

Assignment 5 - Fundamentals of Machine Learning

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```
library(cluster)
library(stats)
library(factoextra)
```

```
## Loading required package: ggplot2
```

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

```
library(cluster)
library(fpc)
```

```
rm(list=ls())
cereal <- read.csv("Cereals.csv", header=TRUE)
```

```
head(cereal)
```

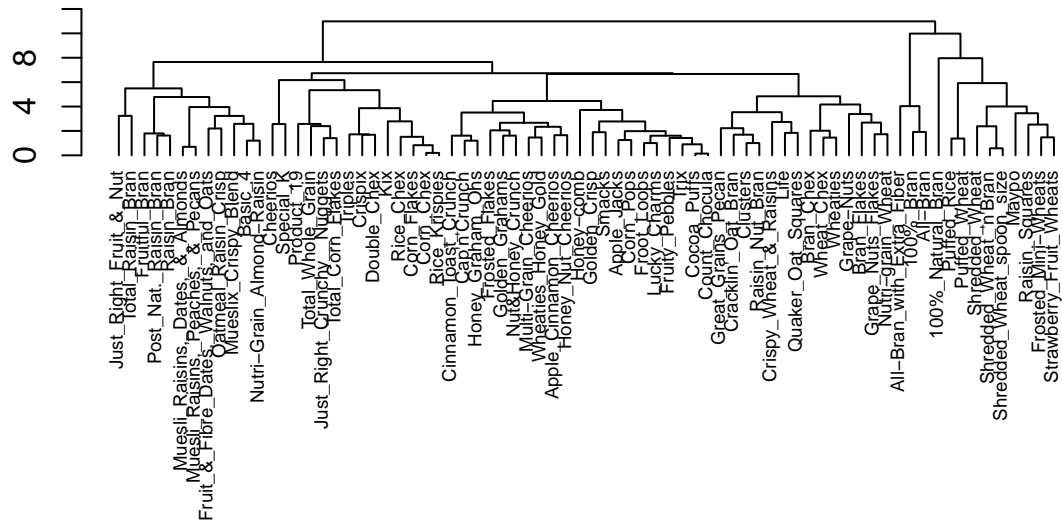
```
##           name mfr type calories protein fat sodium fiber carbo
## 1      100%_Bran   N    C       70        4  1   130  10.0   5.0
## 2 100%_Natural_Bran Q    C      120        3  5    15   2.0   8.0
## 3       All-Bran   K    C       70        4  1   260   9.0   7.0
## 4 All-Bran_with_Extra_Fiber K    C       50        4  0   140  14.0   8.0
## 5      Almond_Delight R    C      110        2  2   200   1.0  14.0
## 6 Apple_Cinnamon_Cheerios G    C      110        2  2   180   1.5  10.5
##  sugars potass vitamins shelf weight cups  rating
## 1      6    280      25     3      1 0.33 68.40297
## 2      8    135       0     3      1 1.00 33.98368
## 3      5    320      25     3      1 0.33 59.42551
## 4      0    330      25     3      1 0.50 93.70491
## 5      8     NA      25     3      1 0.75 34.38484
## 6     10     70      25     1      1 0.75 29.50954
```

```
cereal <- na.omit(cereal)
row.names(cereal) <- cereal[,1]
cereal$name = NULL
cereal <- subset(cereal, select = -c(1:2))
cereal <- scale(cereal)
head(cereal)
```

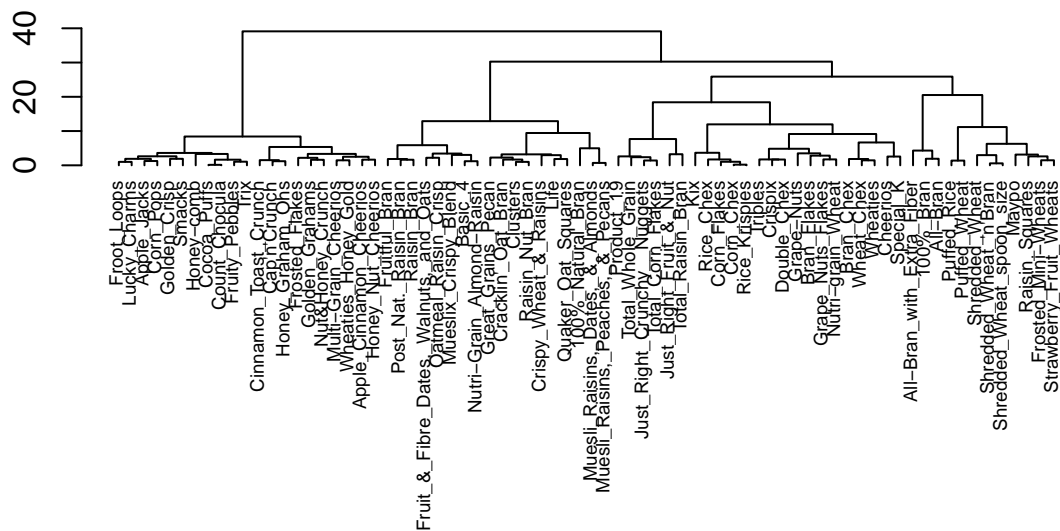
	calories	protein	fat	sodium
## 100%_Bran	-1.8659155	1.3817478	0.0000000	-0.3910227
## 100%_Natural_Bran	0.6537514	0.4522084	3.9728810	-1.7804186
## All-Bran	-1.8659155	1.3817478	0.0000000	1.1795987
## All-Bran_with_Extra_Fiber	-2.8737823	1.3817478	-0.9932203	-0.2702057
## Apple_Cinnamon_Cheerios	0.1498180	-0.4773310	0.9932203	0.2130625
## Apple_Jacks	0.1498180	-0.4773310	-0.9932203	-0.4514312
	fiber	carbo	sugars	potass
## 100%_Bran	3.22866747	-2.5001396	-0.2542051	2.5605229
## 100%_Natural_Bran	-0.07249167	-1.7292632	0.2046041	0.5147738
## All-Bran	2.81602258	-1.9862220	-0.4836096	3.1248675
## All-Bran_with_Extra_Fiber	4.87924705	-1.7292632	-1.6306324	3.2659536
## Apple_Cinnamon_Cheerios	-0.27881412	-1.0868662	0.6634132	-0.4022862
## Apple_Jacks	-0.48513656	-0.9583868	1.5810314	-0.9666308
	vitamins	shelf	weight	cups
## 100%_Bran	-0.1818422	0.9419715	-0.2008324	-2.0856582
## 100%_Natural_Bran	-1.3032024	0.9419715	-0.2008324	0.7567534
## All-Bran	-0.1818422	0.9419715	-0.2008324	-2.0856582
## All-Bran_with_Extra_Fiber	-0.1818422	0.9419715	-0.2008324	-1.3644493
## Apple_Cinnamon_Cheerios	-0.1818422	-1.4616799	-0.2008324	-0.3038480
## Apple_Jacks	-0.1818422	-0.2598542	-0.2008324	0.7567534
	rating			
## 100%_Bran	1.8549038			
## 100%_Natural_Bran	-0.5977113			
## All-Bran	1.2151965			
## All-Bran_with_Extra_Fiber	3.6578436			
## Apple_Cinnamon_Cheerios	-0.9165248			
## Apple_Jacks	-0.6553998			

