Cereals Data Markdown

```
setwd("E:/Data Science/R/class 7")
getwd()

## [1] "E:/Data Science/R/class 7"

library(tidyverse)

## -- Attaching packages ---------------------------------------------------
------------------------------ tidyverse 1.3.0 --

## v ggplot2 3.3.0     v purrr   0.3.3
## v tibble  3.0.0     v dplyr   0.8.5
## v tidyr   1.0.2     v stringr 1.4.0
## v readr   1.3.1     v forcats 0.5.0

## -- Conflicts ------------------------------------------------------------
------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()

library(psych)

##
## Attaching package: 'psych'

## The following objects are masked from 'package:ggplot2':
##
##     %+%, alpha

#-----------Importing the cereals_data file-----------------
cereals_data<-read.csv("cereals_data.csv")
View(cereals_data)
dim(cereals_data)

## [1] 77 16

str(cereals_data)

## 'data.frame':    77 obs. of  16 variables:
##  $ name    : Factor w/ 77 levels "100%_Bran","100%_Natural_Bran",..: 47 45
46 71 50 40 8 52 13 29 ...
##  $ mfr     : Factor w/ 7 levels "A","G","K","N",..: 3 7 7 2 3 3 2 2 2 3
...
##  $ type    : Factor w/ 2 levels "C","H": 1 1 1 1 1 1 1 1 1 ...
```

```
##  $ calories: int  160 150 150 140 140 140 130 130 120 120 ...
##  $ protein : int  3 4 4 3 3 3 3 3 1 3 ...
##  $ fat     : int  2 3 3 1 2 1 2 2 3 0 ...
##  $ sodium  : int  150 95 150 190 220 170 210 170 210 240 ...
##  $ fiber   : num  3 3 3 4 3 2 2 1.5 0 5 ...
##  $ carbo   : num  17 16 16 15 21 20 18 13.5 13 14 ...
##  $ sugars  : int  13 11 11 14 7 9 8 10 9 12 ...
##  $ potass  : int  160 170 170 230 130 95 100 120 45 190 ...
##  $ vitamins: int  25 25 25 100 25 100 25 25 25 25 ...
##  $ shelf   : int  3 3 3 3 3 3 3 3 2 3 ...
##  $ weight  : num  1.5 1 1 1.5 1.33 1.3 1.33 1.25 1 1.33 ...
##  $ cups    : num  0.67 1 1 1 0.67 0.75 0.75 0.5 0.75 0.67 ...
##  $ rating  : num  30.3 37.1 34.1 28.6 40.7 ...
```

```
cereals_data1<-cereals_data
head(cereals_data1)
```

```
##                               name mfr type calories protein fat sodium
fiber
## 1              Mueslix_Crispy_Blend   K    C      160       3   2    150
3
## 2  Muesli_Raisins,_Dates,_&_Almonds   R    C      150       4   3     95
3
## 3 Muesli_Raisins,_Peaches,_&_Pecans   R    C      150       4   3    150
3
## 4                Total_Raisin_Bran   G    C      140       3   1    190
4
## 5         Nutri-Grain_Almond-Raisin   K    C      140       3   2    220
3
## 6            Just_Right_Fruit_&_Nut   K    C      140       3   1    170
2
##   carbo sugars potass vitamins shelf weight cups   rating
## 1    17     13    160       25     3   1.50 0.67 30.31335
## 2    16     11    170       25     3   1.00 1.00 37.13686
## 3    16     11    170       25     3   1.00 1.00 34.13976
## 4    15     14    230      100     3   1.50 1.00 28.59278
## 5    21      7    130       25     3   1.33 0.67 40.69232
## 6    20      9     95      100     3   1.30 0.75 36.47151
```

```
#=============Data Clening & wrangling===============

#---------Replacing short column names with complete name--------
colnames(cereals_data1) <-c("Name", "Manufacturer", "Type", "Calories",
"Protein", "Fat",
                            "Sodium", "Fiber", "Carbohydrates", "Sugar",
"Potassium",
                            "Vitamins", "Shelf", "Weight", "Cups", "Rating")
variable.names(cereals_data1)
```

```
##  [1] "Name"          "Manufacturer"  "Type"          "Calories"
##  [5] "Protein"       "Fat"           "Sodium"        "Fiber"
```

```
##  [9] "Carbohydrates" "Sugar"         "Potassium"     "Vitamins"
## [13] "Shelf"         "Weight"        "Cups"          "Rating"
```

```
variable.names(cereals_data)
```

```
##  [1] "name"     "mfr"      "type"     "calories" "protein"  "fat"
##  [7] "sodium"   "fiber"    "carbo"    "sugars"   "potass"   "vitamins"
## [13] "shelf"    "weight"   "cups"     "rating"
```

```
#----------creating anothe variable Manufacturer_Name------
cereals_data1$Manufacturer_Name <- cereals_data1$Manufacturer
dim(cereals_data1)
```

```
## [1] 77 17
```

```
cereals_data1$Manufacturer_Name <- gsub(pattern = "P", replacement = "Post",x
= cereals_data1$Manufacturer_Name)
cereals_data1$Manufacturer_Name <- gsub(pattern = "A", replacement =
"American Home..",x = cereals_data1$Manufacturer_Name)
cereals_data1$Manufacturer_Name <- gsub(pattern = "G", replacement = "General
Mills",x = cereals_data1$Manufacturer_Name)
cereals_data1$Manufacturer_Name <- gsub(pattern = "K", replacement =
"Kelloggs",x = cereals_data1$Manufacturer_Name)
cereals_data1$Manufacturer_Name <- gsub(pattern = "N", replacement =
"Nabisco",x = cereals_data1$Manufacturer_Name)
cereals_data1$Manufacturer_Name <- gsub(pattern = "Q", replacement = "Quaker
Oats",x = cereals_data1$Manufacturer_Name)
cereals_data1$Manufacturer_Name <- gsub(pattern = "R", replacement = "Ralston
Purina",x = cereals_data1$Manufacturer_Name)
variable.names(cereals_data1)
```

```
##  [1] "Name"              "Manufacturer"      "Type"
##  [4] "Calories"          "Protein"           "Fat"
##  [7] "Sodium"            "Fiber"             "Carbohydrates"
## [10] "Sugar"             "Potassium"         "Vitamins"
## [13] "Shelf"             "Weight"            "Cups"
## [16] "Rating"            "Manufacturer_Name"
```

```
cereals_data1$Manufacturer_Name
```

```
##  [1] "Kelloggs"        "Ralston Purina"  "Ralston Purina"  "General Mills"
##  [5] "Kelloggs"        "Kelloggs"        "General Mills"   "General Mills"
##  [9] "General Mills"   "Kelloggs"        "Kelloggs"        "Kelloggs"
## [13] "Post"            "Post"            "Post"            "Quaker Oats"
## [17] "Quaker Oats"     "Quaker Oats"     "General Mills"   "General Mills"
## [21] "General Mills"   "General Mills"   "General Mills"   "General Mills"
## [25] "General Mills"   "General Mills"   "General Mills"   "General Mills"
## [29] "General Mills"   "General Mills"   "General Mills"   "Kelloggs"
## [33] "Kelloggs"        "Kelloggs"        "Kelloggs"        "Kelloggs"
## [37] "Kelloggs"        "Kelloggs"        "Kelloggs"        "Kelloggs"
## [41] "Kelloggs"        "Post"            "Post"            "Post"
## [45] "Ralston Purina"  "Ralston Purina"  "Ralston Purina"  "American
```

```
Home.."
## [49] "General Mills"   "General Mills"   "General Mills"   "General Mills"
## [53] "General Mills"   "Kelloggs"        "Kelloggs"        "Kelloggs"
## [57] "Nabisco"         "Post"            "Post"            "Quaker Oats"
## [61] "Quaker Oats"     "Quaker Oats"     "Ralston Purina"  "Ralston
Purina"
## [65] "Kelloggs"        "Kelloggs"        "Nabisco"         "Nabisco"
## [69] "Nabisco"         "Post"            "Ralston Purina"  "Nabisco"
## [73] "Kelloggs"        "Nabisco"         "Kelloggs"        "Quaker Oats"
## [77] "Quaker Oats"

dim(cereals_data1)

## [1] 77 17

#--------Replace H and C in Type with Hot and Cold-------
cereals_data1$Type <- gsub("H", "Hot", x = cereals_data1$Type)
cereals_data1$Type <- gsub("C", "Cold", x = cereals_data1$Type)

#--------Rounding off Rating to two decimal points-------
cereals_data1$Rating<-round(cereals_data1$Rating,2)
#----Removing 1st variable "Names" and alloting to rows------
library(dplyr)
rownames(cereals_data1)<-cereals_data1[ ,1] #---OR---rownames(cereals_data1)=
cereals_data1$Name;rownames(cereals_data1)
head(cereals_data1)

##                                                          Name
## Mueslix_Crispy_Blend                       Mueslix_Crispy_Blend
## Muesli_Raisins,_Dates,_&_Almonds   Muesli_Raisins,_Dates,_&_Almonds
## Muesli_Raisins,_Peaches,_&_Pecans Muesli_Raisins,_Peaches,_&_Pecans
## Total_Raisin_Bran                             Total_Raisin_Bran
## Nutri-Grain_Almond-Raisin                Nutri-Grain_Almond-Raisin
## Just_Right_Fruit_&_Nut                      Just_Right_Fruit_&_Nut
##                                  Manufacturer Type Calories Protein Fat
Sodium
## Mueslix_Crispy_Blend                        K Cold      160       3   2
150
## Muesli_Raisins,_Dates,_&_Almonds            R Cold      150       4   3
95
## Muesli_Raisins,_Peaches,_&_Pecans           R Cold      150       4   3
150
## Total_Raisin_Bran                           G Cold      140       3   1
190
## Nutri-Grain_Almond-Raisin                   K Cold      140       3   2
220
## Just_Right_Fruit_&_Nut                      K Cold      140       3   1
170
##                                  Fiber Carbohydrates Sugar Potassium
Vitamins
## Mueslix_Crispy_Blend                 3            17    13       160
```

```
25
## Muesli_Raisins,_Dates,_&_Almonds      3            16    11       170
25
## Muesli_Raisins,_Peaches,_&_Pecans     3            16    11       170
25
## Total_Raisin_Bran                     4            15    14       230
100
## Nutri-Grain_Almond-Raisin             3            21     7       130
25
## Just_Right_Fruit_&_Nut                2            20     9        95
100
##                                    Shelf Weight Cups Rating
Manufacturer_Name
## Mueslix_Crispy_Blend                  3   1.50 0.67  30.31
Kelloggs
## Muesli_Raisins,_Dates,_&_Almonds      3   1.00 1.00  37.14    Ralston
Purina
## Muesli_Raisins,_Peaches,_&_Pecans     3   1.00 1.00  34.14    Ralston
Purina
## Total_Raisin_Bran                     3   1.50 1.00  28.59     General
Mills
## Nutri-Grain_Almond-Raisin             3   1.33 0.67  40.69
Kelloggs
## Just_Right_Fruit_&_Nut                3   1.30 0.75  36.47
Kelloggs
```

```
cereals_data2 <-cereals_data1[ ,-1]
rownames(cereals_data2)
```

```
##  [1] "Mueslix_Crispy_Blend"
##  [2] "Muesli_Raisins,_Dates,_&_Almonds"
##  [3] "Muesli_Raisins,_Peaches,_&_Pecans"
##  [4] "Total_Raisin_Bran"
##  [5] "Nutri-Grain_Almond-Raisin"
##  [6] "Just_Right_Fruit_&_Nut"
##  [7] "Basic_4"
##  [8] "Oatmeal_Raisin_Crisp"
##  [9] "Cinnamon_Toast_Crunch"
## [10] "Fruitful_Bran"
## [11] "Raisin_Bran"
## [12] "Nut&Honey_Crunch"
## [13] "Great_Grains_Pecan"
## [14] "Fruit_&_Fibre_Dates,_Walnuts,_and_Oats"
## [15] "Post_Nat._Raisin_Bran"
## [16] "100%_Natural_Bran"
## [17] "Honey_Graham_Ohs"
## [18] "Cap'n'Crunch"
## [19] "Cheerios"
## [20] "Clusters"
## [21] "Kix"
```

```
## [22] "Triples"
## [23] "Total_Corn_Flakes"
## [24] "Wheaties_Honey_Gold"
## [25] "Honey_Nut_Cheerios"
## [26] "Apple_Cinnamon_Cheerios"
## [27] "Trix"
## [28] "Lucky_Charms"
## [29] "Golden_Grahams"
## [30] "Cocoa_Puffs"
## [31] "Count_Chocula"
## [32] "Special_K"
## [33] "Crispix"
## [34] "Rice_Krispies"
## [35] "Cracklin'_Oat_Bran"
## [36] "Just_Right_Crunchy__Nuggets"
## [37] "Corn_Pops"
## [38] "Apple_Jacks"
## [39] "Froot_Loops"
## [40] "Frosted_Flakes"
## [41] "Smacks"
## [42] "Grape-Nuts"
## [43] "Honey-comb"
## [44] "Fruity_Pebbles"
## [45] "Rice_Chex"
## [46] "Corn_Chex"
## [47] "Almond_Delight"
## [48] "Maypo"
## [49] "Wheaties"
## [50] "Total_Whole_Grain"
## [51] "Multi-Grain_Cheerios"
## [52] "Raisin_Nut_Bran"
## [53] "Crispy_Wheat_&_Raisins"
## [54] "Frosted_Mini-Wheats"
## [55] "Corn_Flakes"
## [56] "Product_19"
## [57] "Cream_of_Wheat_(Quick)"
## [58] "Grape_Nuts_Flakes"
## [59] "Golden_Crisp"
## [60] "Quaker_Oatmeal"
## [61] "Quaker_Oat_Squares"
## [62] "Life"
## [63] "Wheat_Chex"
## [64] "Double_Chex"
## [65] "Nutri-grain_Wheat"
## [66] "Raisin_Squares"
## [67] "Shredded_Wheat_'n'Bran"
## [68] "Shredded_Wheat_spoon_size"
## [69] "Strawberry_Fruit_Wheats"
## [70] "Bran_Flakes"
## [71] "Bran_Chex"
```

```
## [72] "Shredded_Wheat"
## [73] "All-Bran"
## [74] "100%_Bran"
## [75] "All-Bran_with_Extra_Fiber"
## [76] "Puffed_Wheat"
## [77] "Puffed_Rice"
```

```
head(cereals_data2)
```

```
##                                 Manufacturer Type Calories Protein Fat
Sodium
## Mueslix_Crispy_Blend                       K Cold      160       3   2
150
## Muesli_Raisins,_Dates,_&_Almonds           R Cold      150       4   3
95
## Muesli_Raisins,_Peaches,_&_Pecans          R Cold      150       4   3
150
## Total_Raisin_Bran                          G Cold      140       3   1
190
## Nutri-Grain_Almond-Raisin                  K Cold      140       3   2
220
## Just_Right_Fruit_&_Nut                     K Cold      140       3   1
170
##                                 Fiber Carbohydrates Sugar Potassium
Vitamins
## Mueslix_Crispy_Blend                3            17    13       160
25
## Muesli_Raisins,_Dates,_&_Almonds    3            16    11       170
25
## Muesli_Raisins,_Peaches,_&_Pecans   3            16    11       170
25
## Total_Raisin_Bran                   4            15    14       230
100
## Nutri-Grain_Almond-Raisin           3            21     7       130
25
## Just_Right_Fruit_&_Nut              2            20     9        95
100
##                                 Shelf Weight Cups Rating
Manufacturer_Name
## Mueslix_Crispy_Blend                3   1.50 0.67  30.31
Kelloggs
## Muesli_Raisins,_Dates,_&_Almonds    3   1.00 1.00  37.14    Ralston
Purina
## Muesli_Raisins,_Peaches,_&_Pecans   3   1.00 1.00  34.14    Ralston
Purina
## Total_Raisin_Bran                   3   1.50 1.00  28.59     General
Mills
## Nutri-Grain_Almond-Raisin           3   1.33 0.67  40.69
Kelloggs
```

```
## Just_Right_Fruit_&_Nut                3   1.30 0.75  36.47
Kelloggs

# ------Change cereal type,shelf to factor----
str(cereals_data2)

## 'data.frame':    77 obs. of  16 variables:
##  $ Manufacturer     : Factor w/ 7 levels "A","G","K","N",..: 3 7 7 2 3 3 2
2 2 3 ...
##  $ Type             : chr  "Cold" "Cold" "Cold" "Cold" ...
##  $ Calories         : int  160 150 150 140 140 140 130 130 120 120 ...
##  $ Protein          : int  3 4 4 3 3 3 3 3 1 3 ...
##  $ Fat              : int  2 3 3 1 2 1 2 2 3 0 ...
##  $ Sodium           : int  150 95 150 190 220 170 210 170 210 240 ...
##  $ Fiber            : num  3 3 3 4 3 2 2 1.5 0 5 ...
##  $ Carbohydrates    : num  17 16 16 15 21 20 18 13.5 13 14 ...
##  $ Sugar            : int  13 11 11 14 7 9 8 10 9 12 ...
##  $ Potassium        : int  160 170 170 230 130 95 100 120 45 190 ...
##  $ Vitamins         : int  25 25 25 100 25 100 25 25 25 25 ...
##  $ Shelf            : int  3 3 3 3 3 3 3 3 2 3 ...
##  $ Weight           : num  1.5 1 1 1.5 1.33 1.3 1.33 1.25 1 1.33 ...
##  $ Cups             : num  0.67 1 1 1 0.67 0.75 0.75 0.5 0.75 0.67 ...
##  $ Rating           : num  30.3 37.1 34.1 28.6 40.7 ...
##  $ Manufacturer_Name: chr  "Kelloggs" "Ralston Purina" "Ralston Purina"
"General Mills" ...

cereals_data2$Type <- factor(cereals_data2$Type)
cereals_data2$Shelf <- factor(cereals_data2$Shelf)
sapply(cereals_data2, FUN = class)

##      Manufacturer              Type          Calories           Protein
##          "factor"          "factor"         "integer"         "integer"
##               Fat            Sodium             Fiber     Carbohydrates
##         "integer"         "integer"         "numeric"         "numeric"
##             Sugar         Potassium          Vitamins             Shelf
##         "integer"         "integer"         "integer"          "factor"
##            Weight              Cups            Rating Manufacturer_Name
##         "numeric"         "numeric"         "numeric"       "character"

#=========Evaluating each variable through concepts of sample statistics=====

summary(cereals_data2)

##  Manufacturer   Type       Calories        Protein           Fat
##  A: 1         Cold:74   Min.   : 50.0   Min.   :1.000   Min.   :0.000
##  G:22         Hot : 3   1st Qu.:100.0   1st Qu.:2.000   1st Qu.:0.000
##  K:23                   Median :110.0   Median :3.000   Median :1.000
##  N: 6                   Mean   :106.9   Mean   :2.545   Mean   :1.013
##  P: 9                   3rd Qu.:110.0   3rd Qu.:3.000   3rd Qu.:2.000
##  Q: 8                   Max.   :160.0   Max.   :6.000   Max.   :5.000
##  R: 8
```

```
##      Sodium          Fiber         Carbohydrates      Sugar
##  Min.   :  0.0   Min.   : 0.000   Min.   : 5.0   Min.   : 0.000
##  1st Qu.:130.0   1st Qu.: 1.000   1st Qu.:12.0   1st Qu.: 3.000
##  Median :180.0   Median : 2.000   Median :14.5   Median : 7.000
##  Mean   :159.7   Mean   : 2.152   Mean   :14.8   Mean   : 7.026
##  3rd Qu.:210.0   3rd Qu.: 3.000   3rd Qu.:17.0   3rd Qu.:11.000
##  Max.   :320.0   Max.   :14.000   Max.   :23.0   Max.   :15.000
##                                   NA's   :1      NA's   :1
##    Potassium         Vitamins      Shelf      Weight          Cups
##  Min.   : 15.00   Min.   :  0.00   1:20   Min.   :0.50   Min.   :0.250
##  1st Qu.: 42.50   1st Qu.: 25.00   2:21   1st Qu.:1.00   1st Qu.:0.670
##  Median : 90.00   Median : 25.00   3:36   Median :1.00   Median :0.750
##  Mean   : 98.67   Mean   : 28.25          Mean   :1.03   Mean   :0.821
##  3rd Qu.:120.00   3rd Qu.: 25.00          3rd Qu.:1.00   3rd Qu.:1.000
##  Max.   :330.00   Max.   :100.00          Max.   :1.50   Max.   :1.500
##  NA's   :2
##      Rating      Manufacturer_Name
##  Min.   :18.04   Length:77
##  1st Qu.:33.17   Class :character
##  Median :40.40   Mode  :character
##  Mean   :42.67
##  3rd Qu.:50.83
##  Max.   :93.70
##
```

```
describe(cereals_data2[,4:11])
```

