : 0.000   Min.   :15.00   Min.   :  0.00  Min.   :1.000
##  1st Qu.: 3.000   1st Qu.:41.25   1st Qu.: 25.00  1st Qu.:1.250
##  Median  : 7.000   Median  :90.00   Median  : 25.00  Median  :2.000
##  Mean    : 7.108   Mean    :98.51   Mean    : 29.05  Mean    :2.216
##  3rd Qu.:11.000   3rd Qu.:120.00  3rd Qu.: 25.00  3rd Qu.:3.000
##  Max.    :15.000   Max.    :330.00  Max.    :100.00 Max.    :3.000
##      weight          cups          rating
##  Min.   :0.500   Min.   :0.2500   Min.   :18.04
##  1st Qu.:1.000   1st Qu.:0.6700   1st Qu.:32.45
##  Median  :1.000   Median  :0.7500   Median  :40.25
##  Mean    :1.031   Mean    :0.8216   Mean    :42.37

```

```

## 3rd Qu.:1.000 3rd Qu.:1.0000 3rd Qu.:50.52
## Max. :1.500 Max. :1.5000 Max. :93.70

#from the summary, it is clear that the value of sodium, potassium will
#influence the model due to its high magnitude nature, if not normalized

cereals.num <- cereals[, 4:16] #creating dataset only with numeric variables

```

Task 1: Hierarchical clustering and Agnes

```

#Applying hierarchical clustering to the data using Euclidean distance to the
#normalized measurements.
df <- scale(cereals.num) #normalizing data
dist <- dist(df, method="euclidean") #calculating euclidean distance matrix

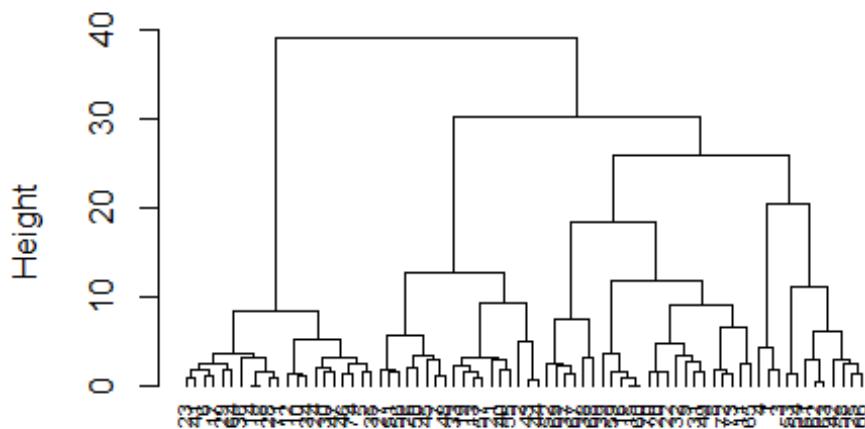
hc.ward <- hclust(dist, method="ward")

## The "ward" method has been renamed to "ward.D"; note new "ward.D2"

plot(hc.ward, cex=0.6, hang=-1)

```

Cluster Dendrogram



```

dist
hclust (*, "ward.D")

```

```

#Agnes clustering with different linkage methods, using the normalized data
hc_single <- agnes(df, method="single")
hc_complete <- agnes(df, method="complete")
hc_average <- agnes(df, method="average")
hc_ward <- cluster::agnes(df, method="ward")
#comparing agglomerative coefficients
print(hc_single$ac)

```

```

## [1] 0.6067859
print(hc_complete$ac)
## [1] 0.8353712
print(hc_average$ac)
## [1] 0.7766075
print(hc_ward$ac)
## [1] 0.9046042

#Even if I use the euclidean distance data with agnes instead of the only normalized data, it shows the same result.
hc_ward1 <- agnes(dist, method="ward")
print(hc_ward1$ac)

## [1] 0.9046042

#From agglomerative coefficient values, ward linkage is the best method for this dataset, as it shows the highest value, which is 0.9046042, among all four methods.

```

Task 2: Choosing the cluster number