```
d <- dist(cereal, method = "euclidean")
hc1 <- hclust(d, method = "complete")
SingleMethod <- hclust(d, method = "single")
HCfit <- hclust(d, method = "ward.D")
HCward <- hclust(d, method = "ward.D2")
```

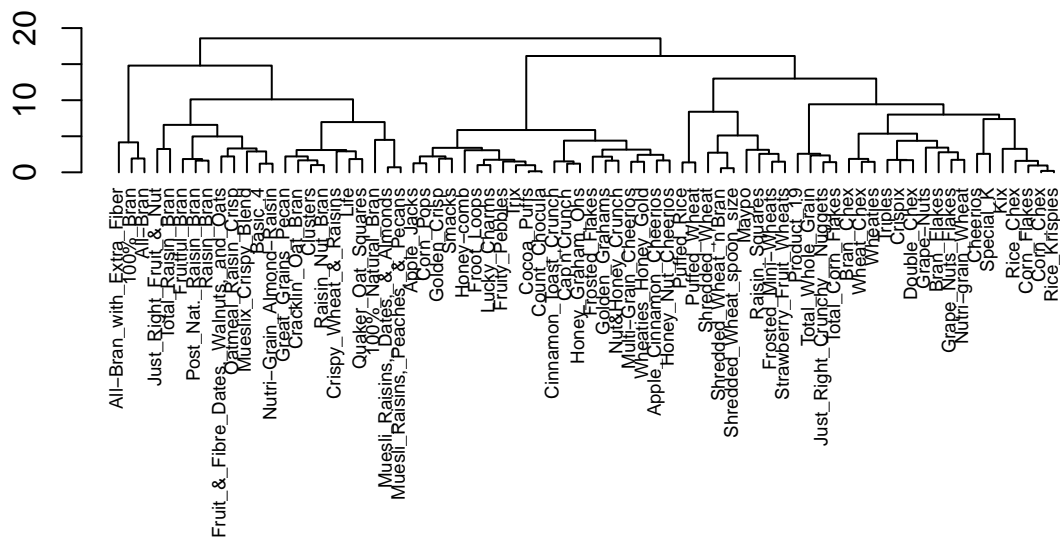
```
plot(hc1, cex = 0.6, hang = -1, ann = FALSE)
```



```
plot(HCfit, cex = 0.6, hang = -1, ann = FALSE)
```



```
plot(HCward, cex = 0.6, hang = -1, ann = FALSE)
```



```
HCsingle <- agnes(cereal, method = "single")
HCcomplete <- agnes(cereal, method = "complete")
HCaverage <- agnes(cereal, method = "average")
```

```
print(HCsingle$ac)
```

```
## [1] 0.6067859
```

```
print(HCcomplete$ac)
```

```
## [1] 0.8353712
```

```
print(HCaverage$ac)
```

```
## [1] 0.7766075
```

```
print(HCward$ac)
```

```
## NULL
```

```
print(hc1)
```

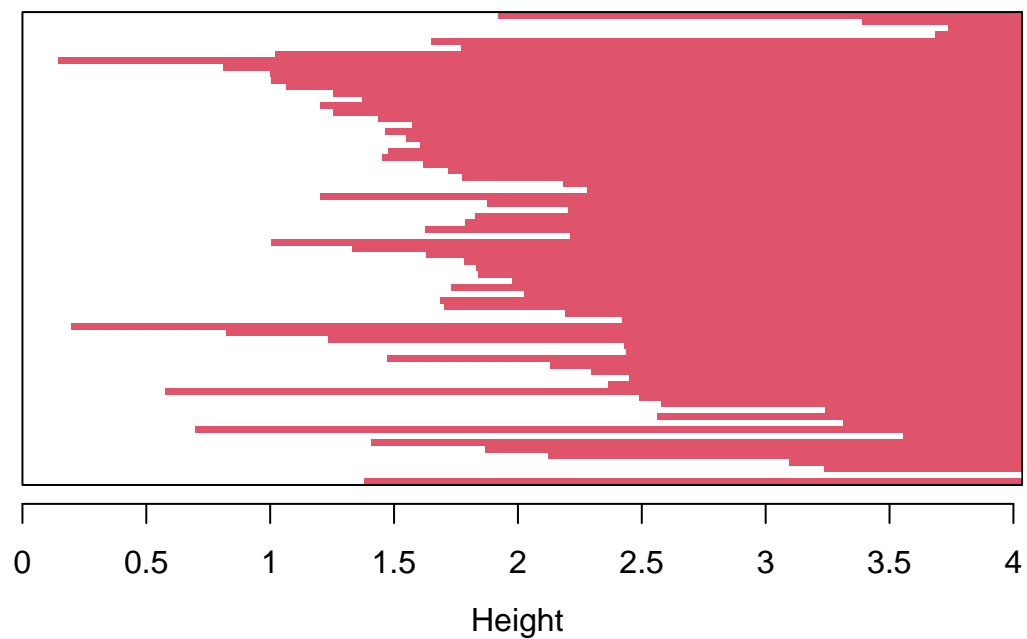
```
##  
## Call:  
## hclust(d = d, method = "complete")  
##  
## Cluster method   : complete  
## Distance         : euclidean  
## Number of objects: 74
```