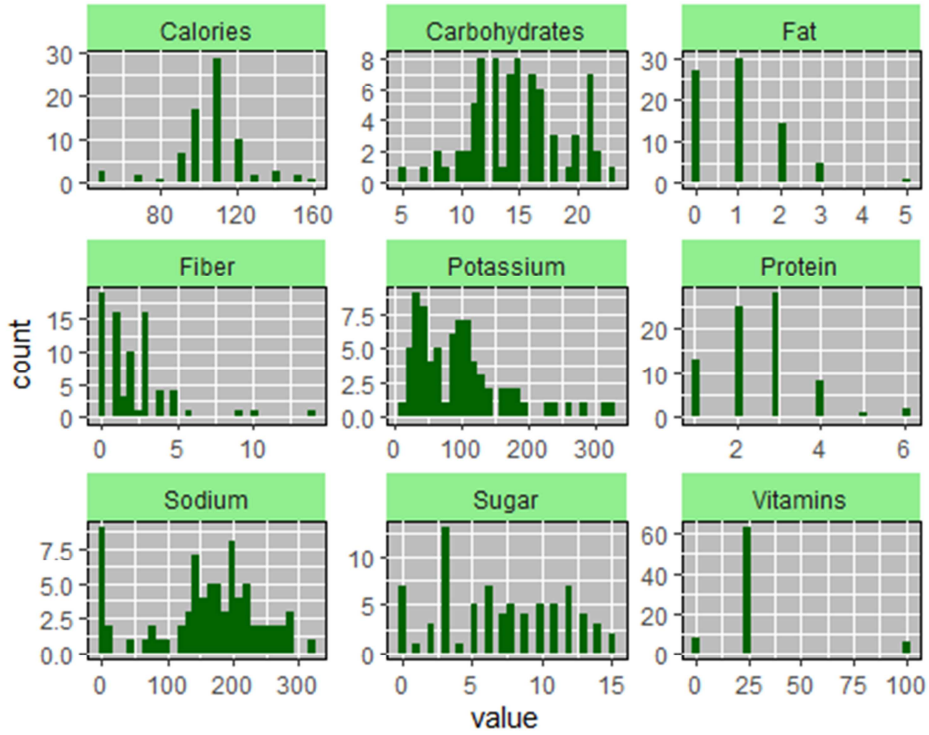
```
##               vars  n   mean    sd median trimmed   mad min max range
skew
## Protein          1 77   2.55  1.09    3.0    2.48  1.48   1   6     5
0.72
## Fat              2 77   1.01  1.01    1.0    0.89  1.48   0   5     5
1.12
## Sodium           3 77 159.68 83.83  180.0  163.25 59.30   0 320   320 -
0.55
## Fiber            4 77   2.15  2.38    2.0    1.77  1.48   0  14    14
2.34
## Carbohydrates    5 76  14.80  3.91   14.5   14.79  3.71   5  23    18
0.11
## Sugar            6 76   7.03  4.38    7.0    7.03  5.93   0  15    15
0.04
## Potassium        7 75  98.67 70.41   90.0   88.11 66.72  15 330   315
1.34
## Vitamins         8 77  28.25 22.34   25.0   24.60  0.00   0 100   100
2.37
##               kurtosis   se
## Protein           0.93 0.12
## Fat               1.71 0.11
## Sodium           -0.47 9.55
## Fiber             7.73 0.27
```

```
## Carbohydrates    -0.46 0.45
## Sugar            -1.20 0.50
## Potassium         1.63 8.13
## Vitamins          5.55 2.55

#===========Data Visualization-I ============

library(ggplot2)
library(gplots)

##
## Attaching package: 'gplots'

## The following object is masked from 'package:stats':
##
##     lowess

library(superheat)
library(corrplot)

## corrplot 0.84 loaded

library(readr)
library(plotrix)

##
## Attaching package: 'plotrix'

## The following object is masked from 'package:gplots':
##
##     plotCI

## The following object is masked from 'package:psych':
##
##     rescale

library(ggcorrplot)
library(ggpubr)

## Loading required package: magrittr

##
## Attaching package: 'magrittr'

## The following object is masked from 'package:purrr':
##
##     set_names

## The following object is masked from 'package:tidyr':
##
##     extract
```

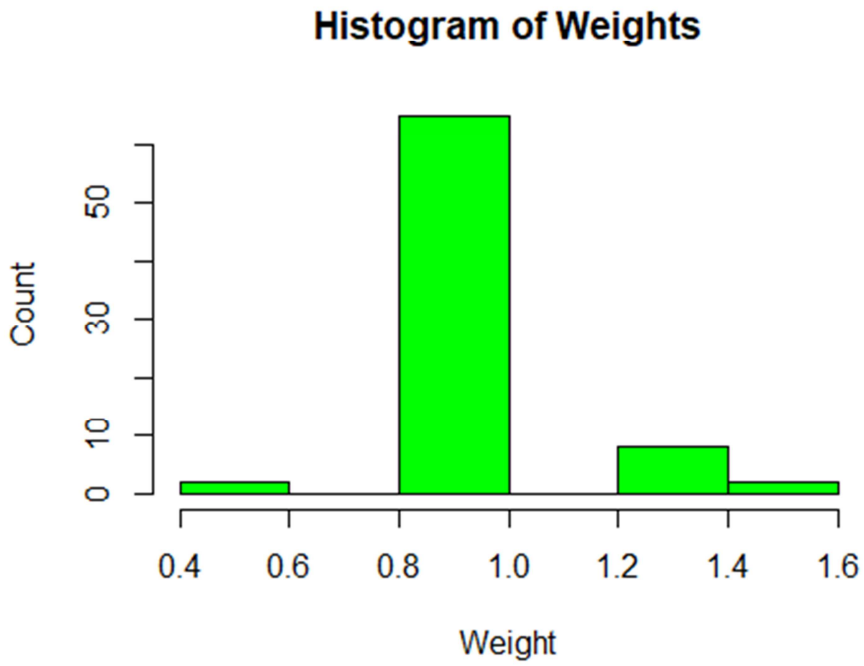
```
#-----All nutrients in single plot---
c1<- subset(cereals_data2, select = c(Calories:Vitamins))
as.data.frame(c1)%>%
  gather() %>%
  ggplot(aes(value)) +
  facet_wrap(~ key, scales = "free") +
  geom_histogram(fill = "darkgreen") + theme(strip.background =
element_rect(fill="lightgreen"))+
  theme(panel.background = element_rect(fill = 'grey', colour = 'black'))
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

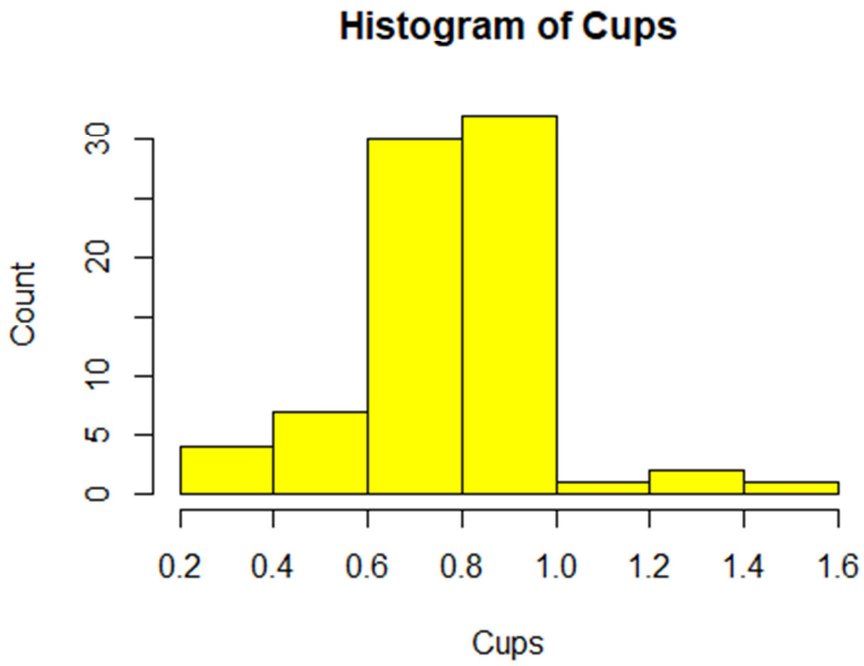
```
## Warning: Removed 4 rows containing non-finite values (stat_bin).
```



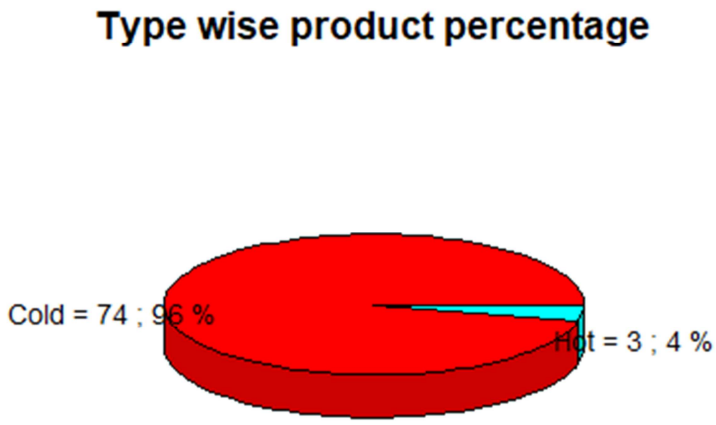

```
#-----Histogram-Distribution of weight and cups-----

p<-cereals_data2$Weight

hist(p,
       breaks=7,
       col="green",
       xlab = "Weight",
       ylab = "Count",
       main = "Histogram of Weights", plot=TRUE)
```



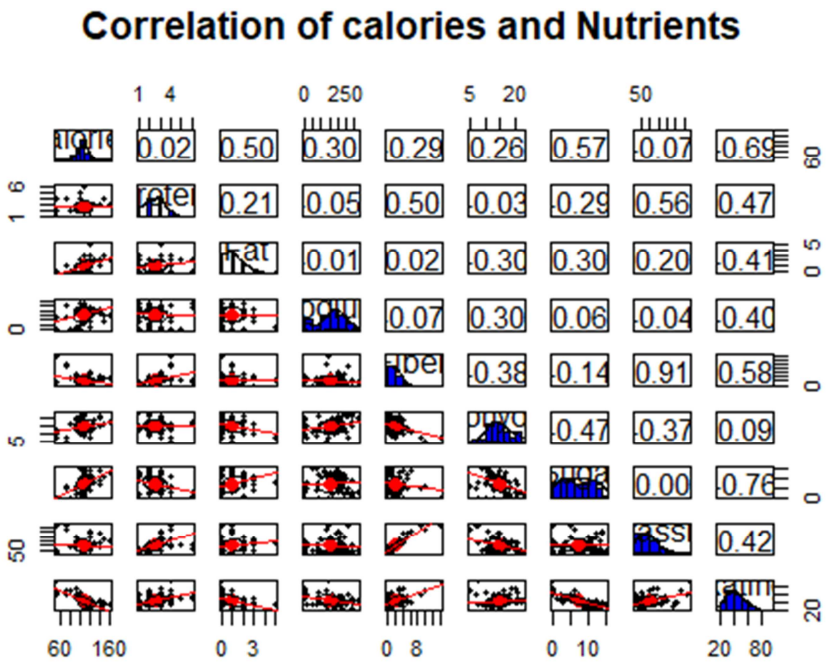

```
q<-cereals_data2$Cups
hist(q,
     breaks=7,
     col="yellow",
     xlab = "Cups",
     ylab = "Count",
     main = "Histogram of Cups", plot=TRUE)
```