```

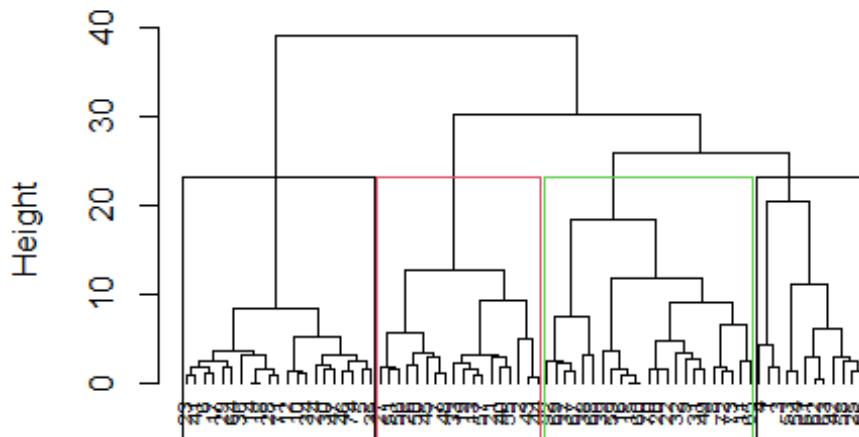
#From the lecture slides, we learned that agnes ( ) and hclust ( ) functions behave very similarly, so I am using ward linkage here to find the cluster number based on euclidean distance matrix
hc.ward <- hclust(dist, method="ward")

## The "ward" method has been renamed to "ward.D"; note new "ward.D2"

plot(hc.ward, cex=0.6, hang=-1)
#visualization of clusters
rect.hclust(hc.ward, k=4, border=1:3)

```

Cluster Dendrogram



```
dist  
hclust (*, "ward.D")
```

```
#adding the cluster number with the original dataset  
df <- as.data.frame(df)  
df.clusters <- cutree(hc.ward, k = 4)  
df$cluster <- df.clusters  
table(df.clusters)  
  
## df.clusters  
## 1 2 3 4  
## 12 18 21 23  
  
#From the tree structure, 3 or 4 clusters would be a good separation of data.  
If cut the tree into 5 or more clusters then the chances of getting small  
groups are high. Also, then I will need to jump a larger vertical gaps.  
Finally, between those choice, I will proceed with cluster 4.
```

Task 3: Stability checking

```
set.seed(246)  
#Partitioning the data (e.g., 70% training, 30% test)  
train.index <- createDataPartition(1:nrow(df), p = 0.7, list = FALSE)  
train.data=df[train.index,]      #70%  
test.data=df[-train.index,]     #30%  
  
#clustering partition A (training data)  
train.data.dist <- dist(train.data, method="euclidean")  
hc.clusterA <- hclust(train.data.dist, method="ward")  #making cluster  
partition A using Ward Linkage
```

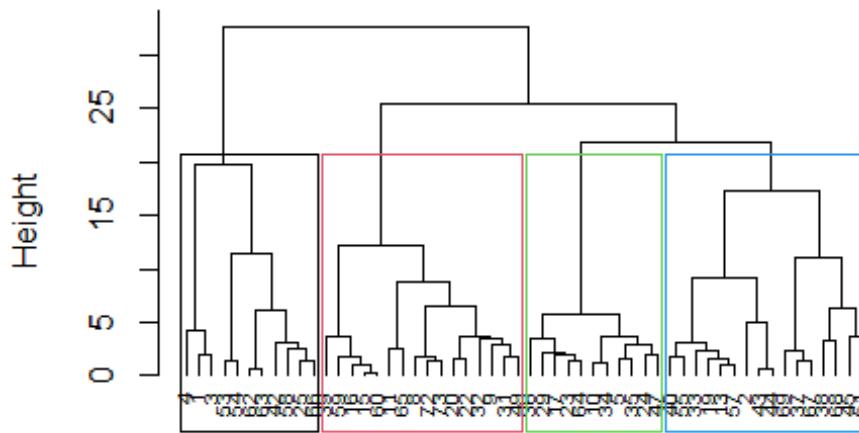
```

## The "ward" method has been renamed to "ward.D"; note new "ward.D2"

#doing this part for my visualization
plot(hc.clusterA, cex=0.6, hang=-1)
rect.hclust(hc.clusterA,k=4,border=1:4)

```

Cluster Dendrogram



```

train.data.dist
hclust (*, "ward.D")

#calculating training data cluster centroids
train_clusters <- cutree(hc.clusterA, k = 4)
train.data <- as.data.frame(train.data)
train.data$cluster <- train_clusters
centroid.A <- aggregate(train.data, by = list(Cluster = train_clusters),
mean)

*****I couldn't solve the next part. I think this part is not covered in the
class****#

```

Task 4: Healthy diet cereal clustering

#To make the cluster of healthy diets, I am using the hierarchical clustering and ward linkage method. The code will be almost same as task-1

```

diet <- cereals
diet <- na.omit(diet) #removing the observation with null values
summary(diet)          #from the summary, it is clear that the value of
potassium will influence the model due to its high magnitude nature, if not
normalized

```