```
print(HCfit)
```

```
##  
## Call:  
## hclust(d = d, method = "ward.D")  
##  
## Cluster method   : ward.D  
## Distance         : euclidean  
## Number of objects: 74
```

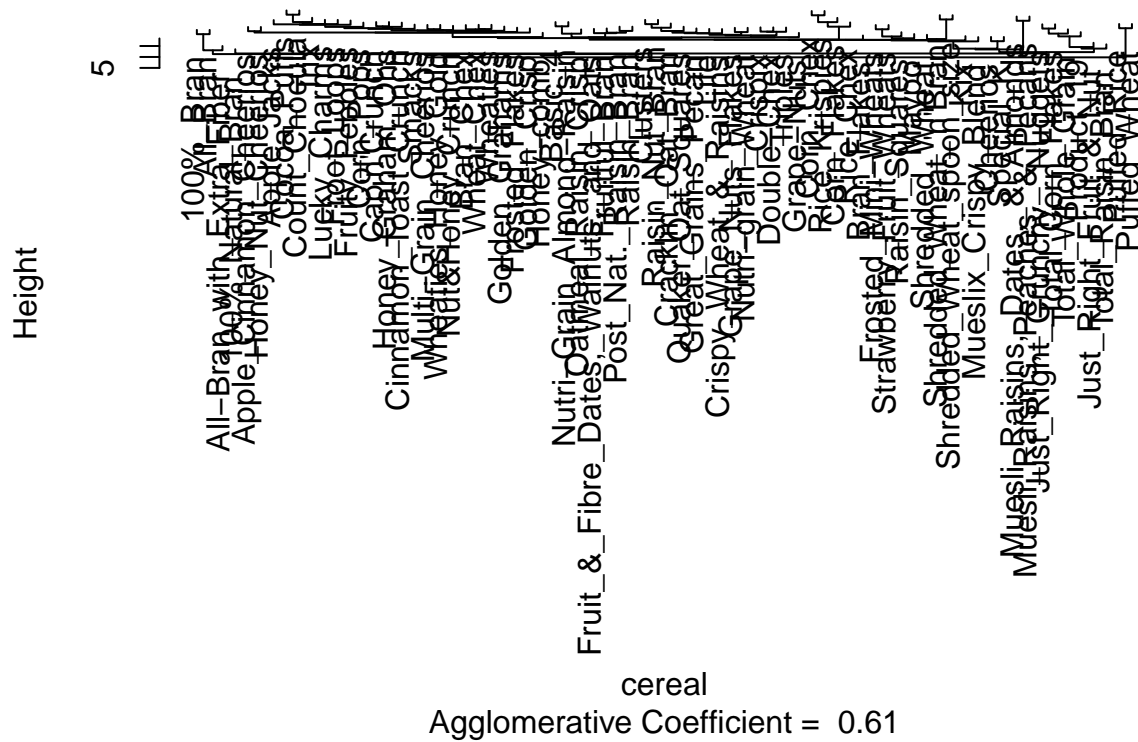
```
plot(HCsingle)
```

Banner of `agnes(x = cereal, method = "single")`



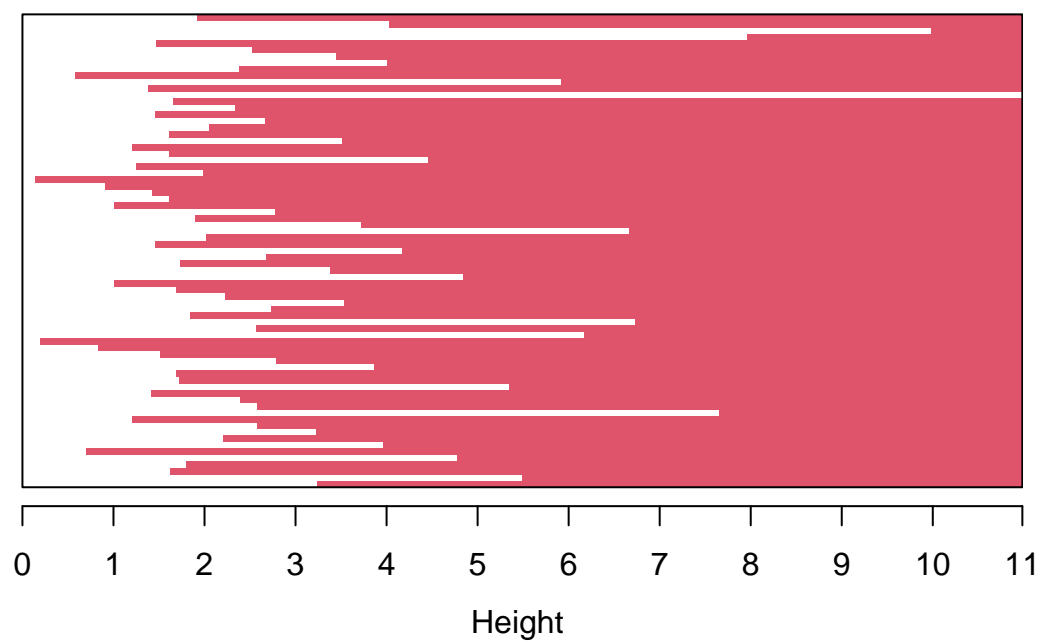
Agglomerative Coefficient = 0.61

Dendrogram of `agnes(x = cereal, method = "single")`



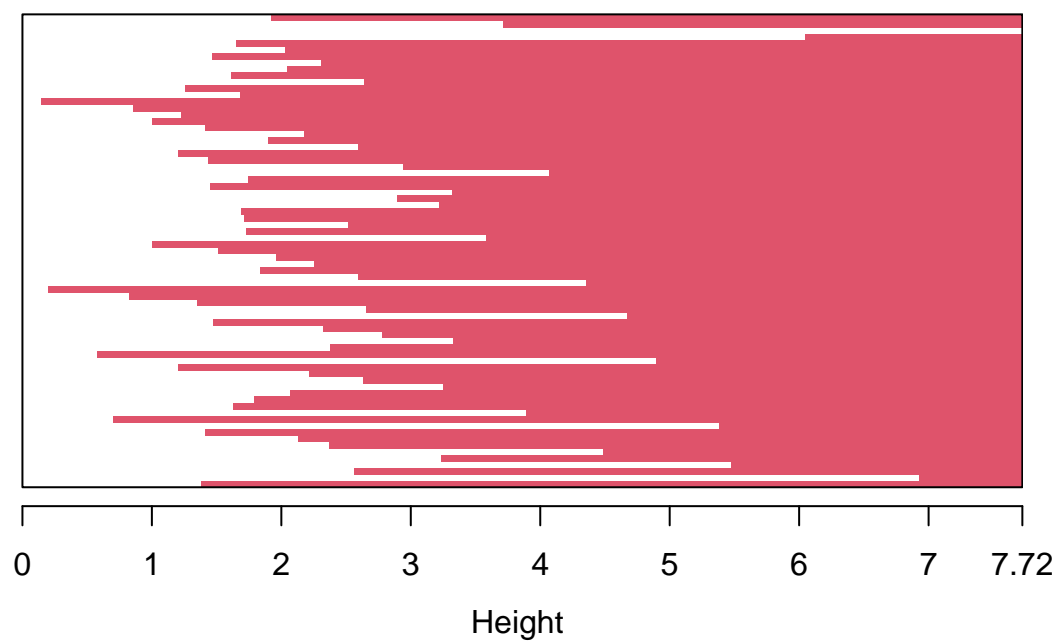
```
plot(HCcomplete)
```

Banner of `agnes(x = cereal, method = "complete")`



Agglomerative Coefficient = 0.84

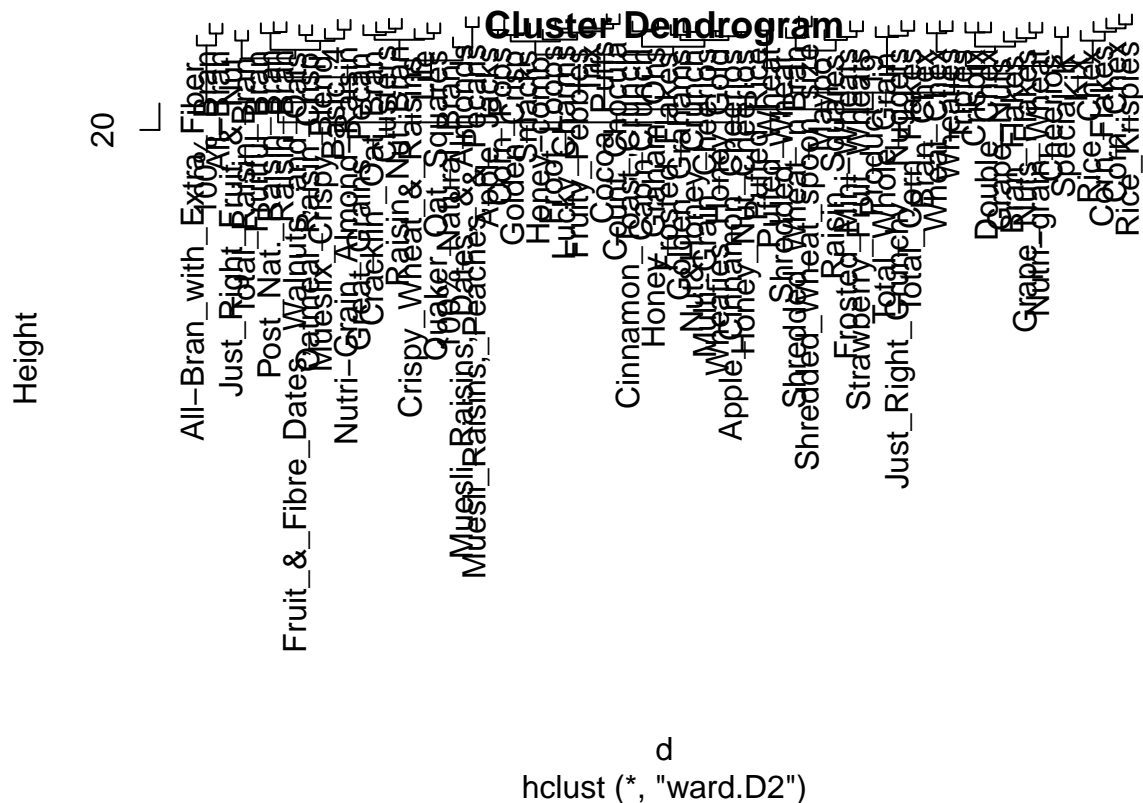
Banner of `agnes(x = cereal, method = "average")`



Agglomerative Coefficient = 0.78

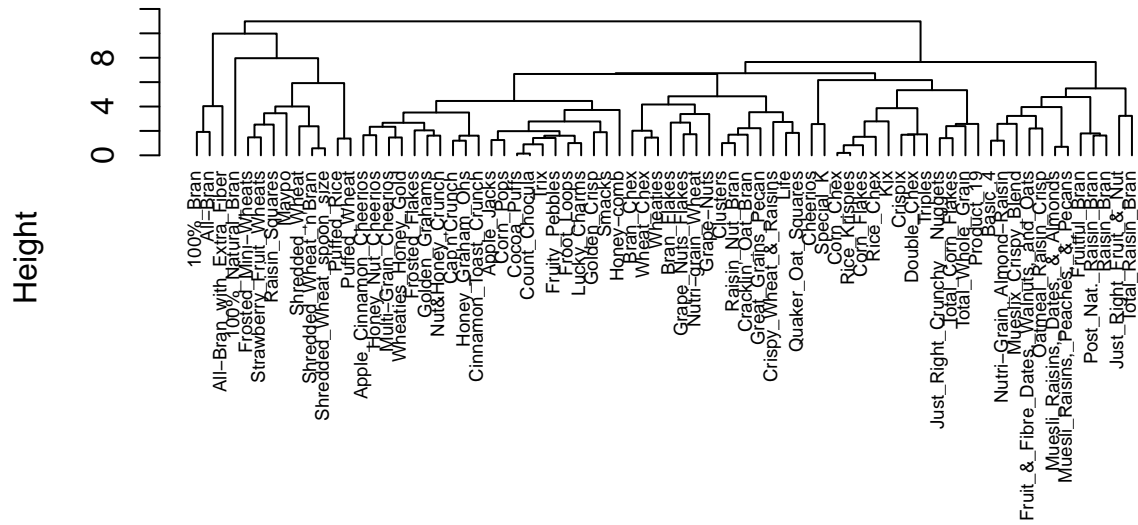
[illegible]