```
#--------3d--Pie Chart- Type wise product percentage------

ctype_cat<-c("Cold","Hot")
ctype_count<-c(74,3)
ctype_count_pct<-round(ctype_count/sum(ctype_count)*100)
ctype_count_pct

## [1] 96  4

lbls<-paste(ctype_cat,"= ",ctype_count, ";", ctype_count_pct,"%",sep = " ")
#pie(ctype_count,labels=lbls,col = rainbow(length(lbls)),radius=0.85,main =
"Cereal's count in each type")

a<-table(cereals_data2$Type)
grp<-c("Cold","Hot")
cnt<-round(a)
grpd<-paste(grp,"=",cnt)
lbl<-paste(grpd,";",ctype_count_pct,"%")
pie3D(a,
      labels = lbl,
      labelcex=0.9,
      main = "Type wise product percentage",
      col = rainbow(length(a)))
```




```
#------Co-relation plot------
variable.names(cereals_data2)

##  [1] "Manufacturer"      "Type"              "Calories"
##  [4] "Protein"           "Fat"               "Sodium"
##  [7] "Fiber"             "Carbohydrates"     "Sugar"
## [10] "Potassium"         "Vitamins"          "Shelf"
## [13] "Weight"            "Cups"              "Rating"
## [16] "Manufacturer_Name"

pairs.panels(cereals_data2[,-c(1,2,12,13,14,16,11,17,18)],
             method = "pearson", #coorelation method
             hist.col = "blue",
             main="Correlation of calories and Nutrients",
             density = TRUE, # show density plots
             ellipses = TRUE, # show correlation ellipses
             lm=TRUE, #linear regression fits
             cex.cor = 2,
             cex.labels=1.5
)
```




```
#==============Data Manipulation===========

#-----------Creating additional variable Calories_Cat,Rating_Cat---------
table(cereals_data2$Calories)

##
##  50  70  80  90 100 110 120 130 140 150 160
##   3   2   1   7  17  29  10   2   3   2   1

cereals_data2 <- within(cereals_data2, {
  Calories_cat <- NA
  Calories_cat[cereals_data2$Calories <= 100] <-"Low_Calories"
  Calories_cat[cereals_data2$Calories > 100 & cereals_data2$Calories < 130]
<-"Medium_Calories"
  Calories_cat[cereals_data2$Calories >= 130] <-"High_Calories"
})
table(cereals_data2$Calories_cat)

##
##   High_Calories     Low_Calories Medium_Calories
##               8               30               39

cereals_data2$Calories_cat<-factor(cereals_data2$Calories_cat)
str(cereals_data2$Calories_cat)

##  Factor w/ 3 levels "High_Calories",..: 1 1 1 1 1 1 1 1 3 3 ...
```

```r
cereals_data2<- within(cereals_data2, {
  Rating_Cat <- NA
  Rating_Cat[cereals_data2$Rating <= 40] <- "Poor"
  Rating_Cat[cereals_data2$Rating > 40 & cereals_data2$Rating < 64] <-
"Satisfactory"
  Rating_Cat[cereals_data2$Rating >= 64] <- "Good"
})
table(cereals_data2$Rating_Cat)
```

```
##
##         Good         Poor Satisfactory
##            6           37           34
```

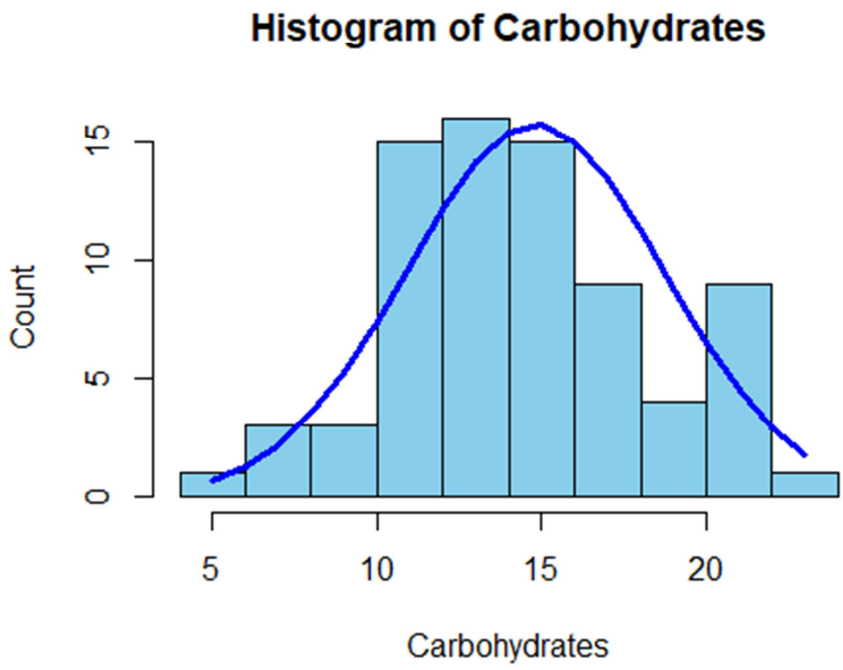
```r
#==============Missing Value Treatment using kNN Imputation==============

#----Calculate NAs------
sum(is.na(cereals_data2))
```

```
## [1] 4
```

```r
summary(cereals_data2)
```

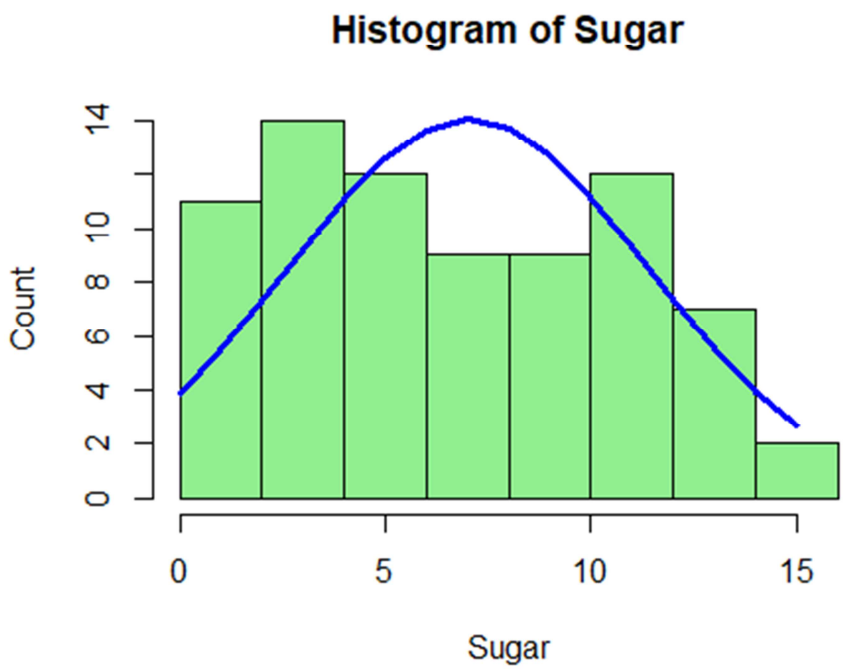
```
##  Manufacturer   Type       Calories        Protein           Fat
##  A: 1         Cold:74   Min.   : 50.0   Min.   :1.000   Min.   :0.000
##  G:22         Hot : 3   1st Qu.:100.0   1st Qu.:2.000   1st Qu.:0.000
##  K:23                   Median :110.0   Median :3.000   Median :1.000
##  N: 6                   Mean   :106.9   Mean   :2.545   Mean   :1.013
##  P: 9                   3rd Qu.:110.0   3rd Qu.:3.000   3rd Qu.:2.000
##  Q: 8                   Max.   :160.0   Max.   :6.000   Max.   :5.000
##  R: 8
##      Sodium          Fiber         Carbohydrates      Sugar
##  Min.   :  0.0   Min.   : 0.000   Min.   : 5.0   Min.   : 0.000
##  1st Qu.:130.0   1st Qu.: 1.000   1st Qu.:12.0   1st Qu.: 3.000
##  Median :180.0   Median : 2.000   Median :14.5   Median : 7.000
##  Mean   :159.7   Mean   : 2.152   Mean   :14.8   Mean   : 7.026
##  3rd Qu.:210.0   3rd Qu.: 3.000   3rd Qu.:17.0   3rd Qu.:11.000
##  Max.   :320.0   Max.   :14.000   Max.   :23.0   Max.   :15.000
##                                   NA's   :1      NA's   :1
##    Potassium         Vitamins      Shelf      Weight          Cups
##  Min.   : 15.00   Min.   :  0.00   1:20   Min.   :0.50   Min.   :0.250
##  1st Qu.: 42.50   1st Qu.: 25.00   2:21   1st Qu.:1.00   1st Qu.:0.670
##  Median : 90.00   Median : 25.00   3:36   Median :1.00   Median :0.750
##  Mean   : 98.67   Mean   : 28.25          Mean   :1.03   Mean   :0.821
##  3rd Qu.:120.00   3rd Qu.: 25.00          3rd Qu.:1.00   3rd Qu.:1.000
##  Max.   :330.00   Max.   :100.00          Max.   :1.50   Max.   :1.500
##  NA's   :2
##      Rating      Manufacturer_Name          Calories_cat  Rating_Cat
##  Min.   :18.04   Length:77          High_Calories  : 8    Length:77
##  1st Qu.:33.17   Class :character   Low_Calories   :30    Class :character
##  Median :40.40   Mode  :character   Medium_Calories:39    Mode  :character
##  Mean   :42.67
```

```
##  3rd Qu.:50.83
##  Max.   :93.70
##

#-------Histograms to check the distribution for imputation-----

#par(mfrow=c(1,3))
x<-cereals_data2$Carbohydrates
h<-hist(x,
       breaks=10,
       col="skyblue",
       xlab = "Carbohydrates",
       ylab = "Count",
       main = "Histogram of Carbohydrates")
xfit<-seq(min(x,na.rm = T),max(x,na.rm = T),length(40))
yfit<-dnorm(xfit, mean = mean(x,na.rm = T), sd=sd(x,na.rm = T))
yfit<-yfit * diff(h$mids[1:2]*length(x)) #h$mids are mid points of the
intervals
lines(xfit, yfit, col="blue",lwd=3)
```

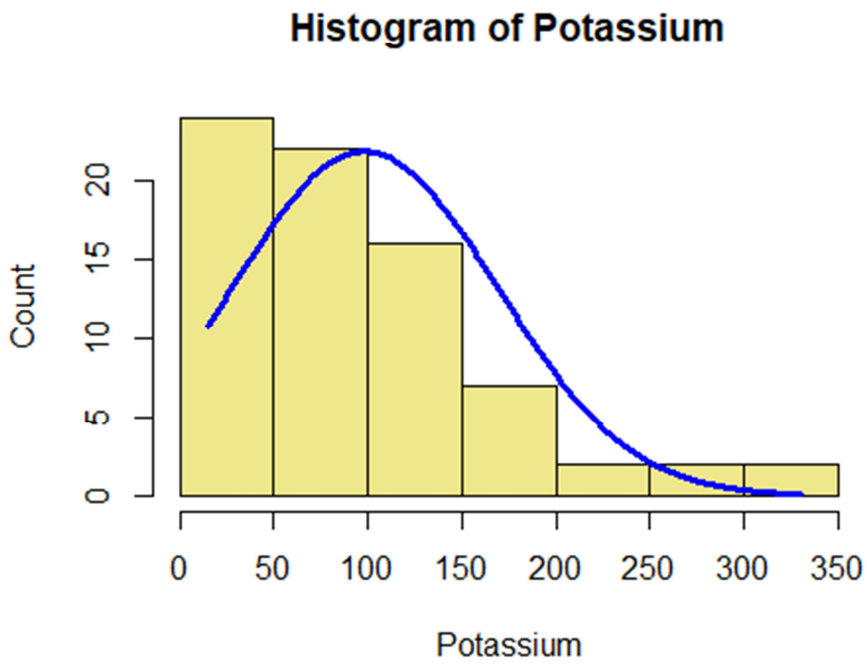



```
y<-cereals_data2$Sugar
h<-hist(y,
        breaks=10,
        col="lightgreen",
        xlab = "Sugar",
        ylab = "Count",
```

```
        main = "Histogram of Sugar")
xfit<-seq(min(y,na.rm = T),max(y,na.rm = T),length(40));xfit

##  [1]  0  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15

yfit<-dnorm(xfit, mean = mean(y,na.rm = T), sd=sd(y,na.rm = T))
yfit<-yfit * diff(h$mids[1:2]*length(y))
lines(xfit, yfit, col="blue",lwd=3)
```




```
z<-cereals_data2$Potassium
h<-hist(z,
        breaks=10,
        col="khaki",
        xlab = "Potassium",
        ylab = "Count",
        main = "Histogram of Potassium")
xfitt<-seq(min(z,na.rm = T),max(z,na.rm = T),length(40))
yfitt<-dnorm(xfitt, mean = mean(z,na.rm = T), sd=sd(z,na.rm = T))
yfitt<-yfitt * diff(h$mids[1:2]*length(z))
lines(xfitt, yfitt, col="blue",lwd=3)
```




```
#----kNN Imputation-----
library(VIM)

## Loading required package: colorspace

## Loading required package: grid

## Loading required package: data.table

##
## Attaching package: 'data.table'

## The following objects are masked from 'package:dplyr':
##
##     between, first, last

## The following object is masked from 'package:purrr':
##
##     transpose

## VIM is ready to use.
##  Since version 4.0.0 the GUI is in its own package VIMGUI.
##
##           Please use the package to use the new (and old) GUI.

## Suggestions and bug-reports can be submitted at:
https://github.com/alexkowa/VIM/issues
```

```
##
## Attaching package: 'VIM'

## The following object is masked from 'package:datasets':
##
##     sleep

cereals_data2<-kNN(cereals_data2, k=5)

## Warning in gowerD(don_dist_var, imp_dist_var, weights = weightsx,
numericalX, :
## NAs introduced by coercion

## Warning in gowerD(don_dist_var, imp_dist_var, weights = weightsx,
numericalX, :
## NAs introduced by coercion

## Warning in gowerD(don_dist_var, imp_dist_var, weights = weightsx,
numericalX, :
## NAs introduced by coercion

## Warning in gowerD(don_dist_var, imp_dist_var, weights = weightsx,
numericalX, :
## NAs introduced by coercion

## Warning in gowerD(don_dist_var, imp_dist_var, weights = weightsx,
numericalX, :
## NAs introduced by coercion

## Warning in gowerD(don_dist_var, imp_dist_var, weights = weightsx,
numericalX, :
## NAs introduced by coercion

## Warning in gowerD(don_dist_var, imp_dist_var, weights = weightsx,
numericalX, :
## NAs introduced by coercion

## Warning in gowerD(don_dist_var, imp_dist_var, weights = weightsx,
numericalX, :
## NAs introduced by coercion

## Warning in gowerD(don_dist_var, imp_dist_var, weights = weightsx,
numericalX, :
## NAs introduced by coercion

## Warning in gowerD(don_dist_var, imp_dist_var, weights = weightsx,
```

```
numericalX, :
## NAs introduced by coercion

## Warning in gowerD(don_dist_var, imp_dist_var, weights = weightsx,
numericalX, :
## NAs introduced by coercion

sum(is.na(cereals_data2))

## [1] 0

variable.names(cereals_data2)

##  [1] "Manufacturer"          "Type"                  "Calories"
##  [4] "Protein"               "Fat"                   "Sodium"
##  [7] "Fiber"                 "Carbohydrates"         "Sugar"
## [10] "Potassium"             "Vitamins"              "Shelf"
## [13] "Weight"                "Cups"                  "Rating"
## [16] "Manufacturer_Name"     "Calories_cat"          "Rating_Cat"
## [19] "Manufacturer_imp"      "Type_imp"              "Calories_imp"
## [22] "Protein_imp"           "Fat_imp"               "Sodium_imp"
## [25] "Fiber_imp"             "Carbohydrates_imp"     "Sugar_imp"
## [28] "Potassium_imp"         "Vitamins_imp"          "Shelf_imp"
## [31] "Weight_imp"            "Cups_imp"              "Rating_imp"
## [34] "Manufacturer_Name_imp" "Calories_cat_imp"      "Rating_Cat_imp"