```

##      name          mfr        type      calories
##  Length:74      Length:74      Length:74      Min.   : 50
##  Class :character  Class :character  Class :character  1st Qu.:100
##  Mode  :character  Mode  :character  Mode  :character  Median  :110
##                                         Mean   :107
##                                         3rd Qu.:110
##                                         Max.   :160
##      protein       fat       sodium      fiber      carbo
##  Min.   :1.000   Min.   :0     Min.   : 0.0  Min.   : 0.000   Min.   :
##  1st Qu.:2.000   1st Qu.:0     1st Qu.:135.0  1st Qu.: 0.250   1st
##  Median :2.500   Median :1     Median :180.0  Median : 2.000   Median
##  Mean   :2.514   Mean   :1     Mean   :162.4  Mean   : 2.176   Mean
##  3rd Qu.:3.000   3rd Qu.:1     3rd Qu.:217.5  3rd Qu.: 3.000   3rd
##  Max.   :6.000   Max.   :5     Max.   :320.0  Max.   :14.000   Max.
##                                         :23.00
##      sugars       potass      vitamins      shelf
##  Min.   : 0.000   Min.   :15.00  Min.   : 0.00  Min.   :1.000
##  1st Qu.: 3.000   1st Qu.:41.25  1st Qu.:25.00  1st Qu.:1.250
##  Median : 7.000   Median :90.00  Median :25.00  Median :2.000
##  Mean   : 7.108   Mean   :98.51  Mean   :29.05  Mean   :2.216
##  3rd Qu.:11.000   3rd Qu.:120.00 3rd Qu.:25.00  3rd Qu.:3.000
##  Max.   :15.000   Max.   :330.00  Max.   :100.00  Max.   :3.000
##      weight       cups       rating
##  Min.   :0.500   Min.   :0.2500  Min.   :18.04
##  1st Qu.:1.000   1st Qu.:0.6700  1st Qu.:32.45
##  Median :1.000   Median :0.7500  Median :40.25
##  Mean   :1.031   Mean   :0.8216  Mean   :42.37
##  3rd Qu.:1.000   3rd Qu.:1.0000  3rd Qu.:50.52
##  Max.   :1.500   Max.   :1.5000  Max.   :93.70

diet.num <- diet[, 4:16] #removing the non-numeric variables

diet <- scale(diet.num)  #normalizing data
summary(diet)           # now all variables are in same scale

##      calories      protein       fat       sodium
##  Min.   :-2.8738  Min.   :-1.40687  Min.   :-0.9932  Min.   :-1.9616
##  1st Qu.:-0.3541  1st Qu.:-0.47733  1st Qu.:-0.9932  1st Qu.:-0.3306
##  Median : 0.1498  Median :-0.01256  Median : 0.0000  Median : 0.2131
##  Mean   : 0.0000  Mean   : 0.00000  Mean   : 0.0000  Mean   : 0.0000
##  3rd Qu.: 0.1498  3rd Qu.: 0.45221  3rd Qu.: 0.0000  3rd Qu.: 0.6661
##  Max.   : 2.6695  Max.   : 3.24083  Max.   : 3.9729  Max.   : 1.9045
##      fiber       carbo       sugars      potass
##  Min.   :-0.89778  Min.   :-2.50014  Min.   :-1.6306  Min.   :-1.1783
##  1st Qu.:-0.79462  1st Qu.:-0.70143  1st Qu.:-0.9424  1st Qu.:-0.8079

```

```

## Median :-0.07249   Median :-0.05903   Median :-0.0248   Median :-0.1201
## Mean   : 0.00000   Mean   : 0.00000   Mean   : 0.0000   Mean   : 0.0000
## 3rd Qu.: 0.34015   3rd Qu.: 0.58337   3rd Qu.: 0.8928   3rd Qu.: 0.3031
## Max.   : 4.87925   Max.   : 2.12512   Max.   : 1.8104   Max.   : 3.2660
##      vitamins       shelf       weight       cups
## Min.  :-1.3032    Min.  :-1.4617    Min.  :-3.4600    Min.  :-2.4251
## 1st Qu.:-0.1818   1st Qu.:-1.1612   1st Qu.:-0.2008   1st Qu.:-0.6432
## Median :-0.1818   Median :-0.2599   Median :-0.2008   Median :-0.3038
## Mean   : 0.0000   Mean   : 0.0000   Mean   : 0.0000   Mean   : 0.0000
## 3rd Qu.:-0.1818   3rd Qu.: 0.9420   3rd Qu.:-0.2008   3rd Qu.: 0.7568
## Max.   : 3.1822   Max.   : 0.9420   Max.   : 3.0583   Max.   : 2.8780
##      rating
## Min.  :-1.7336
## 1st Qu.:-0.7071
## Median :-0.1510
## Mean   : 0.0000
## 3rd Qu.: 0.5807
## Max.   : 3.6578