```
plot(HCward)
```



```
pltree(HCcomplete, cex = 0.6, hang = -1, main = "Agnes Dendrogram")
```

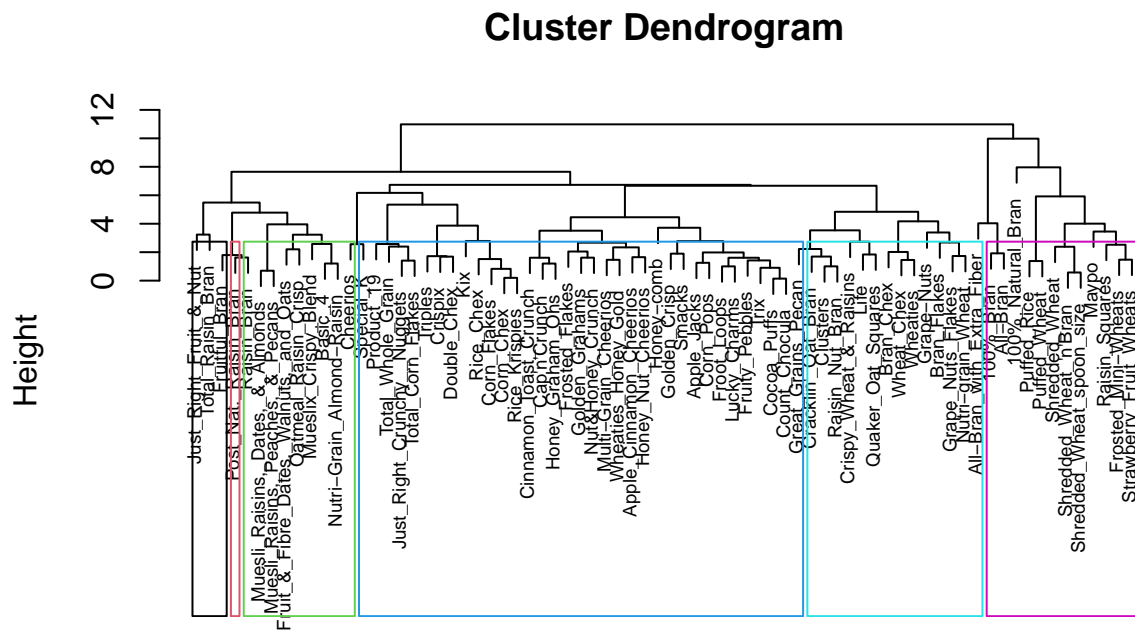
Agnes Dendrogram



cereal
agnes (*, "complete")

```
df <- cereal
d <- dist(df, method = "euclidean")
hc_complete <- hclust(d, method = "complete")
```

```
plot(hc_complete, cex = 0.6)
rect.hclust(HCcomplete, k = 6, border = 1:6)
```



d
hclust (*, "complete")

```
set.seed(1)
```

```
k3 <- kmeans(cereal, centers = 3, nstart = 10)
k3$centers
```

```
##      calories      protein        fat      sodium      fiber      carbo      sugars
## 1  1.0687554  0.5615659  1.0516450 -0.06055257  0.4615194 -0.1270496  0.5959413
## 2  0.1053533 -0.7233856 -0.2044865  0.40850178 -0.6307759  0.1374668  0.2990648
## 3 -0.9456893  0.6542821 -0.4750184 -0.55911595  0.5913284 -0.1093056 -0.8825741
##      potass  vitamins      shelf      weight      cups      rating
## 1  0.8550404  0.1479696  0.8712759  1.1219880 -0.5084816 -0.3609136
## 2 -0.6969072  0.2139320 -0.3658977 -0.2008324  0.4460596 -0.6196933
## 3  0.3982244 -0.4256162 -0.1030943 -0.5324128 -0.2835582  1.1828305
```

```
k3$size
```

```
## [1] 17 34 23
```

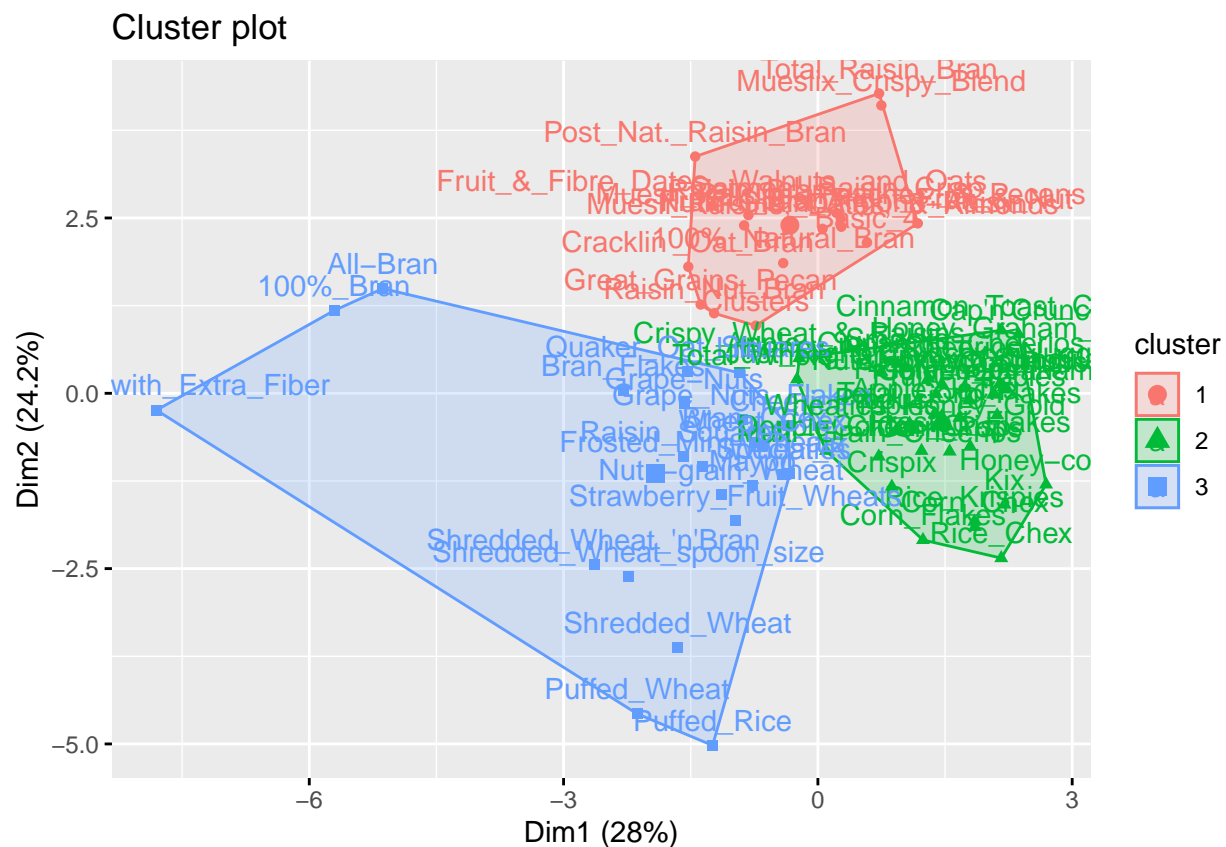
```
k3$cluster[15]
```