#--------Removing additional rows form 18 to 34 after kNN-------
cereals_data2<-select(cereals_data2,-19:-36)
dim(cereals_data2)

## [1] 77 18

sum(is.na(cereals_data2))

## [1] 0

variable.names(cereals_data2)

##  [1] "Manufacturer"      "Type"              "Calories"
##  [4] "Protein"           "Fat"               "Sodium"
##  [7] "Fiber"             "Carbohydrates"     "Sugar"
## [10] "Potassium"         "Vitamins"          "Shelf"
## [13] "Weight"            "Cups"              "Rating"
## [16] "Manufacturer_Name" "Calories_cat"      "Rating_Cat"

#============Data Visualisation-II ===========

#---Box plot of all nutrients----

cereals_data3<-cereals_data2
names(cereals_data3)
```

```
##  [1] "Manufacturer"      "Type"              "Calories"
##  [4] "Protein"           "Fat"               "Sodium"
##  [7] "Fiber"             "Carbohydrates"     "Sugar"
## [10] "Potassium"         "Vitamins"          "Shelf"
## [13] "Weight"            "Cups"              "Rating"
## [16] "Manufacturer_Name" "Calories_cat"      "Rating_Cat"
```

```
cereals_data3<- subset(cereals_data3, select = c(Calories:Potassium))
str(cereals_data3)
```

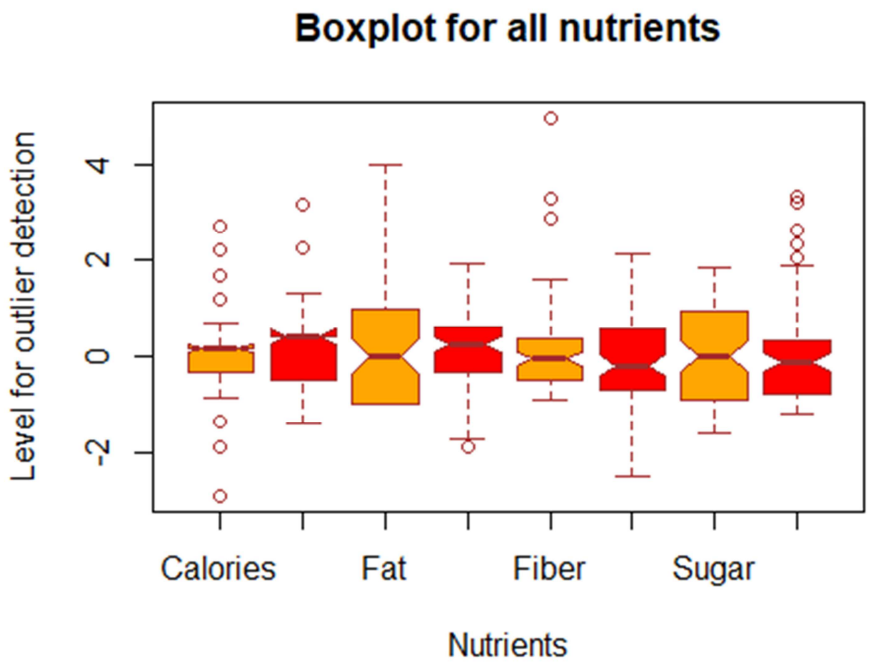
```
## 'data.frame':    77 obs. of  8 variables:
##  $ Calories     : int  160 150 150 140 140 140 130 130 120 120 ...
##  $ Protein      : int  3 4 4 3 3 3 3 3 1 3 ...
##  $ Fat          : int  2 3 3 1 2 1 2 2 3 0 ...
##  $ Sodium       : int  150 95 150 190 220 170 210 170 210 240 ...
##  $ Fiber        : num  3 3 3 4 3 2 2 1.5 0 5 ...
##  $ Carbohydrates: num  17 16 16 15 21 20 18 13.5 13 14 ...
##  $ Sugar        : int  13 11 11 14 7 9 8 10 9 12 ...
##  $ Potassium    : int  160 170 170 230 130 95 100 120 45 190 ...
```

```
cereals_data3<- scale(cereals_data3)
head(cereals_data3,5)
```

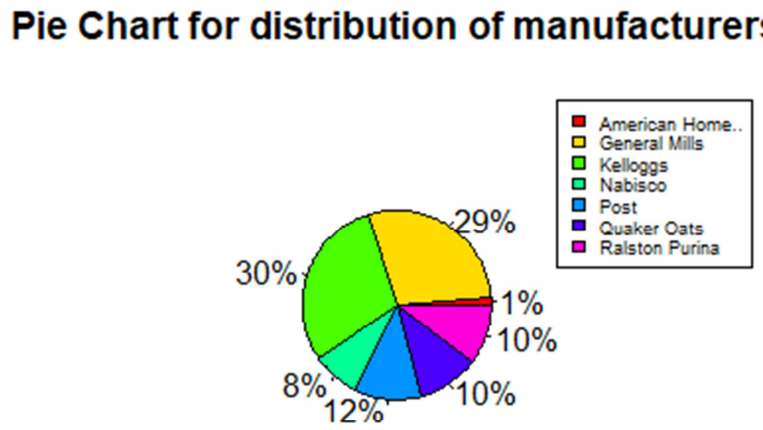
```
##   Calories   Protein         Fat     Sodium     Fiber Carbohydrates
Sugar
## 1 2.726163 0.4151897  0.98066557 -0.1154129 0.3558214    0.56863582
1.37771570
## 2 2.212924 1.3286071  1.97423464 -0.7714846 0.3558214    0.31107724
0.92045661
## 3 2.212924 1.3286071  1.97423464 -0.1154129 0.3558214    0.31107724
0.92045661
## 4 1.699686 0.4151897 -0.01290349  0.3617302 0.7753964    0.05351867
1.60634524
## 5 1.699686 0.4151897  0.98066557  0.7195875 0.3558214    1.59887013
0.00593843
##   Potassium
## 1 0.8865187
## 2 1.0303795
## 3 1.0303795
## 4 1.8935441
## 5 0.4549364
```

```
boxplot(cereals_data3,
        main = "Boxplot for all nutrients",
        xlab = "Nutrients",
        ylab = "Level for outlier detection",
        col = c("orange","red","orange","red","orange","red","orange","red"),
        border = "brown",
        horizontal = F,
        notch = TRUE)
```

```
## Warning in bxp(list(stats = structure(c(-0.866506555101683,
## -0.353268057079917, : some notches went outside hinges ('box'): maybe set
## notch=FALSE
```




```
#----Pie Chart for Manufacturer wise distribution-------

cereals_data4<- cereals_data2%>%
  count(Manufacturer_Name) %>%
  arrange(Manufacturer_Name) %>%
  mutate(prop = round(n * 100 / sum(n), 0),
         lab.ypos = (cumsum(prop) - (0.8*prop)),
         labl = paste0(prop, "", "%"))
pie(cereals_data4$n,
    radius = 0.5,
    labels = cereals_data4$labl,
    main = "Pie Chart for distribution of manufacturers",
    col = rainbow(length(cereals_data4$n)))
legend("topright",as.vector(cereals_data4$Manufacturer_Name), cex = 0.55,
       fill = rainbow(length(cereals_data4$n)))
```




```
#----------Manufacturer wise average content of nutrient----------

head(cereals_data2)

##   Manufacturer Type Calories Protein Fat Sodium Fiber Carbohydrates Sugar
## 1            K Cold      160       3   2    150     3            17    13
## 2            R Cold      150       4   3     95     3            16    11
## 3            R Cold      150       4   3    150     3            16    11
## 4            G Cold      140       3   1    190     4            15    14
## 5            K Cold      140       3   2    220     3            21     7
## 6            K Cold      140       3   1    170     2            20     9
##   Potassium Vitamins Shelf Weight Cups Rating Manufacturer_Name
Calories_cat
## 1       160       25     3   1.50 0.67  30.31          Kelloggs
High_Calories
## 2       170       25     3   1.00 1.00  37.14    Ralston Purina
High_Calories
## 3       170       25     3   1.00 1.00  34.14    Ralston Purina
High_Calories
## 4       230      100     3   1.50 1.00  28.59     General Mills
High_Calories
## 5       130       25     3   1.33 0.67  40.69          Kelloggs
High_Calories
## 6        95      100     3   1.30 0.75  36.47          Kelloggs
High_Calories
##     Rating_Cat
## 1         Poor
```

```
## 2         Poor
## 3         Poor
## 4         Poor
## 5 Satisfactory
## 6         Poor
```

```
str(cereals_data2)
```

```
## 'data.frame':    77 obs. of  18 variables:
##  $ Manufacturer     : Factor w/ 7 levels "A","G","K","N",..: 3 7 7 2 3 3 2
2 2 3 ...
##  $ Type             : Factor w/ 2 levels "Cold","Hot": 1 1 1 1 1 1 1 1 1 1
...
##  $ Calories         : int  160 150 150 140 140 140 130 130 120 120 ...
##  $ Protein          : int  3 4 4 3 3 3 3 3 1 3 ...
##  $ Fat              : int  2 3 3 1 2 1 2 2 3 0 ...
##  $ Sodium           : int  150 95 150 190 220 170 210 170 210 240 ...
##  $ Fiber            : num  3 3 3 4 3 2 2 1.5 0 5 ...
##  $ Carbohydrates    : num  17 16 16 15 21 20 18 13.5 13 14 ...
##  $ Sugar            : int  13 11 11 14 7 9 8 10 9 12 ...
##  $ Potassium        : int  160 170 170 230 130 95 100 120 45 190 ...
##  $ Vitamins         : int  25 25 25 100 25 100 25 25 25 25 ...
##  $ Shelf            : Factor w/ 3 levels "1","2","3": 3 3 3 3 3 3 3 3 2 3
...
##  $ Weight           : num  1.5 1 1 1.5 1.33 1.3 1.33 1.25 1 1.33 ...
##  $ Cups             : num  0.67 1 1 1 0.67 0.75 0.75 0.5 0.75 0.67 ...
##  $ Rating           : num  30.3 37.1 34.1 28.6 40.7 ...
##  $ Manufacturer_Name: chr  "Kelloggs" "Ralston Purina" "Ralston Purina"
"General Mills" ...
##  $ Calories_cat     : Factor w/ 3 levels "High_Calories",..: 1 1 1 1 1 1 1
1 3 3 ...
##  $ Rating_Cat       : chr  "Poor" "Poor" "Poor" "Poor" ...
```

```
hist_data <- cereals_data2
hist_data <- cereals_data2[, c(3:11,16)]
str(hist_data)
```

```
## 'data.frame':    77 obs. of  10 variables:
##  $ Calories         : int  160 150 150 140 140 140 130 130 120 120 ...
##  $ Protein          : int  3 4 4 3 3 3 3 3 1 3 ...
##  $ Fat              : int  2 3 3 1 2 1 2 2 3 0 ...
##  $ Sodium           : int  150 95 150 190 220 170 210 170 210 240 ...
##  $ Fiber            : num  3 3 3 4 3 2 2 1.5 0 5 ...
##  $ Carbohydrates    : num  17 16 16 15 21 20 18 13.5 13 14 ...
##  $ Sugar            : int  13 11 11 14 7 9 8 10 9 12 ...
##  $ Potassium        : int  160 170 170 230 130 95 100 120 45 190 ...
##  $ Vitamins         : int  25 25 25 100 25 100 25 25 25 25 ...
##  $ Manufacturer_Name: chr  "Kelloggs" "Ralston Purina" "Ralston Purina"
"General Mills" ...
```

```r
rownames(hist_data) <- c()
head(hist_data)
```

```
##   Calories Protein Fat Sodium Fiber Carbohydrates Sugar Potassium Vitamins
## 1      160       3   2    150     3            17    13       160       25
## 2      150       4   3     95     3            16    11       170       25
## 3      150       4   3    150     3            16    11       170       25
## 4      140       3   1    190     4            15    14       230      100
## 5      140       3   2    220     3            21     7       130       25
## 6      140       3   1    170     2            20     9        95      100
##   Manufacturer_Name
## 1          Kelloggs
## 2    Ralston Purina
## 3    Ralston Purina
## 4     General Mills
## 5          Kelloggs
## 6          Kelloggs
```

```r
hist_data1 <- hist_data %>%
  group_by(Manufacturer_Name) %>%
  summarise(Calories = round(mean(Calories),2),
            Protein = round(mean(Protein),2),
            Fat = round(mean(Fat),2),
            Fiber = round(mean(Fiber),2),
            Sugar = round(mean(Sugar),2),
            Potassium = round(mean(Potassium),2),
  )

head(hist_data1,20)
```

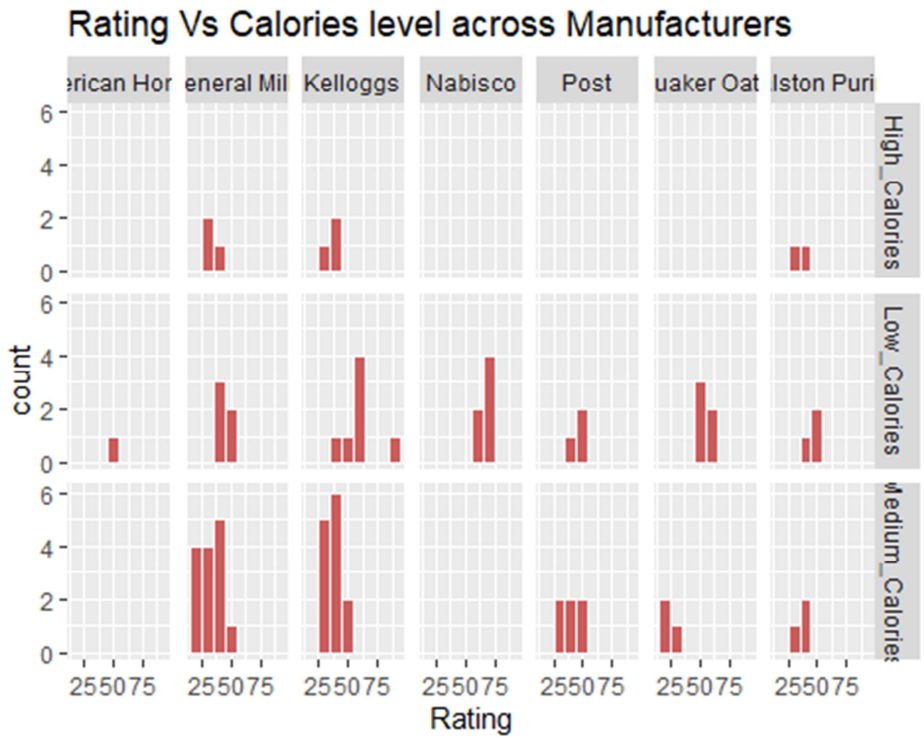
```
## # A tibble: 7 x 7
##   Manufacturer_Name Calories Protein   Fat Fiber Sugar Potassium
##   <chr>                <dbl>   <dbl> <dbl> <dbl> <dbl>     <dbl>
## 1 American Home..      100      4     1     0     3         95
## 2 General Mills        111.     2.32  1.36  1.27  7.95      85.2
## 3 Kelloggs             109.     2.65  0.61  2.74  7.57     103.
## 4 Nabisco               86.7    2.83  0.17  4     1.83     137.
## 5 Post                 109.     2.44  0.89  2.78  8.78     114.
## 6 Quaker Oats           95      2.62  1.75  1.34  5.75      74.4
## 7 Ralston Purina       115      2.5   1.25  1.88  6.12      99.4
```

