## Untitled

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```
library(readr)
library(cluster)
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
setwd("~/Downloads")
Cereals <- read_csv("Cereals.csv")</pre>
## 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.
View(Cereals)
head(Cereals)
## # A tibble: 6 x 16
          mfr type calor~1 protein
                                             fat sodium fiber carbo sugars potass
    name
               <chr> <chr> <dbl> <</pre>
    <chr>
## 1 100%_Bran N C
                               70
                                        4
                                              1
                                                   130 10
                                                              5
                                                                            280
## 2 100%_Natur~ Q
                    С
                              120
                                         3
                                                              8
                                              5
                                                   15 2
                                                                      8
                                                                            135
## 3 All-Bran
              K
                    C
                               70
                                             1 260 9
                                                             7
                                                                            320
                    C
                                             0 140 14
## 4 All-Bran_w~ K
                               50
                                         4
                                                             8
                                                                       0
                                                                            330
```

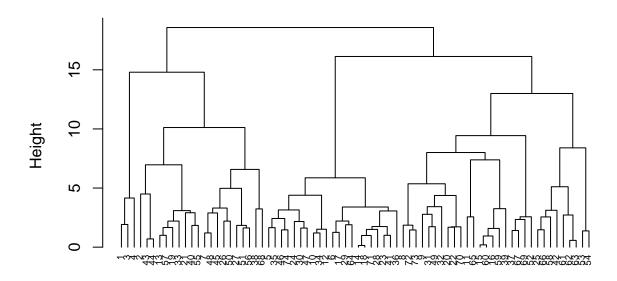
```
## 5 Almond Del~ R
                                110
                                          2
                                                2
                                                     200 1 14
                      С
                                110
                                          2
                                                2
                                                     180 1.5 10.5
                                                                                70
## 6 Apple_Cinn~ G
## # ... with 5 more variables: vitamins <dbl>, shelf <dbl>, weight <dbl>,
## # cups <dbl>, rating <dbl>, and abbreviated variable name 1: calories
Cereals <- na.omit(Cereals)</pre>
head(Cereals)
## # A tibble: 6 x 16
##
    name
                mfr type calor~1 protein
                                              fat sodium fiber carbo sugars potass
##
     <chr>>
                <chr> <chr>
                              <dbl>
                                      <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
## 1 100%_Bran N
                      C
                                 70
                                          4
                                                     130 10
                                                                 5
                                                                          6
                                                                                280
                                                1
## 2 100%_Natur~ Q
                      С
                                 120
                                          3
                                                5
                                                      15
                                                           2
                                                                  8
                                                                          8
                                                                                135
## 3 All-Bran
                K
                      С
                                 70
                                          4
                                                     260
                                                          9
                                                                 7
                                                                          5
                                                                                320
                                                1
## 4 All-Bran w~ K
                      C
                                 50
                                          4
                                                0
                                                     140 14
                                                                                330
## 5 Apple_Cinn~ G
                      С
                                          2
                                                     180
                                                                                70
                                110
                                                2
                                                          1.5 10.5
                                                                          10
## 6 Apple_Jacks K
                      C
                                110
                                          2
                                                0
                                                      125
                                                           1
                                                                 11
                                                                                30
## # ... with 5 more variables: vitamins <dbl>, shelf <dbl>, weight <dbl>,
## # cups <dbl>, rating <dbl>, and abbreviated variable name 1: calories
Cereals.norm <- Cereals %>%
   as_tibble() %>%
   mutate(across(where(is.numeric), scale))
distance <- dist(Cereals.norm[4:16], method = "euclidean")</pre>
hc_single <- agnes(Cereals.norm[4:16], method = "single")</pre>
hc_complete <- agnes(Cereals.norm[4:16], method = "complete")</pre>
hc_average <- agnes(Cereals.norm[4:16], method = "average")</pre>
hc_ward <- agnes(Cereals.norm[4:16], method = "ward")</pre>
print(hc_single)
            agnes(x = Cereals.norm[4:16], method = "single")
## Agglomerative coefficient: 0.6067859
## Order of objects:
## [1] 1 3 4 2 5 35 6 14 18 71 41 23 28 17 10 34 12 64 46 74 47 8 72 73 30
## [26] 24 29 36  7 48 50 26 27 51 56 13 57 19 55 33 40 21 31 49 20 22 70 32 15 60
## [51] 16 59 9 25 66 58 42 61 62 63 39 45 11 65 43 44 37 67 69 52 38 68 53 54
## Height (summary):
     Min. 1st Qu. Median
                             Mean 3rd Qu.
## 0.1431 1.3777 1.7695 1.8668 2.2787 4.0361
##
## Available components:
## [1] "order" "height" "ac"
                                 "merge" "diss"
                                                   "call"
                                                             "method" "data"
print(hc_complete)
            agnes(x = Cereals.norm[4:16], method = "complete")
## Agglomerative coefficient: 0.8353712
## Order of objects:
## [1] 1 3 4 2 25 66 58 42 61 62 63 53 54 5 35 46 74 24 30 47 10 34 12 6 17
```