```
## Corn_Chex
##          2
```

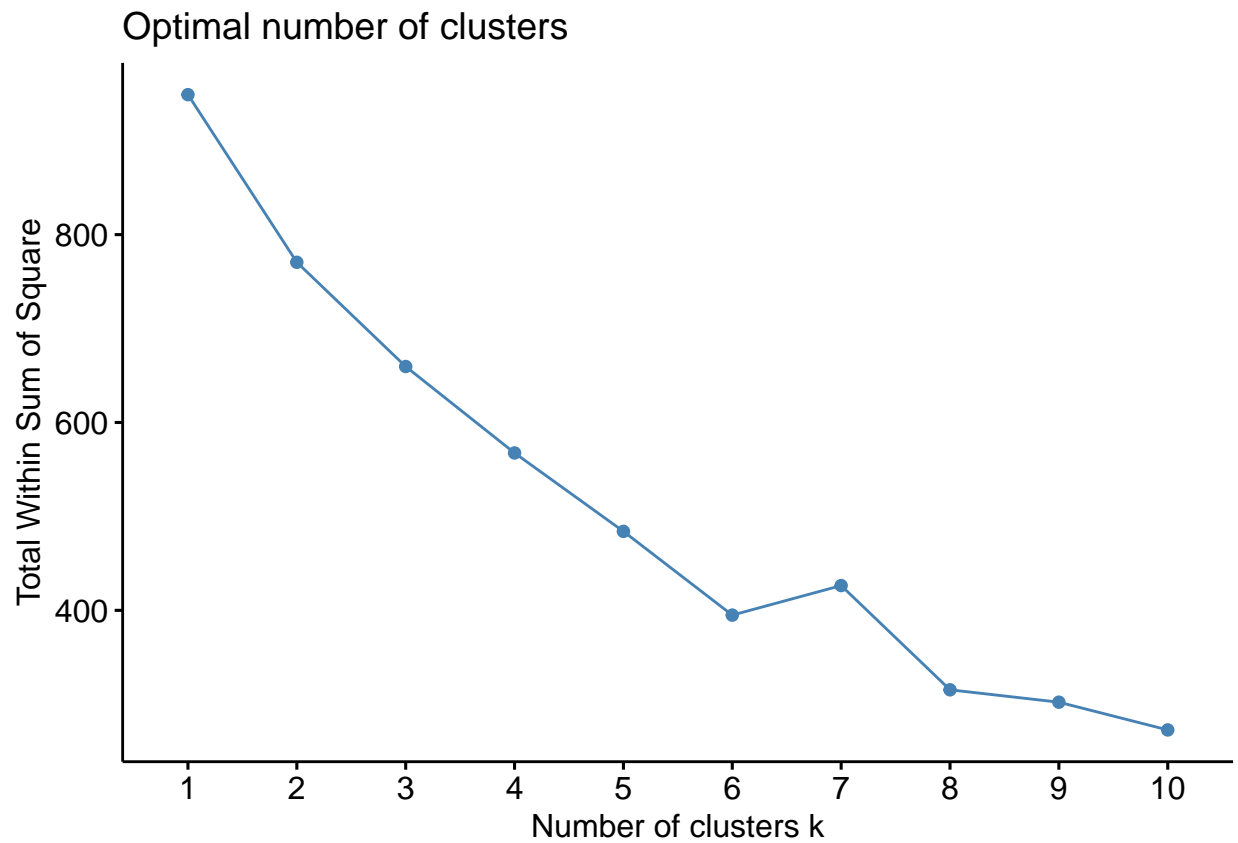
```
str(k3)
```

```
## List of 9
## $ cluster      : Named int [1:74] 3 1 3 3 2 2 1 3 3 2 ...
##   .. attr(*, "names")= chr [1:74] "100%_Bran" "100%_Natural_Bran" "All-Bran" "All-Bran_with_Extra_Fiber" ...
## $ centers       : num [1:3, 1:13] 1.069 0.105 -0.946 0.562 -0.723 ...
##   .. attr(*, "dimnames")=List of 2
##     .. $ : chr [1:3] "1" "2" "3"
##     .. $ : chr [1:13] "calories" "protein" "fat" "sodium" ...
## $ totss        : num 949
## $ withinss     : num [1:3] 134 225 279
## $ tot.withinss : num 638
## $ betweenss    : num 311
## $ size         : int [1:3] 17 34 23
## $ iter         : int 3
## $ ifault       : int 0
## - attr(*, "class")= chr "kmeans"
```