```r
str(hist_data1)
```

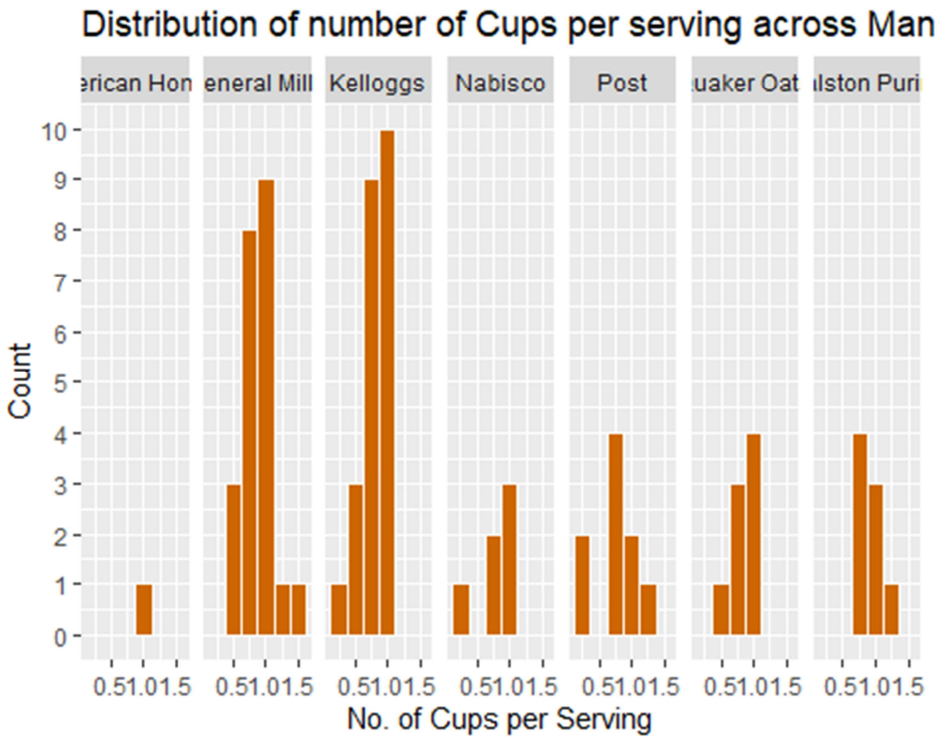
```
## tibble [7 x 7] (S3: tbl_df/tbl/data.frame)
##  $ Manufacturer_Name: chr [1:7] "American Home.." "General Mills"
"Kelloggs" "Nabisco" ...
##  $ Calories         : num [1:7] 100 111.4 108.7 86.7 108.9 ...
##  $ Protein          : num [1:7] 4 2.32 2.65 2.83 2.44 2.62 2.5
##  $ Fat              : num [1:7] 1 1.36 0.61 0.17 0.89 1.75 1.25
##  $ Fiber            : num [1:7] 0 1.27 2.74 4 2.78 1.34 1.88
```

```
##  $ Sugar            : num [1:7] 3 7.95 7.57 1.83 8.78 5.75 6.12
##  $ Potassium        : num [1:7] 95 85.2 103 136.7 113.9 ...

n1 <- ggplot(hist_data1, aes(x = Manufacturer_Name, y = Calories)) +
  geom_bar(stat = "identity", fill = "brown1") +
  geom_text(aes(label = Calories), position = position_stack(vjust = 0.5)) +
  theme(axis.text.x = element_text(angle = 75, size = 10, face = "bold")) +
  labs(title = "Avg. content of Calories (per serving)",
       x = "",
       y = "")
n2 <- ggplot(hist_data1, aes(x = Manufacturer_Name, y = Protein)) +
  geom_bar(stat = "identity", fill = "cyan1") +
  geom_text(aes(label = Protein), position = position_stack(vjust = 0.5)) +
  theme(axis.text.x = element_text(angle = 75, size = 10, face = "bold")) +
  labs(title = "Avg. content of Protien (grams)",
       x = "",
       y = "")
n3 <- ggplot(hist_data1, aes(x = Manufacturer_Name, y = Fiber)) +
  geom_bar(stat = "identity", fill = "darkorchid1") +
  geom_text(aes(label = Fiber), position = position_stack(vjust = 0.5)) +
  theme(axis.text.x = element_text(angle = 75, size = 10, face = "bold")) +
  labs(title = "Avg. content of Fiber (grams)",
       x = "",
       y = "")
n4 <- ggplot(hist_data1, aes(x = Manufacturer_Name, y = Sugar)) +
  geom_bar(stat = "identity", fill = "indianred") +
  geom_text(aes(label = Sugar), position = position_stack(vjust = 0.5)) +
  theme(axis.text.x = element_text(angle = 75, size = 10, face = "bold")) +
  labs(title = "Avg. content of Sugar (grams)",
       x = "",
       y = "")
n5 <- ggplot(hist_data1, aes(x = Manufacturer_Name, y = Fat)) +
  geom_bar(stat = "identity", fill = "olivedrab1") +
  geom_text(aes(label = Fat), position = position_stack(vjust = 0.5)) +
  theme(axis.text.x = element_text(angle = 75, size = 10, face = "bold")) +
  labs(title = "Avg. content of Fat (grams)",
       x = "",
       y = "")
n6 <- ggplot(hist_data1, aes(x = Manufacturer_Name, y = Potassium )) +
  geom_bar(stat = "identity", fill = "khaki4") +
  geom_text(aes(label = Fat), position = position_stack(vjust = 0.5)) +
  theme(axis.text.x = element_text(angle = 75, size = 10, face = "bold")) +
  labs(title = "Avg. content of Potassium  (milligrams)",
       x = "",
       y = "")

figure <- ggarrange(n1,n2,n3,n4,n5,n6, ncol = 3, nrow = 2)
figure
```

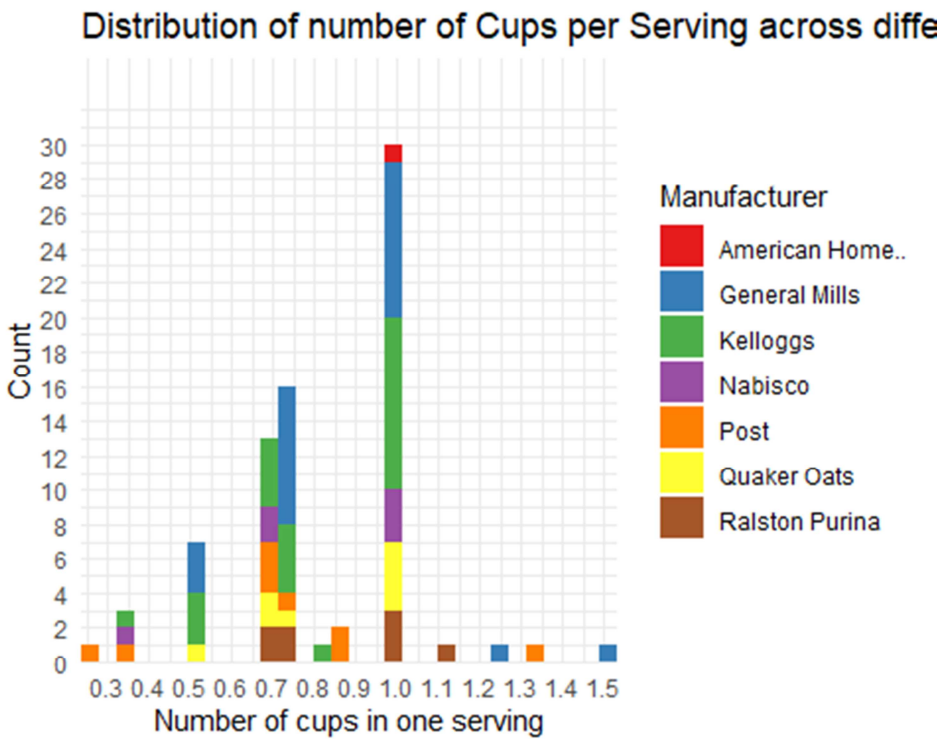
```r
#----------Histogram of Rating Vs Calories level across manufacturers---

ggplot(cereals_data2, aes(x = Rating)) +
  geom_histogram(color = "white",
                 fill = "indianred",
                 binwidth = 10) +
  facet_grid(Calories_cat ~ Manufacturer_Name) +
  labs(title = "Rating Vs Calories level across Manufacturers",
       x = "Rating")
```



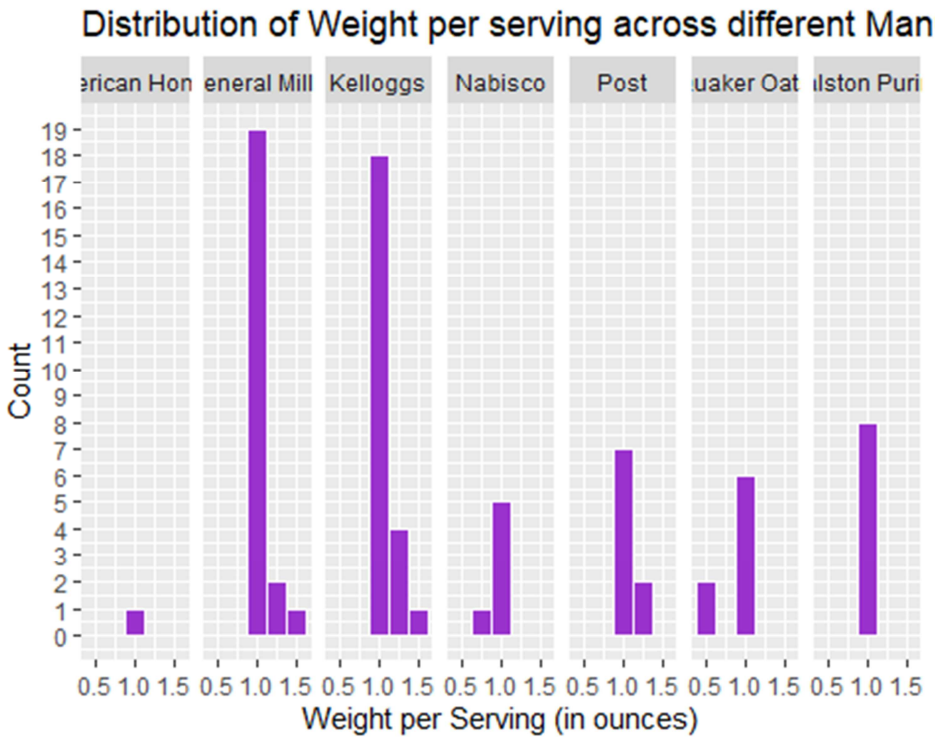

```
#------Histogram of Distribution of Cups per serving across manufacturers-I--
--
ggplot(cereals_data2, aes(x = Cups)) +
  geom_histogram(color = "white",
                 fill = "darkorange3",
                 binwidth = 0.25) +
  scale_x_continuous(breaks = seq(0,1.5,0.5)) +
  scale_y_continuous(breaks = seq(0,25,1)) +
  facet_grid(~ Manufacturer_Name) +
  labs(title = "Distribution of number of Cups per serving across
Manufacturers",
       x = "No. of Cups per Serving", y = "Count")
```



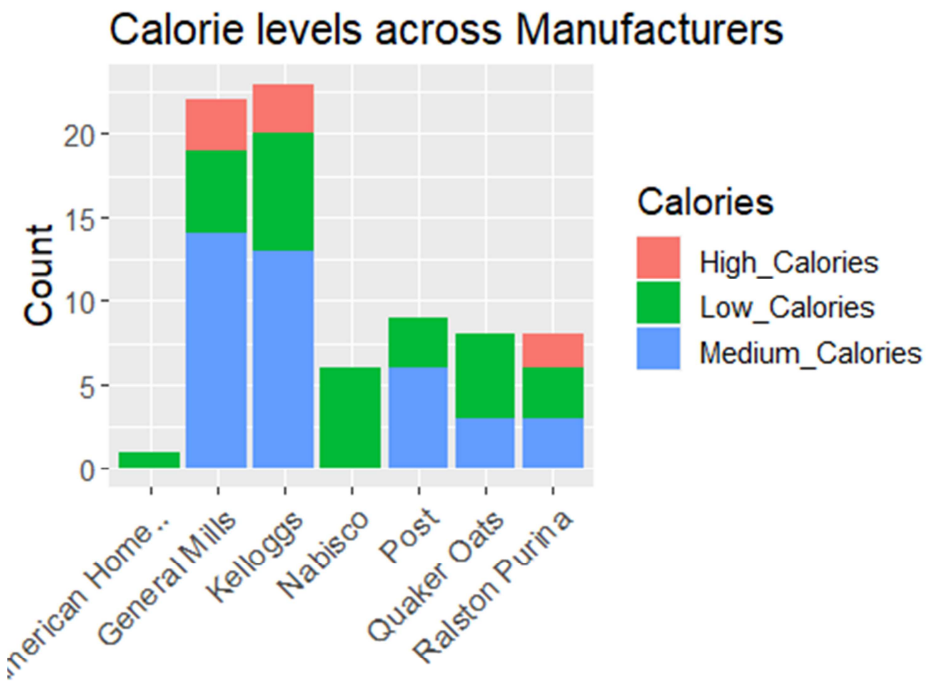

```
#------Histogram of Distribution of Cups per serving across manufacturers-II-
---
cereals_data2 %>%
  ggplot(aes(x = Cups, fill = Manufacturer_Name)) +
  geom_histogram() +
  scale_fill_brewer(palette = "Set1") +
  scale_x_continuous(name = "Number of cups in one serving", expand =
c(0,0),breaks = seq(0,1.5,0.1)) +
  scale_y_continuous(name = "Count", expand = c(0,0), limits = c(0,
35),breaks = seq(0,30,2)) +
  labs(fill = "Manufacturer", title = "Distribution of number of Cups per
Serving across different manufacturers") +
  theme_minimal()

## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



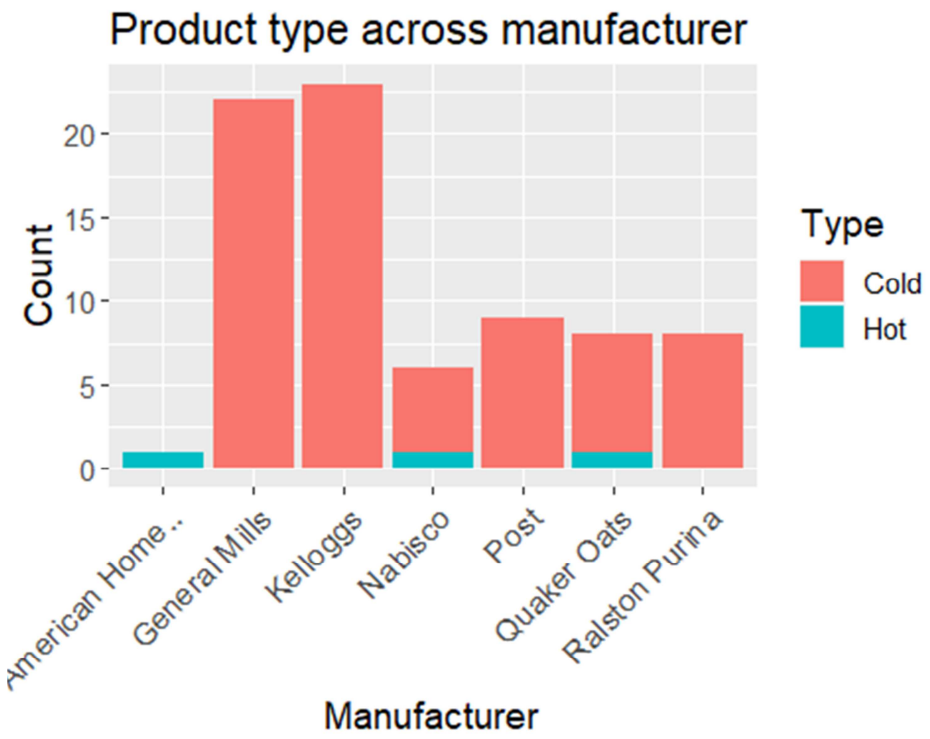

```
#------Histogram of Distribution of Weight per serving across manufacturers--
--
ggplot(cereals_data2, aes(x = Weight)) +
  geom_histogram(color = "white",
                 fill = "darkorchid3",
                 binwidth = 0.25) +
  scale_x_continuous(breaks = seq(0,2,0.5)) +
  scale_y_continuous(breaks = seq(0,25,1)) +
  facet_grid(~ Manufacturer_Name) +
  labs(title = "Distribution of Weight per serving across different
Manufacturers",
       x = "Weight per Serving (in ounces)", y = "Count")
```