dist <- dist(diet, method="euclidean")    #calculating euclidean distance
matrix

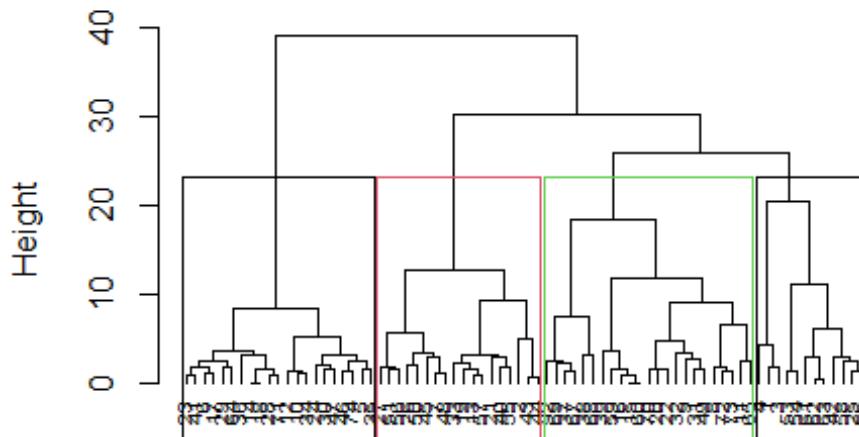
#performing hierarchical clustering with ward Linkage as it's agglomerative
coefficient value is high (got from task-1)
hc.ward <- hclust(dist, method="ward")

## The "ward" method has been renamed to "ward.D"; note new "ward.D2"

plot(hc.ward, cex=0.6, hang=-1)
rect.hclust(hc.ward,k=4,border=1:3)

```

Cluster Dendrogram



```
dist  
hclust (*, "ward.D")
```

```
#adding the cluster number with the scaled dataset  
diet <- as.data.frame(df)  
diet.clusters <- cutree(hc.ward, k = 4)  
diet$cluster <- diet.clusters  
#some cluster summary  
table(df.clusters)  
  
## df.clusters  
## 1 2 3 4  
## 12 18 21 23  
  
cereal.diet <- aggregate(diet, by = list(diet$cluster), FUN = mean)  
  
#I will use the protein, fiber, vitamins, fat and potassium variables to  
#interpret the clusters to select the best set of cereals  
cereal.diet %>% group_by(cluster) %>% select(calories, protein, fiber,  
vitamins, fat, potass, sodium, sugars, carbo)  
  
## Adding missing grouping variables: `cluster`  
  
## # A tibble: 4 × 10  
## # Groups:   cluster [4]  
##   cluster calories protein   fiber vitamins     fat potass sodium sugars  
carbo  
##       <dbl>      <dbl>    <dbl>    <dbl>    <dbl>    <dbl>    <dbl>    <dbl>  
<dbl>  
## 1        1 -1.49      0.297   0.890    -0.649   -0.745    0.662   -1.41   -1.02  -
```

```
0.402
## 2    2  0.766    0.607  0.386   -0.244  1.05    0.730 -0.123  0.459 -
0.302
## 3    3  0.198   -0.920 -0.662   -0.182  0       -0.742  0.121  0.958 -
0.542
## 4    4 -0.00355   0.210 -0.162    0.696 -0.432 -0.240   0.723 -0.703
0.941
```

#The following conclusions were obtained based on the averages of each cluster:

#Cluster 1 = High Protein, High Fiber, High Potassium

#Cluster 2 = High Calories, High Protein, High Fiber, High Fat, High Potassium, High Sugars

#Cluster 3 = High Calories, No Fat, High Potassium, High Carbohydrates

#Cluster 4 = High Protein, High Vitamins, High Sodium, High Carbohydrates

#The choice of health cereals will depend on what nutrition we want to provide the children. For example, without no doubt high protein, high vitamins, high fiber cereals are good for children, at the same time carbohydrate, calories, sodium, fat are good for children too but to a certain limit, for which I need expert help.

#Finally, I am in support of normalizing the dataset. Otherwise Variables with Larger numerical ranges (e.g., sodium, potassium) would influence the distance calculations.