```
fviz_cluster(k3, data = cereal)
```



```
set.seed(1)
fviz_nbclust(cereal, kmeans, method = "wss")
```

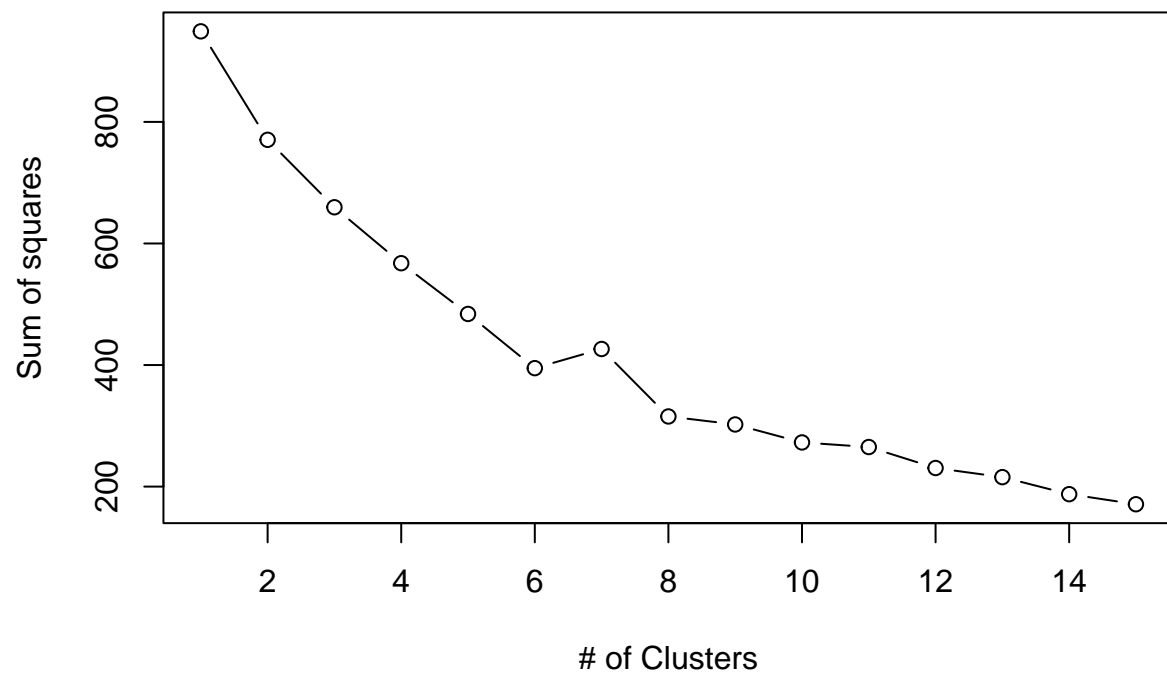


#we should have 6 clusters

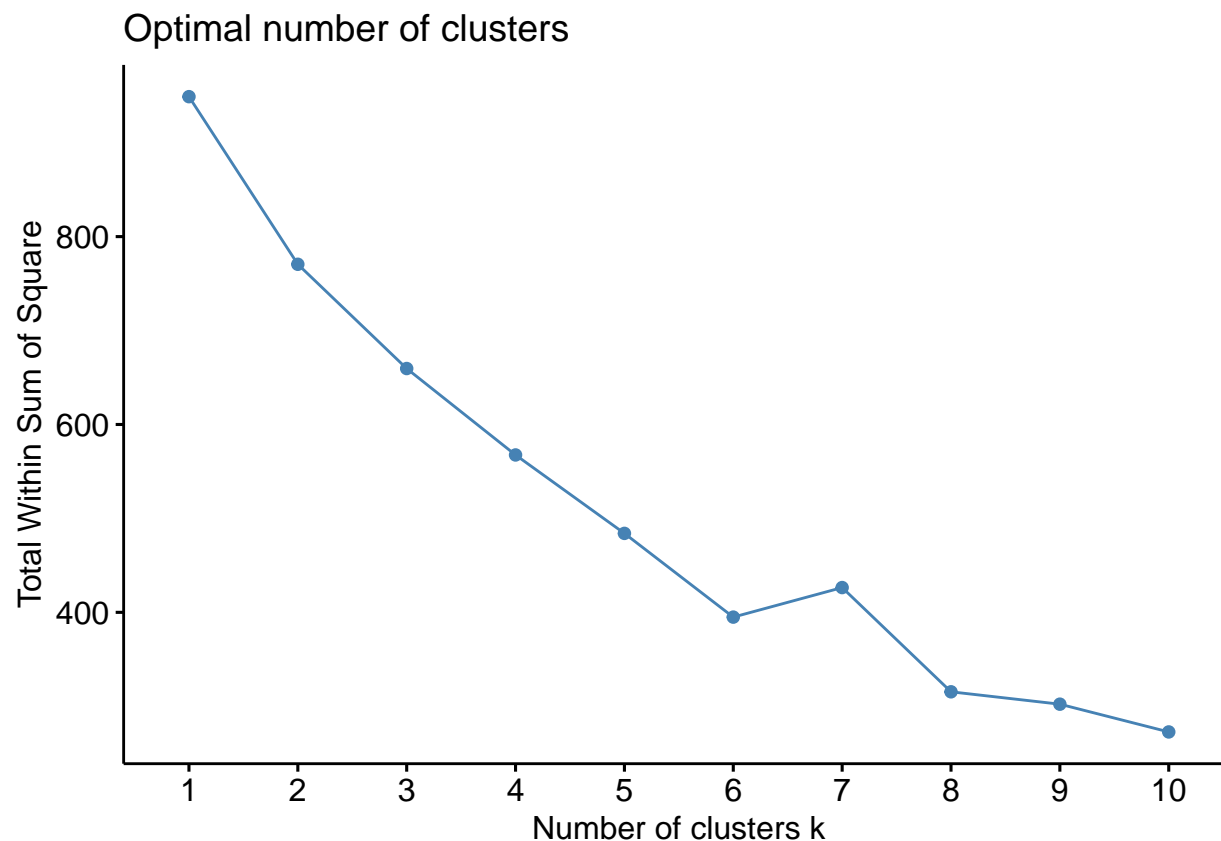
```
wss <- 0
for(i in 1:15) wss[i] <- sum(kmeans(cereal, centers = i)$withinss)
wss
```

```
## [1] 949.0000 770.5400 659.5665 567.5490 484.0579 394.9120 426.3782 315.4030
## [9] 302.2273 272.6700 265.1042 230.5733 215.5769 187.5606 170.9735
```

```
plot(1:15, wss, type = "b", xlab="# of Clusters", ylab="Sum of squares")
```

```
fviz_nbclust(cereal, kmeans, method = "wss")
```



```
k6 <- kmeans(cereal, centers = 6)
k6clust <- k6$cluster
cereal_clust <- as.data.frame(cbind(k6$clust, cereal))
head(cereal_clust)
```

```
##           V1  calories  protein      fat  sodium
## 100%_Bran      2 -1.8659155  1.3817478  0.0000000 -0.3910227
## 100%_Natural_Bran  6  0.6537514  0.4522084  3.9728810 -1.7804186
## All-Bran      2 -1.8659155  1.3817478  0.0000000  1.1795987
## All-Bran_with_Extra_Fiber  2 -2.8737823  1.3817478 -0.9932203 -0.2702057
## Apple_Cinnamon_Cheerios  3  0.1498180 -0.4773310  0.9932203  0.2130625
## Apple_Jacks    3  0.1498180 -0.4773310 -0.9932203 -0.4514312
##           fiber  carbo  sugars  potass
## 100%_Bran      3.22866747 -2.5001396 -0.2542051  2.5605229
## 100%_Natural_Bran -0.07249167 -1.7292632  0.2046041  0.5147738
## All-Bran      2.81602258 -1.9862220 -0.4836096  3.1248675
## All-Bran_with_Extra_Fiber  4.87924705 -1.7292632 -1.6306324  3.2659536
## Apple_Cinnamon_Cheerios -0.27881412 -1.0868662  0.6634132 -0.4022862
## Apple_Jacks    -0.48513656 -0.9583868  1.5810314 -0.9666308
##           vitamins  shelf  weight  cups
## 100%_Bran      -0.1818422  0.9419715 -0.2008324 -2.0856582
## 100%_Natural_Bran -1.3032024  0.9419715 -0.2008324  0.7567534
## All-Bran      -0.1818422  0.9419715 -0.2008324 -2.0856582
## All-Bran_with_Extra_Fiber -0.1818422  0.9419715 -0.2008324 -1.3644493
## Apple_Cinnamon_Cheerios -0.1818422 -1.4616799 -0.2008324 -0.3038480
```

```
## Apple_Jacks          -0.1818422 -0.2598542 -0.2008324  0.7567534
##                      rating
## 100%_Bran             1.8549038
## 100%_Natural_Bran     -0.5977113
## All-Bran              1.2151965
## All-Bran_with_Extra_Fiber 3.6578436
## Apple_Cinnamon_Cheerios -0.9165248
## Apple_Jacks          -0.6553998
```

```
hclust_stability <- clusterboot(cereal, clustermethod = hclustCBI, method = "ward.D", k=6)
```

```
## boot 1
## boot 2
## boot 3
## boot 4
## boot 5
## boot 6
## boot 7
## boot 8
## boot 9
## boot 10
## boot 11
## boot 12
## boot 13
## boot 14
## boot 15
## boot 16
## boot 17
## boot 18
## boot 19
## boot 20
## boot 21
## boot 22
## boot 23
## boot 24
## boot 25
## boot 26
## boot 27
## boot 28
## boot 29
## boot 30
## boot 31
## boot 32
## boot 33
## boot 34
## boot 35
## boot 36
## boot 37
## boot 38
## boot 39
## boot 40
## boot 41
## boot 42
## boot 43
```

boot 44
boot 45
boot 46
boot 47
boot 48
boot 49
boot 50
boot 51
boot 52
boot 53
boot 54
boot 55
boot 56
boot 57
boot 58
boot 59
boot 60
boot 61
boot 62
boot 63
boot 64
boot 65
boot 66
boot 67
boot 68
boot 69
boot 70
boot 71
boot 72
boot 73
boot 74
boot 75
boot 76
boot 77
boot 78
boot 79
boot 80
boot 81
boot 82
boot 83
boot 84
boot 85
boot 86
boot 87
boot 88
boot 89
boot 90
boot 91
boot 92
boot 93
boot 94
boot 95
boot 96
boot 97