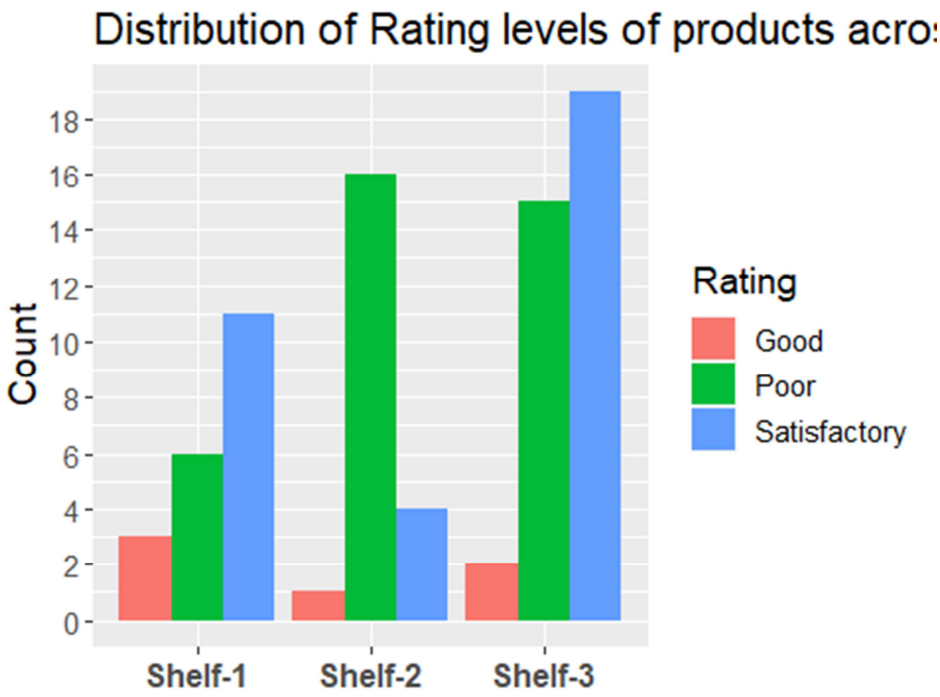

```r
#---------Calorie level across Manufacturers-----
ggplot(cereals_data2,
       aes(x = Manufacturer_Name,
           fill = Calories_cat)) +
  geom_bar(position = "stack")  +
  labs(y = "Count",
       fill = "Calories",
       x = "",
       title = "Calorie levels across Manufacturers") +
  theme(axis.text.x= element_text(angle = 45, hjust = 1, size = 12),
        text = element_text(size = 14))
```




```
#---------Product Type across Manufacturers-----
ggplot(cereals_data2,
       aes(x = Manufacturer_Name,
           fill = Type)) +
  geom_bar(position = "stack")  +
  labs(y = "Count",
       fill = "Type",
       x = "Manufacturer",
       title = "Product type across manufacturer") +
  theme(axis.text.x= element_text(angle = 45, hjust = 1,size = 12),
        text = element_text(size = 14))
```




```
#----------Rating category across Shelves----------
ggplot(cereals_data2,
       aes(x = factor(Shelf, labels = c("Shelf-1","Shelf-2","Shelf-3")),
           fill = Rating_Cat)) +
  geom_bar(position = "dodge")  +
  labs(y = "Count",
       fill = "Rating",
       x = "",
       title = "Distribution of Rating levels of products across Shelf
numbers"
  ) +
  scale_y_continuous(breaks = seq(0, 25, 2)) +
  theme(axis.text.x = element_text( size = 12, face = "bold"),
        text = element_text(size = 14))
```

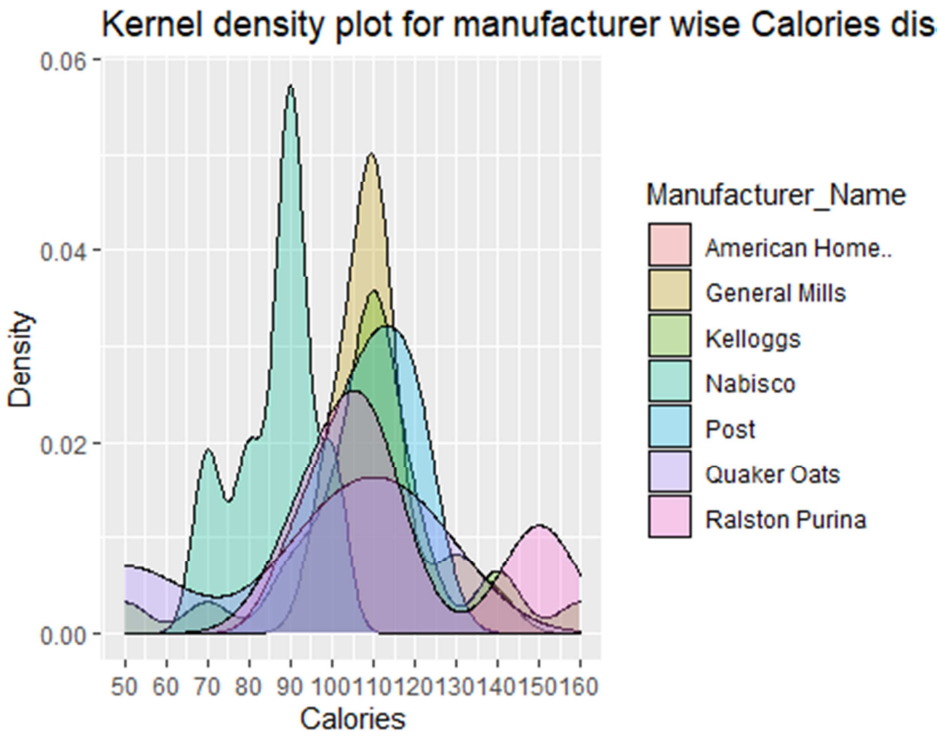



```
#-----Grouped kernel density plots of calorie distribution across
manufacturers----
table(cereals_data2$Manufacturer)
```

```
##
##  A  G  K  N  P  Q  R
##  1 22 23  6  9  8  8
```

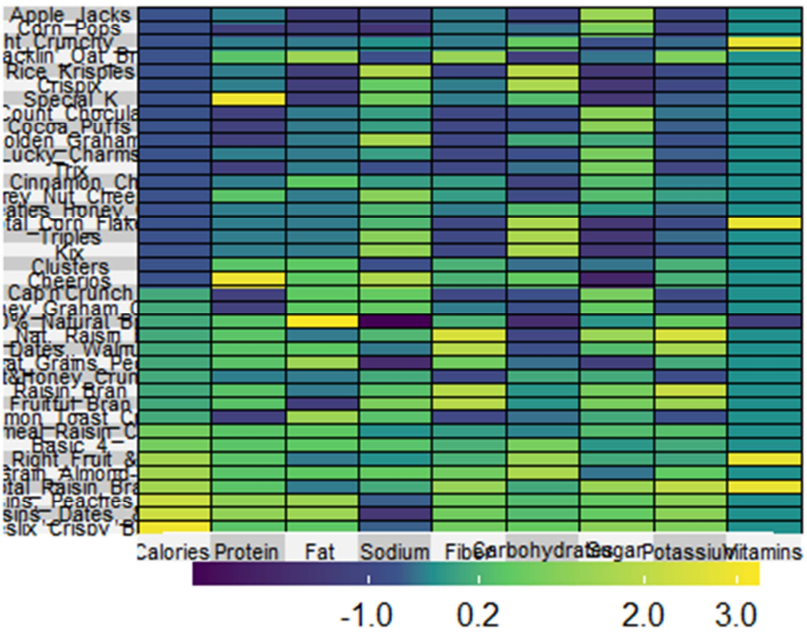
```
ggplot(cereals_data2,
       aes(x = Calories,
           fill = Manufacturer_Name)) +
  geom_density(alpha = 0.3) +
  scale_x_continuous(breaks = seq(50,180,10)) +
  labs(title = "Kernel density plot for manufacturer wise Calories
distribution",
       x = "Calories",
       y = "Density")
```

```
## Warning: Groups with fewer than two data points have been dropped.
```