```
## [26] 14 18 71 28 23 41 29 64 36 8 72 73 9 31 49 32 13 57 19 33 21 40 55 11 65
## [51] 15 60 16 59 39 20 22 70 37 67 69 52 7 48 45 26 50 43 44 27 51 56 38 68
## Height (summary):
     Min. 1st Qu. Median
##
                             Mean 3rd Qu.
                                             Max.
##
  0.1431 1.6076 2.3389 2.9321 3.7169 10.9839
##
## Available components:
## [1] "order" "height" "ac"
                                 "merge" "diss"
                                                   "call"
                                                            "method" "data"
print(hc_average)
## Call:
            agnes(x = Cereals.norm[4:16], method = "average")
## Agglomerative coefficient: 0.7766075
## Order of objects:
## [1] 1 3 4 2 5 35 46 74 24 30 47 6 17 14 18 71 23 41 28 29 64 10 34 12 36
## [26] 8 72 73 9 32 20 22 70 31 49 13 57 19 33 40 55 21 15 60 16 59 39 25 66 58
## [51] 42 61 62 63 7 48 50 45 26 27 51 56 43 44 37 67 69 52 38 68 11 65 53 54
## Height (summary):
     Min. 1st Qu. Median
                             Mean 3rd Qu.
                                             Max.
## 0.1431 1.4633 2.0666 2.4461 2.9445 7.7243
## Available components:
## [1] "order" "height" "ac"
                                 "merge"
                                          "diss"
                                                   "call"
                                                            "method" "data"
print(hc_ward)
            agnes(x = Cereals.norm[4:16], method = "ward")
## Agglomerative coefficient: 0.9046042
## Order of objects:
## [1]
        1 3 4 2 43 44 13 57 19 33 21 40 55 7 48 45 26 50 27 51 56 38 68 5 35
## [26] 46 74 24 30 47 10 34 12 6 17 29 64 14 18 71 28 23 41 36 8 72 73 9 31 49
## [51] 32 20 22 70 11 65 15 60 16 59 39 37 67 69 52 25 66 58 42 61 62 63 53 54
## Height (summary):
##
      Min. 1st Qu. Median
                             Mean 3rd Qu.
                                             Max.
## 0.1431 1.5858 2.3422 3.6092 4.1559 18.5749
## Available components:
## [1] "order" "height" "ac"
                                 "merge" "diss"
                                                   "call"
                                                            "method" "data"
###The highest coefficient will be the best method
Single - 0.607
Compete - 0.835
Average - 0.777
Ward - 0.904
```

Since Ward has the highest coefficient we will look at that

```
pltree(hc_ward, cex = 0.6, hang = -1, main = "Dendrogram of agnes")
```

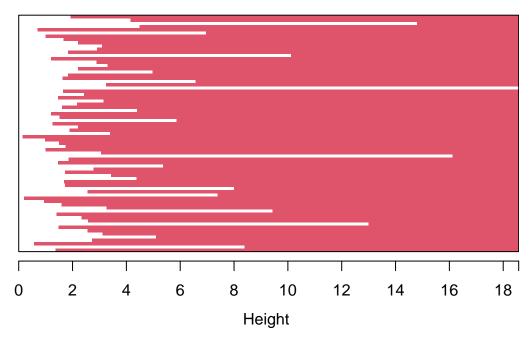
# **Dendrogram of agnes**



Cereals.norm[4:16] agnes (\*, "ward")

plot(hc\_ward)

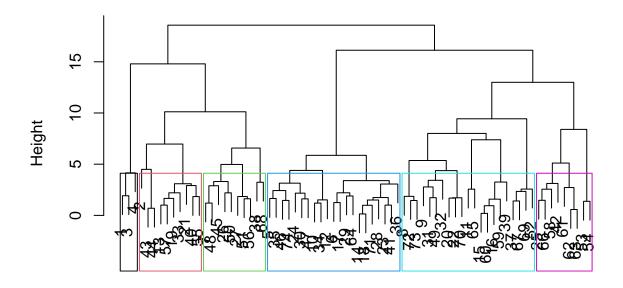
# Banner of agnes(x = Cereals.norm[4:16], method = "ward")



Agglomerative Coefficient = 0.9

rect.hclust(hc\_ward, k = 6, border = 1:6)

## Dendrogram of agnes(x = Cereals.norm[4:16], method = "ward")



# Cereals.norm[4:16] Agglomerative Coefficient = 0.9

#### 6 Clusters would be the best

```
model <- kmeans(Cereals.norm[4:16], centers = 6, nstart = 25)
100 * model$betweenss / model$totss</pre>
```

## [1] 58.62927

#### 58.63% stay in their cluster.

```
cl <- kmeans(Cereals[4:12], centers = 6, nstart = 25)
Cereals <- data.frame(Cereals, cl$cluster)
cl$centers</pre>
```

```
calories protein
                                  sodium
                                            fiber
                                                                        potass
##
                            fat
                                                     carbo
                                                              sugars
## 1 95.0000 3.500000 0.8333333 188.3333 8.000000 10.00000
                                                            8.500000 276.66667
## 2 119.2857 3.071429 1.7142857 163.5714 3.214286 14.00000
                                                            8.785714 149.28571
## 3 110.4000 2.240000 1.0000000 194.8000 1.260000 15.42000
                                                            7.280000
                                                                      67.40000
## 4 108.0000 2.400000 0.6000000 275.0000 0.550000 19.35000
                                                            3.900000
                                                                      51.00000
## 5 86.0000 2.500000 0.6000000 3.0000 2.100000 14.60000 2.900000
                                                                      95.00000
## 6 108.8889 1.888889 0.8888889 105.0000 1.111111 12.11111 11.333333 43.88889
    vitamins
##
```

```
## 1 37.5
## 2 25.0
## 3 37.0
## 4 32.5
## 5 10.0
## 6 25.0
```

The data should be standardized since when it comes to what we eat, we should value what we put into our body. Cluster 1 is probably the most healthy, since it is high in protien, fiber, potassium and higher in vitamins. And less carboydrates and low calories.