```
## boot 98
## boot 99
## boot 100
```

```
hclust_stability
```

```
## * Cluster stability assessment *
## Cluster method: hclust/cutree
## Full clustering results are given as parameter result
## of the clusterboot object, which also provides further statistics
## of the resampling results.
## Number of resampling runs: 100
##
## Number of clusters found in data: 6
##
## Clusterwise Jaccard bootstrap (omitting multiple points) mean:
## [1] 0.7710694 0.7073521 0.8933913 0.5651417 0.6253780 0.6745214
## dissolved:
## [1] 26 24 0 44 41 37
## recovered:
## [1] 74 42 83 12 31 48
```

```
clusters = hclust_stability$results$partition
```

```
cbboot.hclust <- clusterboot(cereal, clustermethod = hclustCBI, method = "ward.D", k=6)
```

```
## boot 1
## boot 2
## boot 3
## boot 4
## boot 5
## boot 6
## boot 7
## boot 8
## boot 9
## boot 10
## boot 11
## boot 12
## boot 13
## boot 14
## boot 15
## boot 16
## boot 17
## boot 18
## boot 19
## boot 20
## boot 21
## boot 22
## boot 23
## boot 24
## boot 25
## boot 26
```

boot 27
boot 28
boot 29
boot 30
boot 31
boot 32
boot 33
boot 34
boot 35
boot 36
boot 37
boot 38
boot 39
boot 40
boot 41
boot 42
boot 43
boot 44
boot 45
boot 46
boot 47
boot 48
boot 49
boot 50
boot 51
boot 52
boot 53
boot 54
boot 55
boot 56
boot 57
boot 58
boot 59
boot 60
boot 61
boot 62
boot 63
boot 64
boot 65
boot 66
boot 67
boot 68
boot 69
boot 70
boot 71
boot 72
boot 73
boot 74
boot 75
boot 76
boot 77
boot 78
boot 79
boot 80

```
## boot 81
## boot 82
## boot 83
## boot 84
## boot 85
## boot 86
## boot 87
## boot 88
## boot 89
## boot 90
## boot 91
## boot 92
## boot 93
## boot 94
## boot 95
## boot 96
## boot 97
## boot 98
## boot 99
## boot 100
```

```
groups <- cboot.hclust$result$partition
cboot.hclust$bootmean
```

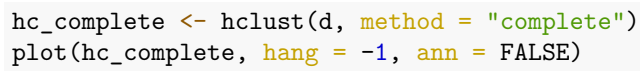
```
## [1] 0.8130602 0.6558469 0.9128397 0.5807440 0.6409682 0.6834519
```

```
cboot.hclust$bootbrd
```

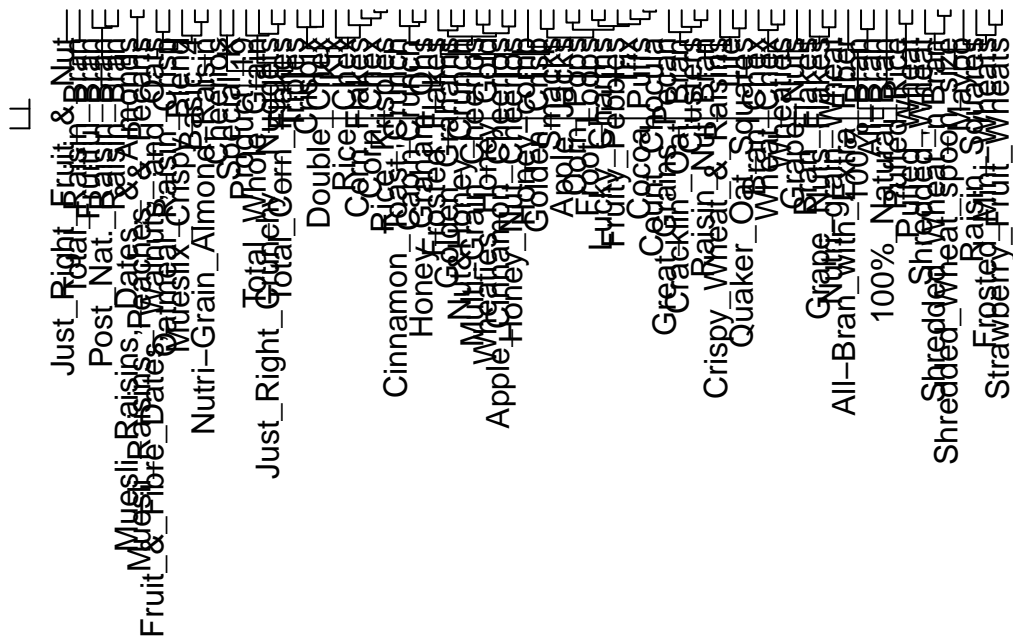
```
## [1] 21 32 0 38 46 38
```

```
d <- dist(cereal, method = "euclidean")
hc_single <- hclust(d, method = "single")
plot(hc_single, hang = -1, ann = FALSE)
```

三



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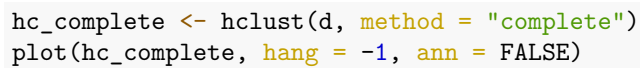


```
dim(cereal)
```

```
## [1] 74 13
```

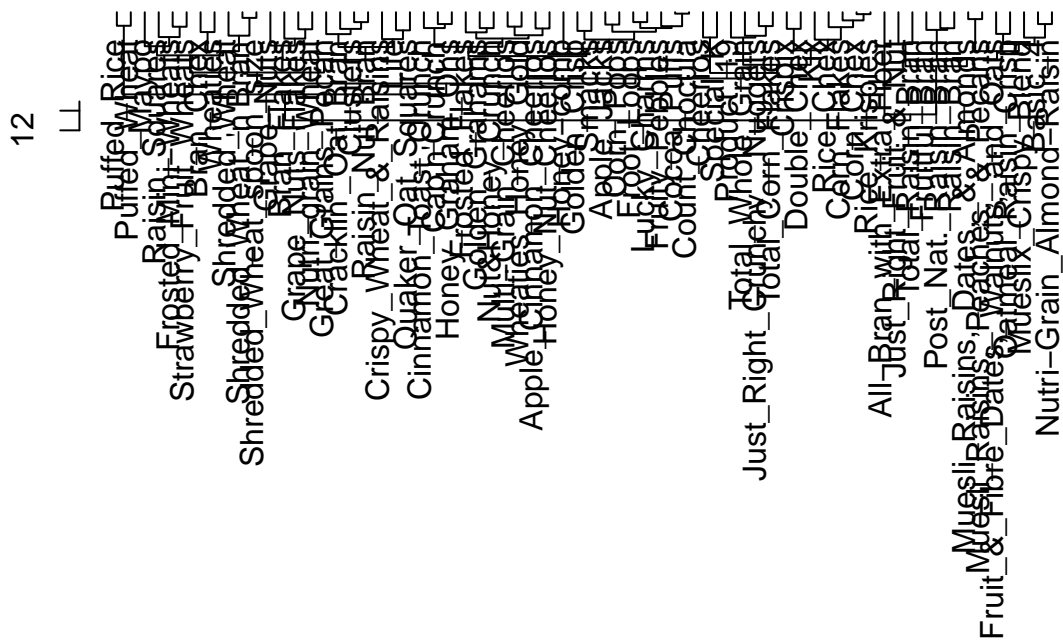
```
d <- dist(cereal[-c(1:3, 70:72),], method = "euclidean")
hc_single <- hclust(d, method = "single")
plot(hc_single, hang = -1, ann = FALSE)
```

二