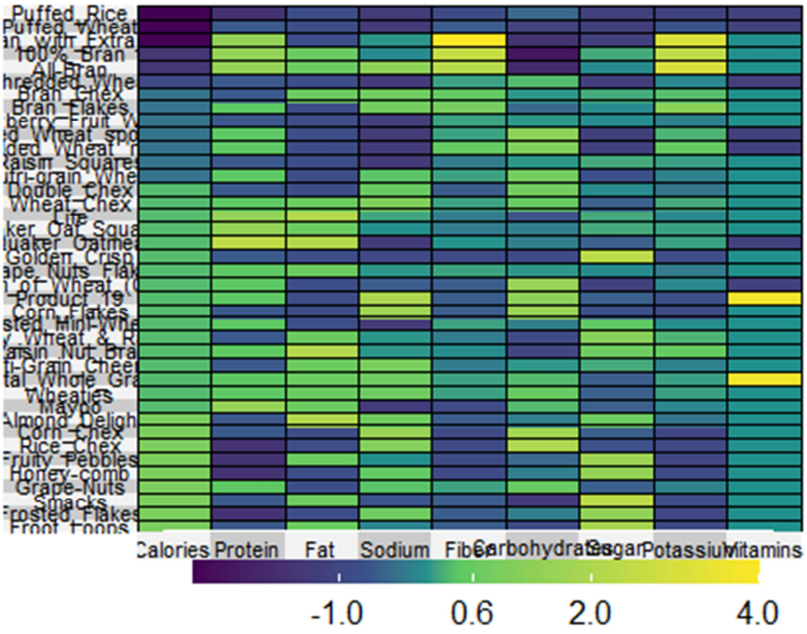



```
#----Heatmap------

names(cereals_data2)

##  [1] "Manufacturer"      "Type"              "Calories"
##  [4] "Protein"           "Fat"               "Sodium"
##  [7] "Fiber"             "Carbohydrates"     "Sugar"
## [10] "Potassium"         "Vitamins"          "Shelf"
## [13] "Weight"            "Cups"              "Rating"
## [16] "Manufacturer_Name" "Calories_cat"      "Rating_Cat"

cereals_datahm<-cereals_data2[ ,3:11]
rownames(cereals_datahm)<-cereals_data[,1]
variable.names(cereals_datahm)

## [1] "Calories"      "Protein"       "Fat"           "Sodium"
## [5] "Fiber"         "Carbohydrates" "Sugar"         "Potassium"
## [9] "Vitamins"

str(cereals_datahm)

## 'data.frame':    77 obs. of  9 variables:
##  $ Calories     : int  160 150 150 140 140 140 130 130 120 120 ...
##  $ Protein      : int  3 4 4 3 3 3 3 3 1 3 ...
##  $ Fat          : int  2 3 3 1 2 1 2 2 3 0 ...
##  $ Sodium       : int  150 95 150 190 220 170 210 170 210 240 ...
##  $ Fiber        : num  3 3 3 4 3 2 2 1.5 0 5 ...
##  $ Carbohydrates: num  17 16 16 15 21 20 18 13.5 13 14 ...
```

```
##  $ Sugar         : int  13 11 11 14 7 9 8 10 9 12 ...
##  $ Potassium     : int  160 170 170 230 130 95 100 120 45 190 ...
##  $ Vitamins      : int  25 25 25 100 25 100 25 25 25 25 ...

head(cereals_datahm)

##                                    Calories Protein Fat Sodium Fiber
## Mueslix_Crispy_Blend                    160       3   2    150     3
## Muesli_Raisins,_Dates,_&_Almonds        150       4   3     95     3
## Muesli_Raisins,_Peaches,_&_Pecans       150       4   3    150     3
## Total_Raisin_Bran                       140       3   1    190     4
## Nutri-Grain_Almond-Raisin               140       3   2    220     3
## Just_Right_Fruit_&_Nut                  140       3   1    170     2
##                                    Carbohydrates Sugar Potassium Vitamins
## Mueslix_Crispy_Blend                          17    13       160       25
## Muesli_Raisins,_Dates,_&_Almonds              16    11       170       25
## Muesli_Raisins,_Peaches,_&_Pecans             16    11       170       25
## Total_Raisin_Bran                             15    14       230      100
## Nutri-Grain_Almond-Raisin                     21     7       130       25
## Just_Right_Fruit_&_Nut                        20     9        95      100

cereals_datahm2<-cereals_datahm[1:38, ]
superheat(cereals_datahm2,scale = TRUE, row.dendrogram = FALSE,
          left.label.text.size=3,
          bottom.label.text.size=3,
          bottom.label.size = .05,)
```



```
cereals_datahm3<-cereals_datahm[39:77, ]
superheat(cereals_datahm3, scale = TRUE, row.dendrogram = FALSE,
          left.label.text.size=3,
          bottom.label.text.size=3,
          bottom.label.size = .05,)
```




```
#===============cluster Analysis=============

#--------Select required Variables from main data-------
cereals_cluster1<- select(cereals_data2,Calories,Protein,Fat,Sugar,Rating)
head(cereals_cluster1)

##   Calories Protein Fat Sugar Rating
## 1      160       3   2    13  30.31
## 2      150       4   3    11  37.14
## 3      150       4   3    11  34.14
## 4      140       3   1    14  28.59
## 5      140       3   2     7  40.69
## 6      140       3   1     9  36.47

cereals_cluster2<-cereals_cluster1
dim(cereals_cluster2)

## [1] 77  5

summary(cereals_cluster2)
```

```
##     Calories        Protein            Fat            Sugar
##  Min.   : 50.0   Min.   :1.000   Min.   :0.000   Min.   : 0.000
##  1st Qu.:100.0   1st Qu.:2.000   1st Qu.:0.000   1st Qu.: 3.000
##  Median :110.0   Median :3.000   Median :1.000   Median : 7.000
##  Mean   :106.9   Mean   :2.545   Mean   :1.013   Mean   : 6.974
##  3rd Qu.:110.0   3rd Qu.:3.000   3rd Qu.:2.000   3rd Qu.:11.000
##  Max.   :160.0   Max.   :6.000   Max.   :5.000   Max.   :15.000
##      Rating
##  Min.   :18.04
##  1st Qu.:33.17
##  Median :40.40
##  Mean   :42.67
##  3rd Qu.:50.83
##  Max.   :93.70
```

```
sum(is.na(cereals_cluster2))
```

```
## [1] 0
```

```
cereals_cluster2<-na.omit(cereals_cluster2)
#-------Scale the data-----
cereals_cluster2.scaled<-scale(cereals_cluster2)
head(cereals_cluster2.scaled)
```

```
##   Calories   Protein         Fat      Sugar     Rating
## 1 2.726163 0.4151897  0.98066557 1.37771570 -0.8795515
## 2 2.212924 1.3286071  1.97423464 0.92045661 -0.3933371
## 3 2.212924 1.3286071  1.97423464 0.92045661 -0.6069012
## 4 1.699686 0.4151897 -0.01290349 1.60634524 -1.0019949
## 5 1.699686 0.4151897  0.98066557 0.00593843 -0.1406195
## 6 1.699686 0.4151897 -0.01290349 0.46319752 -0.4410331
```

```
head(cereals_cluster2.scaled,3)
```

```
##   Calories   Protein       Fat     Sugar     Rating
## 1 2.726163 0.4151897 0.9806656 1.3777157 -0.8795515
## 2 2.212924 1.3286071 1.9742346 0.9204566 -0.3933371
## 3 2.212924 1.3286071 1.9742346 0.9204566 -0.6069012
```

```
str(cereals_cluster2.scaled)
```

```
##  num [1:77, 1:5] 2.73 2.21 2.21 1.7 1.7 ...
##  - attr(*, "dimnames")=List of 2
##   ..$ : chr [1:77] "1" "2" "3" "4" ...
##   ..$ : chr [1:5] "Calories" "Protein" "Fat" "Sugar" ...
##  - attr(*, "scaled:center")= Named num [1:5] 106.88 2.55 1.01 6.97 42.67
##   ..- attr(*, "names")= chr [1:5] "Calories" "Protein" "Fat" "Sugar" ...
##  - attr(*, "scaled:scale")= Named num [1:5] 19.48 1.09 1.01 4.37 14.05
##   ..- attr(*, "names")= chr [1:5] "Calories" "Protein" "Fat" "Sugar" ...
```

```r
#---------Calculate the euclidean distance----
library(cluster)
library(factoextra)

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

dist.ecul_cereals_cluster2.scaled<-dist(cereals_cluster2.scaled,method =
"euclidean")
(dist.ecul_cereals_cluster2.scaled)

##              1           2           3           4           5           6
## 2  1.590727783
## 3  1.538943990 0.213564151
## 4  1.451929191 2.426390449 2.381807145
## 5  1.865863965 1.727754107 1.771633915 2.071339915
## 6  1.751992119 2.292994510 2.298491062 1.273367542 1.134245862
## 7  1.976624165 1.829114470 1.840714195 1.869282031 0.619031639 1.142152013
## 8  1.685605632 1.776020700 1.731022863 1.450678837 1.124832374 1.219229913
## 9  3.151685720 3.407201794 3.335864855 3.168005603 2.791869302 3.121632498
## 10 2.965956826 3.495459019 3.518781089 1.741525427 2.511913925 1.617464863
## 11 2.379077462 2.688646686 2.709038996 1.356354434 1.832480353 1.250418340
## 12 2.621687476 3.182770189 3.155329030 1.789898712 1.916265484 1.451001382
## 13 3.263941285 2.479373596 2.540969664 3.425236958 1.626076705 2.598316165
## 14 2.292498479 2.077718934 2.116001400 1.909874529 1.234652309 1.481033379
## 15 2.354021322 2.761647968 2.773732800 1.219534090 2.154831590 1.539465290
## 16 3.804507729 2.770346678 2.761221838 4.344827745 3.196672057 4.114877735
## 17 2.849916591 3.471101353 3.410256303 2.465249285 2.649958175 2.582147337
## 18 2.892607757 3.573222421 3.497537032 2.480180981 2.880560875 2.751351661
## 19 4.872448904 3.834887167 3.894368346 4.710796333 3.503622729 3.904755088
## 20 2.997174268 2.631792605 2.659147782 2.574108322 1.539853889 1.909256368
## 21 3.746748975 3.855954630 3.870122642 3.178788828 2.244823611 2.264003591
## 22 3.745189882 3.855606926 3.869265445 3.176594323 2.245268186 2.263216322
## 23 3.742022822 3.854955661 3.867555265 3.172117923 2.246313082 2.261701349
## 24 3.144655061 3.460589580 3.463005022 2.319383665 2.084976691 1.804916596
## 25 2.836528464 3.039187583 3.016240006 1.799509911 2.073002008 1.603362257
## 26 2.809512734 2.981010638 2.949581835 2.243405327 2.075795547 2.118960938
## 27 3.315921008 4.021370997 3.991430565 2.433251081 2.974991720 2.561998262
## 28 2.919602088 3.478809574 3.439650382 1.852477628 2.546886399 2.038691381
## 29 3.458462591 4.096735090 4.052557989 2.670413932 2.889636468 2.553736016
## 30 3.346678201 4.114881797 4.066941018 2.435929248 3.195283950 2.738562895
## 31 3.350660756 4.120978201 4.071839902 2.440183722 3.205040119 2.747294486
## 32 5.090110777 4.591040699 4.648597980 4.499287047 3.930523891 3.762344667
## 33 4.241500216 4.501630308 4.539499074 3.495149864 2.861039909 2.573965991
## 34 4.138595090 4.454347216 4.471108225 3.353087005 2.826694577 2.481689170
## 35 3.158379189 2.437379244 2.467199325 3.097348831 1.832537910 2.570759155
## 36 3.341195813 3.579021954 3.582758128 2.620899342 2.081496696 1.917162233
## 37 3.751704940 4.546412022 4.546880158 2.676993991 3.329523594 2.677327886
## 38 3.385574800 4.121513820 4.112392525 2.073291474 3.162539753 2.356736942
## 39 2.902610766 3.439901182 3.424708175 1.823111703 2.537406274 2.033068107
```

```
## 40 3.753257793 4.557726225 4.543694678 2.684554816 3.305558799 2.651892317
## 41 2.936022808 3.537515140 3.518511192 1.814565160 2.826858441 2.286039358
## 42 4.296050229 4.314376954 4.376408861 3.576952293 2.823223053 2.585937538
## 43 3.754059741 4.578842336 4.555874534 2.676898556 3.349148597 2.684609205
## 44 3.314885267 4.018105749 3.989208050 2.432842837 2.968880291 2.557241800
## 45 4.570423643 4.996188991 5.015504893 3.890198183 3.312438764 3.067817890
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## 55 1.428345492 1.370045855 1.411054602 2.618610421 2.192581296 1.712216623
## 56 1.226016441 1.059297439 1.517150428 2.296067102 2.127496639 1.508372792
## 57 1.518612222 1.753835398 2.593330026 3.227770001 3.334923258 1.659774400
## 58 0.458587656 0.598295736 1.269926351 1.494766404 1.849944059 1.181309806
## 59 3.271340121 3.163599462 2.311031459 2.728498697 1.516030768 2.623718976
## 60 2.080248053 2.100625439 3.090142576 2.296059189 3.484984102 2.899822311
## 61 1.151824474 1.160145362 1.945536101 1.586914014 2.252587340 1.506586791
## 62 1.578146556 1.516877835 2.112484935 1.097291580 2.363288402 2.386295416
## 63 0.128138490 0.222818597 1.334029165 1.676276537 2.081908053 1.481504110
## 64 1.515818271 1.434611078 1.062873120 2.315627152 1.621905689 1.428122514
## 65 1.277210568 1.468563693 2.203227054 2.847605247 2.866956211 1.256436905
## 66 1.620571904 1.713564742 1.557089193 2.548250717 1.986300699 1.093725909
## 67 2.091403639 2.374953819 3.154317384 3.699211110 3.839531869 2.035089645
## 68 2.000207508 2.276800418 3.063048440 3.620741728 3.756066082 1.970500491
## 69 1.612440549 1.763912128 1.783473733 2.734166462 2.297898755 1.145425933
## 70 1.214360538 1.297608255 1.737871918 2.370924454 2.208794415 0.775389126
## 71 1.264557660 1.264458871 0.821470190 1.656412788 1.395821489 1.602788628
## 72 2.179564222 2.388647449 2.816503708 3.648275132 3.532254796 2.223729855
## 73 1.930189784 2.059260019 2.766209835 2.575929173 3.123181912 2.099340733
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## 74 2.259982331 2.463869200 3.124721171 2.928406737 3.435892300 2.180908149
## 75 4.226544198 4.482297967 5.229302005 5.430588606 5.736188961 4.039026768
## 76 3.088399933 3.198752641 3.480211056 4.179396343 4.055573476 3.176637559
## 77 3.436048967 3.519631947 3.528402657 4.411850270 4.086050609 3.537429171
##             55          56          57          58          59          60
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## 56 0.991432543
## 57 1.676267652 1.777153600
## 58 1.577344837 1.327979580 1.754844249
## 59 3.066653577 2.925642042 4.115832508 2.912745962
## 60 3.411033444 2.779781351 2.950872812 2.131081663 4.496100095
## 61 2.286561454 1.617745546 2.201492113 0.959205250 3.096612061 1.516833567
## 62 2.850229872 2.308209404 2.921128767 1.450751918 3.469142102 1.207507203
## 63 1.397158906 1.155618992 1.599586848 0.485449896 3.227999537 2.080861865
## 64 0.694482748 1.041155235 2.051574533 1.458043850 2.375913226 3.446867826
## 65 1.435287374 1.408287337 0.770506262 1.417983060 3.598093874 2.827554884
## 66 1.246690259 1.592949804 1.846199163 1.480109468 2.557488476 3.506305558
## 67 2.335580783 2.498518486 0.874142187 2.257852649 4.544674185 3.294237984
## 68 2.232669052 2.387188659 0.781032066 2.175558167 4.472622215 3.235119912
## 69 1.287420799 1.709776641 1.593733630 1.534114276 2.904547636 3.506983437
## 70 1.359948700 1.085968706 1.485991239 1.121721991 2.824500626 2.791005472
## 71 1.463145461 1.688082638 2.273790598 1.092894350 2.541554253 3.040532366
## 72 1.949612960 2.445813253 1.399192346 2.346352525 4.281373434 3.810232383
## 73 2.845851376 2.455712097 2.372937677 1.865161398 3.858152709 2.185435984
## 74 3.179032051 2.886129604 2.479900504 2.146411014 4.061806180 2.495418512
## 75 4.661557022 4.658207272 3.425165348 4.300244377 6.244772544 4.599186145
## 76 2.878361632 3.199196806 2.726056444 3.212329110 4.717172120 4.389225247
## 77 2.958690543 3.503281018 3.161438993 3.549429677 4.741164170 4.985329508
##             61          62          63          64          65          66
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## 63 1.142441187 1.546854702
## 64 2.124324808 2.709867618 1.477049116
## 65 1.855075118 2.630695395 1.339607916 1.660134467
## 66 2.181645035 2.838350032 1.646482554 0.963785029 1.328462891
## 67 2.669064750 3.351336054 2.192671461 2.647293860 1.150490341 2.138367952
## 68 2.591439936 3.279078519 2.098619019 2.551889716 1.042470721 2.064650710
## 69 2.265364147 2.932450635 1.660764516 1.186684643 1.142441187 0.366846157
```

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## 70 1.486732724 2.328400765 1.233884283 1.227358771 0.820671630 0.952513100
## 71 1.897764450 2.158868244 1.253181239 1.191276379 1.794074404 1.087479775
## 72 3.006286874 3.589061920 2.251817025 2.292947345 1.296780979 1.729108722
## 73 1.709296104 2.101830594 1.971061624 2.801914291 1.829161708 2.348535717
## 74 2.044273849 2.460707195 2.330368827 3.111843491 2.024943317 2.498770854
## 75 4.398903670 4.926723458 4.318372866 4.856083406 3.337220043 4.110320093
## 76 3.703406127 4.163801859 3.124576529 3.108131182 2.305556572 2.528893106
## 77 4.195791218 4.596886856 3.462679333 3.177179899 2.787003460 2.660854386
##             67          68          69          70          71          72
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## 68 0.118884044
## 69 1.816079313 1.748291137
## 70 1.890990303 1.797725887 1.009862978
## 71 2.638167256 2.558315762 1.253332299 1.400982518
## 72 1.137734029 1.096869008 1.403500605 1.879934986 2.232711708
## 73 2.308307414 2.255625365 2.319091350 1.750706986 2.232024345 2.507597138
## 74 2.223434064 2.203417831 2.417555589 2.020248108 2.504945511 2.543584321
## 75 2.631152816 2.694919346 3.851595747 3.824003657 4.526853396 2.998835778
## 76 2.390503218 2.352586718 2.364090048 2.613916919 2.839243188 1.584090006
## 77 2.916247305 2.878640812 2.523028124 3.023244005 2.933347857 1.867778663
##             73          74          75          76
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## 74 0.678252363
## 75 3.049481929 2.677016270
## 76 2.598056339 2.721610034 2.847895207
## 77 3.296296040 3.424527892 3.606618811 0.927354713
```

```
head(dist.ecul_cereals_cluster2.scaled)
```

```
## [1] 1.590728 1.538944 1.451929 1.865864 1.751992 1.976624
```

```
str(dist.ecul_cereals_cluster2.scaled)
```

```
##  'dist' num [1:2926] 1.59 1.54 1.45 1.87 1.75 ...
##  - attr(*, "Size")= int 77
##  - attr(*, "Labels")= chr [1:77] "1" "2" "3" "4" ...
##  - attr(*, "Diag")= logi FALSE
##  - attr(*, "Upper")= logi FALSE
##  - attr(*, "method")= chr "euclidean"
##  - attr(*, "call")= language dist(x = cereals_cluster2.scaled, method =
"euclidean")
```

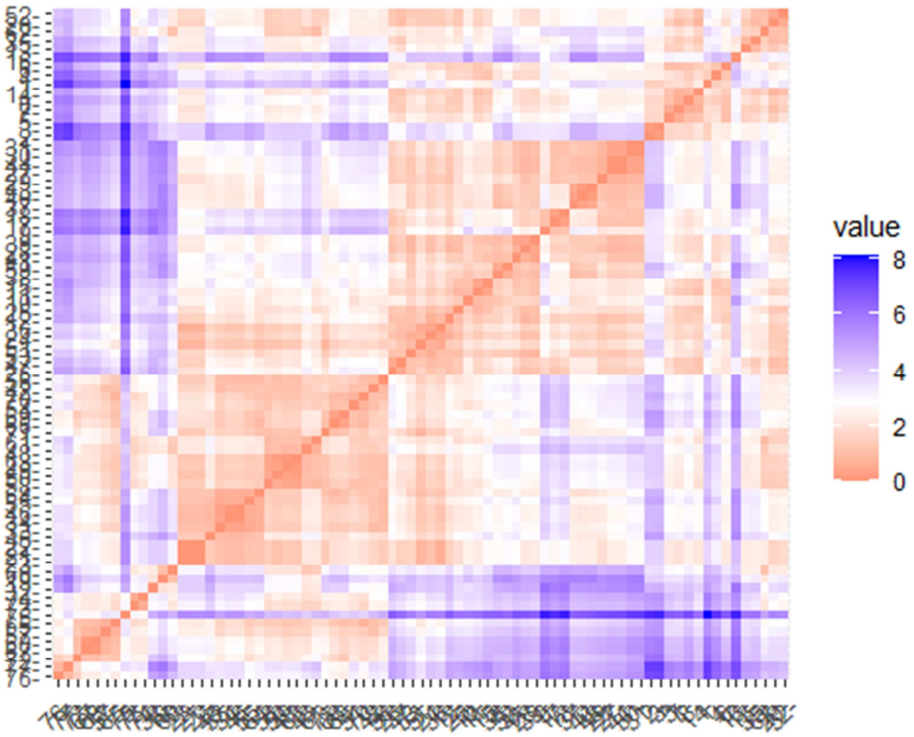
```
class(dist.ecul_cereals_cluster2.scaled)
```

```
## [1] "dist"
```

```
round(as.matrix(dist.ecul_cereals_cluster2.scaled)[1:3,1:3],1) #Show only
three products
```

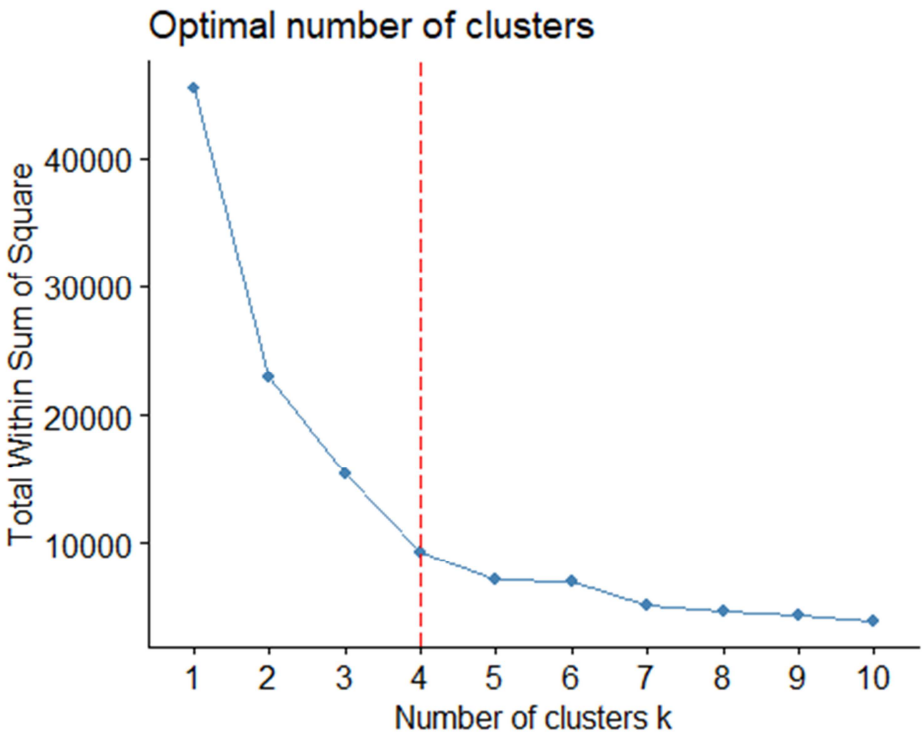
```
##     1   2   3
## 1 0.0 1.6 1.5
## 2 1.6 0.0 0.2
## 3 1.5 0.2 0.0
```