```
single <- cutree(hc_single, k = 6)
single
```

##	All-Bran_with_Extra_Fiber	Apple_Cinnamon_Cheerios
##	1	2
##	Apple_Jacks	Basic_4
##	2	2
##	Bran_Chex	Bran_Flakes
##	2	2
##	Cap'n'Crunch	Cheerios
##	2	3
##	Cinnamon_Toast_Crunch	Clusters
##	2	2
##	Cocoa_Puffs	Corn_Chex
##	2	2
##	Corn_Flakes	Corn_Pops
##	2	2
##	Count_Chocula	Cracklin'_Oat_Bran
##	2	2
##	Crispix	Crispy_Wheat_&_Raisins
##	2	2
##	Double_Chex	Froot_Loops
##	2	2
##	Frosted_Flakes	Frosted_Mini-Wheats
##	2	2



## Fruit_&_Fibre_Dates,_Walnuts,_and_Oats		Fruitful_Bran
##	2	2
## Fruity_Pebbles		Golden_Crisp
##	2	2
## Golden_Grahams		Grape_Nuts_Flakes
##	2	2
## Grape-Nuts		Great_Grains_Pecan
##	2	2
## Honey_Graham_Ohs		Honey_Nut_Cheerios
##	2	2
## Honey-comb		Just_Right_Crunchy__Nuggets
##	2	4
## Just_Right_Fruit_&_Nut		Kix
##	4	2
## Life		Lucky_Charms
##	2	2
## Maypo		Muesli_Raisins,_Dates,_&_Almonds
##	2	5
## Muesli_Raisins,_Peaches,_&_Pecans		Mueslix_Crispy_Blend
##	5	2
## Multi-Grain_Cheerios		Nut&Honey_Crunch
##	2	2
## Nutri-Grain_Almond-Raisin		Nutri-grain_Wheat
##	2	2
## Oatmeal_Raisin_Crisp		Post_Nat._Raisin_Bran
##	2	2
## Product_19		Puffed_Rice
##	4	6
## Puffed_Wheat		Quaker_Oat_Squares
##	6	2
## Raisin_Bran		Raisin_Nut_Bran
##	2	2
## Raisin_Squares		Rice_Chex
##	2	2
## Rice_Krispies		Shredded_Wheat
##	2	2
## Shredded_Wheat_'n'Bran		Shredded_Wheat_spoon_size
##	2	2
## Smacks		Special_K
##	2	3
## Strawberry_Fruit_Wheats		Total_Corn_Flakes
##	2	4
## Total_Raisin_Bran		Total_Whole_Grain
##	4	4
## Wheaties		Wheaties_Honey_Gold
##	2	2

```
complete <- cutree(hc_complete, k = 6)
complete
```

## All-Bran_with_Extra_Fiber		Apple_Cinnamon_Cheerios
##	1	2
## Apple_Jacks		Basic_4
##	2	3

##	Bran_Chex	Bran_Flakes
##	4	4
##	Cap'n'Crunch	Cheerios
##	2	5
##	Cinnamon_Toast_Crunch	Clusters
##	2	4
##	Cocoa_Puffs	Corn_Chex
##	2	5
##	Corn_Flakes	Corn_Pops
##	5	2
##	Count_Chocula	Cracklin'_Oat_Bran
##	2	4
##	Crispix	Crispy_Wheat_&_Raisins
##	5	4
##	Double_Chex	Froot_Loops
##	5	2
##	Frosted_Flakes	Frosted_Mini-Wheats
##	2	4
##	Fruit_&_Fibre_Dates,_Walnuts,_and_Oats	Fruitful_Bran
##	3	3
##	Fruity_Pebbles	Golden_Crisp
##	2	2
##	Golden_Grahams	Grape_Nuts_Flakes
##	2	4
##	Grape-Nuts	Great_Grains_Pecan
##	4	4
##	Honey_Graham_Ohs	Honey_Nut_Cheerios
##	2	2
##	Honey-comb	Just_Right_Crunchy__Nuggets
##	2	5
##	Just_Right_Fruit_&_Nut	Kix
##	3	5
##	Life	Lucky_Charms
##	4	2
##	Maypo	Muesli_Raisins,_Dates,_&_Almonds
##	4	3
##	Muesli_Raisins,_Peaches,_&_Pecans	Mueslix_Crispy_Blend
##	3	3
##	Multi-Grain_Cheerios	Nut&Honey_Crunch
##	2	2
##	Nutri-Grain_Almond-Raisin	Nutri-grain_Wheat
##	3	4
##	Oatmeal_Raisin_Crisp	Post_Nat._Raisin_Bran
##	3	3
##	Product_19	Puffed_Rice
##	5	6
##	Puffed_Wheat	Quaker_Oat_Squares
##	6	4
##	Raisin_Bran	Raisin_Nut_Bran
##	3	4
##	Raisin_Squares	Rice_Chex
##	4	5
##	Rice_Krispies	Shredded_Wheat
##	5	4

```
##          Shredded_Wheat_ 'n' Bran          Shredded_Wheat_spoon_size
##                               4                               4
##          Smacks                               Special_K
##                               2                               5
##          Strawberry_Fruit_Wheats          Total_Corn_Flakes
##                               4                               5
##          Total_Raisin_Bran          Total_Whole_Grain
##                               3                               5
##          Wheaties          Wheaties_Honey_Gold
##                               4                               2
```

```
healthy_cereal <- read.csv("Cereals.csv", header=TRUE)
healthy_cereal <- na.omit(healthy_cereal)
rownames(healthy_cereal) <- healthy_cereal$name
healthy_cereal$name = NULL
healthy_cereal <- subset(healthy_cereal, select = -c(1:3))
healthy_cereal <- scale(healthy_cereal)

fit <- kmeans(healthy_cereal, 6)
aggregate(healthy_cereal, by=list(fit$cluster), FUN=mean)
```

```
##   Group.1   protein      fat      sodium      fiber      carbo      sugars
## 1      1  0.14236189 -0.1655367  0.55537739 -0.14126582  0.8831512 -0.1777369
## 2      2 -0.06420242 -0.8828625 -1.94150793 -0.02664224  0.1551013 -1.0953551
## 3      3  0.14236189 -0.4635028  0.90574678 -0.32007861  1.0801529 -0.8965378
## 4      4  0.58499970  0.8040354 -0.08610352  0.41875225 -0.2486911  0.3029203
## 5      5  1.38174776 -0.3310734  0.17279012  3.64131237 -2.0718749 -0.7894824
## 6      6 -0.94210075  0.0000000  0.09224544 -0.69145901 -0.5729487  1.0189902
##      potass  vitamins      shelf      weight      cups      rating
## 1 -0.03781363  3.1822385  0.9419715  0.6682670  0.5799865 -0.3045121
## 2 -0.11227576 -0.8048201 -0.2598542 -1.0482044  0.1156788  1.4712151
## 3 -0.42580053 -0.1818422 -0.7405845 -0.2008324  0.6775618  0.2755718
## 4  0.67265589 -0.2352403  0.8275119  0.6217081 -0.6775837 -0.1047744
## 5  2.98378133 -0.1818422  0.9419715 -0.2008324 -1.8452553  2.2426479
## 6 -0.77263731 -0.1818422 -0.6204019 -0.2008324  0.2540284 -1.0037561
```

```
#Cluster 5 has the highest protein
#Cluster 6 has the lowest fat
#Cluster 5 has the lowest sodium
#Cluster 5 has the highest fiber
#Cluster 2 has the lowest carbohydrates
#Cluster 4 has the lowest sugar
#Cluster 5 has the highest potassium
#Cluster 1 has the most vitamins
```

```
#Based on the above, I would choose cluster 5. I disregarded negative numbers as you cannot have negative
```