```
#-----Dissimilarity matrix----
#Darker color: Higher Distance ; Light Color:Lesser Distance
fviz_dist(dist.ecul_cereals_cluster2.scaled)
```

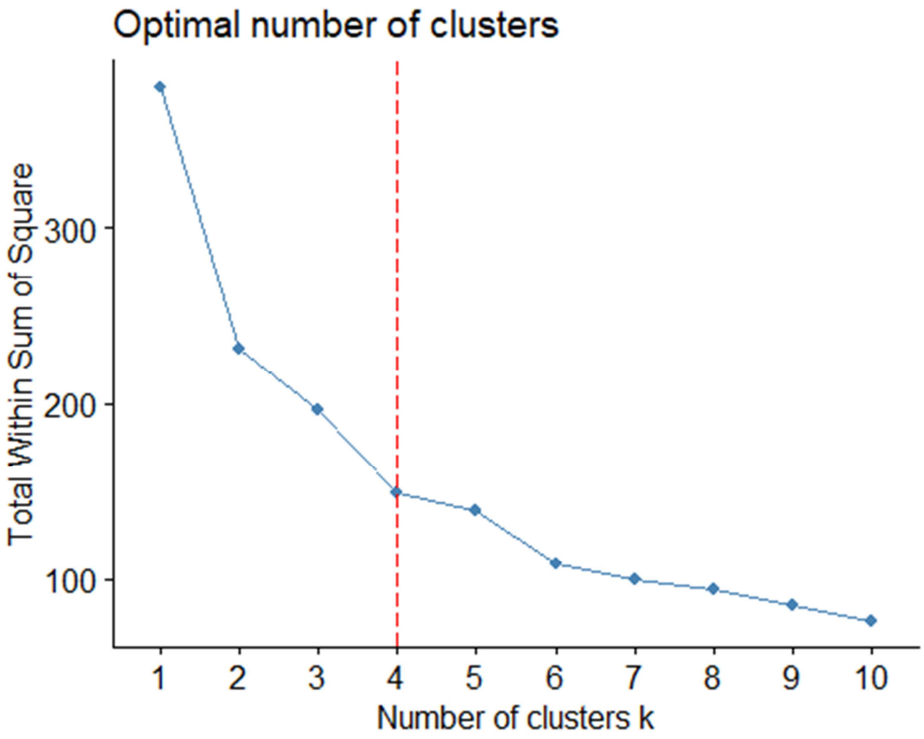



```
#----Optimum number of clusters----

fviz_nbclust(cereals_cluster2, kmeans ,method = 'wss')+
  geom_vline(xintercept = 4 , linetype = 5 , col="red" )
```




```
fviz_nbclust(cereals_cluster2.scaled, kmeans ,method = 'wss')+
  geom_vline(xintercept = 4, linetype = 5 , col="red" )
```



```r
#-----Apply Kmeans----
set.seed(123)
km.cereal<-kmeans(cereals_cluster2.scaled,4,nstart = 20)
km.cereal
```

```
## K-means clustering with 4 clusters of sizes 26, 25, 16, 10
##
## Cluster means:
##     Calories     Protein         Fat      Sugar     Rating
## 1  0.3178900 -0.70901630 -0.01290349  1.0523583 -0.8935153
## 2 -0.2300908  0.04982277 -0.52955941 -0.6799502  0.3309871
## 3  0.8977508  0.87189842  1.35325397  0.1631212 -0.2145661
## 4 -1.6876882  0.32384799 -0.80775875 -1.2972500  1.8389778
##
## Clustering vector:
##  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25
26
##  3  3  3  1  3  3  3  3  1  1  1  1  3  3  1  3  1  1  3  3  2  2  2  1  1
1
## 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50 51
52
##  1  1  1  1  1  2  2  2  3  2  1  1  1  1  1  2  1  1  2  2  1  2  2  2  2
3
## 53 54 55 56 57 58 59 60 61 62 63 64 65 66 67 68 69 70 71 72 73 74 75 76 77
##  1  2  2  2  4  2  1  3  2  3  2  2  4  2  4  4  2  2  2  4  4  4  4  4  4
##
## Within cluster sum of squares by cluster:
## [1] 40.16931 37.76791 46.99282 24.89775
##  (between_SS / total_SS =  60.6 %)
##
## Available components:
##
## [1] "cluster"      "centers"      "totss"        "withinss"
"tot.withinss"
## [6] "betweenss"    "size"         "iter"         "ifault"
```

```r
km.cereal$cluster
```

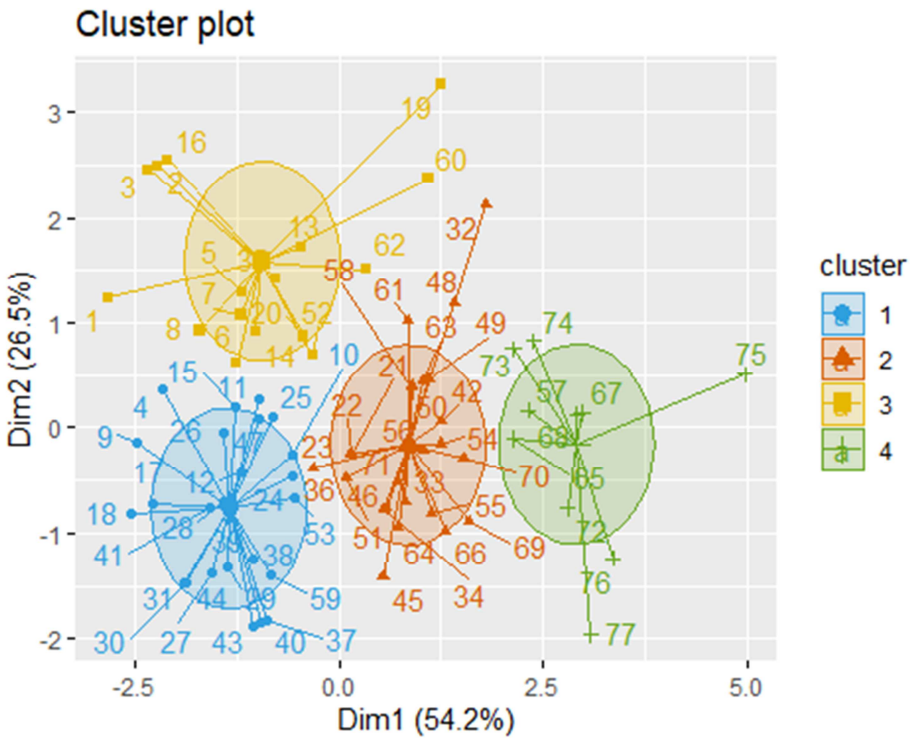
```
##  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25
26
##  3  3  3  1  3  3  3  3  1  1  1  1  3  3  1  3  1  1  3  3  2  2  2  1  1
1
## 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50 51
52
##  1  1  1  1  1  2  2  2  3  2  1  1  1  1  1  2  1  1  2  2  1  2  2  2  2
3
## 53 54 55 56 57 58 59 60 61 62 63 64 65 66 67 68 69 70 71 72 73 74 75 76 77
##  1  2  2  2  4  2  1  3  2  3  2  2  4  2  4  4  2  2  2  4  4  4  4  4  4
```

```r
km.cereal$totss
```

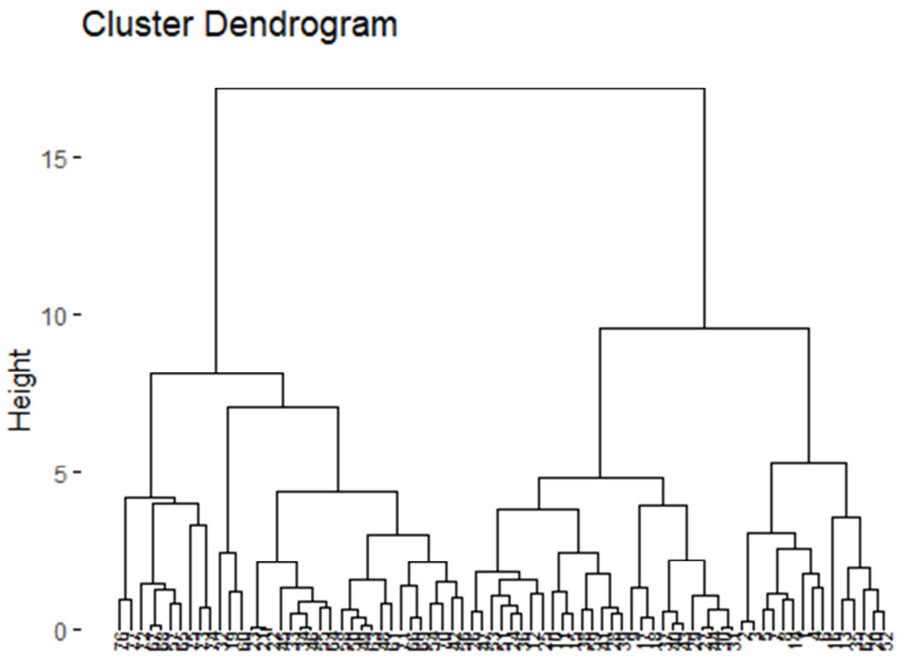
```
## [1] 380

km.cereal$centers

##     Calories     Protein         Fat      Sugar     Rating
## 1  0.3178900 -0.70901630 -0.01290349  1.0523583 -0.8935153
## 2 -0.2300908  0.04982277 -0.52955941 -0.6799502  0.3309871
## 3  0.8977508  0.87189842  1.35325397  0.1631212 -0.2145661
## 4 -1.6876882  0.32384799 -0.80775875 -1.2972500  1.8389778

km.cereal$size

## [1] 26 25 16 10

km.cereal$betweenss

## [1] 230.1722

aggregate(cereals_cluster1, by = list(km.cereal$cluster), mean)

##   Group.1 Calories  Protein   Fat    Sugar   Rating
## 1       1 113.0769 1.769231 1.000 11.57692 30.11385
## 2       2 102.4000 2.600000 0.480  4.00000 47.31480
## 3       3 124.3750 3.500000 2.375  7.68750 39.65125
## 4       4  74.0000 2.900000 0.200  1.30000 68.49800

km.cereal$cluster

##  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25
26
##  3  3  3  1  3  3  3  3  1  1  1  1  3  3  1  3  1  1  3  3  2  2  2  1  1
1
## 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50 51
52
##  1  1  1  1  1  2  2  2  3  2  1  1  1  1  1  2  1  1  2  2  1  2  2  2  2
3
## 53 54 55 56 57 58 59 60 61 62 63 64 65 66 67 68 69 70 71 72 73 74 75 76 77
##  1  2  2  2  4  2  1  3  2  3  2  2  4  2  4  4  2  2  2  4  4  4  4  4  4

cereals_cluster<-cbind(cereals_cluster1,cluster = km.cereal$cluster)
head(cereals_cluster)

##   Calories Protein Fat Sugar Rating cluster
## 1      160       3   2    13  30.31       3
## 2      150       4   3    11  37.14       3
## 3      150       4   3    11  34.14       3
## 4      140       3   1    14  28.59       1
## 5      140       3   2     7  40.69       3
## 6      140       3   1     9  36.47       3

head(cereals_cluster)
```

```
##   Calories Protein Fat Sugar Rating cluster
## 1      160       3   2    13  30.31       3
## 2      150       4   3    11  37.14       3
## 3      150       4   3    11  34.14       3
## 4      140       3   1    14  28.59       1
## 5      140       3   2     7  40.69       3
## 6      140       3   1     9  36.47       3
```

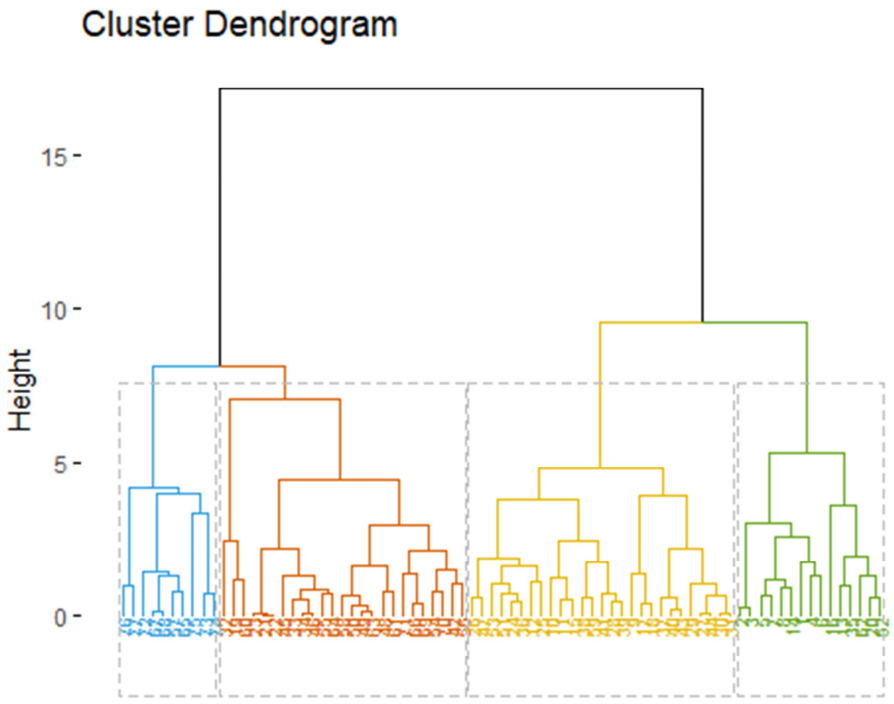
```
#write.csv(km.cereal,"km.cereal.csv")
#----Kmeans cluster plot---
fviz_cluster(km.cereal, data = cereals_cluster2.scaled, palette =
c("#2E9FDF","#D95F02","#E7B800","#66A61E"),
             ellipse.type = "euclid",
             star.plot = TRUE,
             repel = TRUE,
             ggtheme = theme())
```



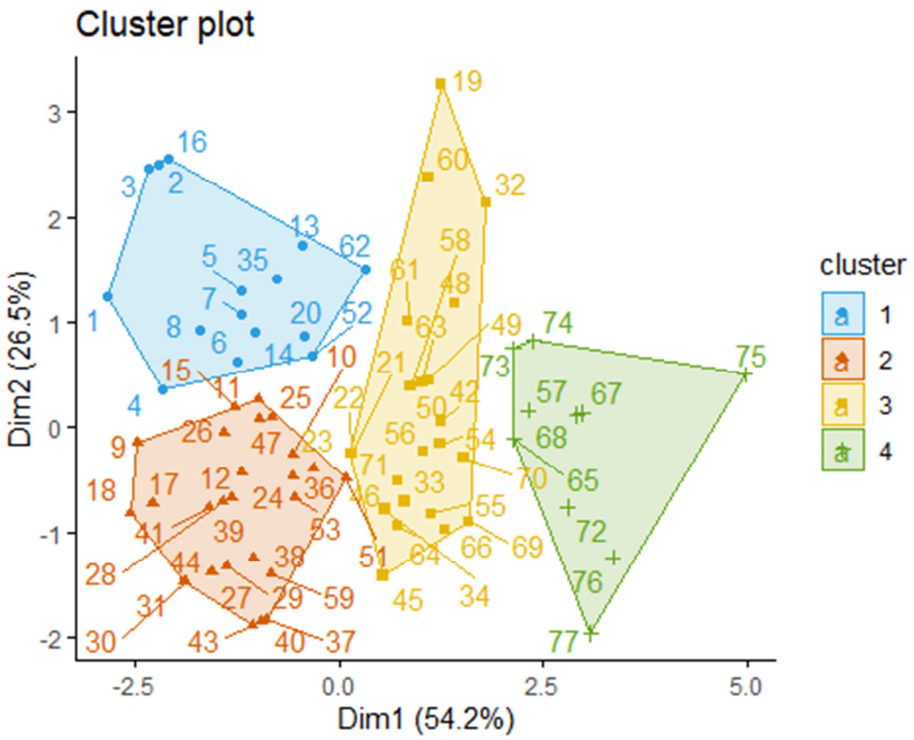

```
#-----Hierarchical Clustering: (Agglomeration) Linkage Methods----
cereals_cluster3<-hclust(d =dist.ecul_cereals_cluster2.scaled, method =
"ward.D2")
#-----Cluster Dendrogram--Black and White---
fviz_dend(cereals_cluster3, cex = 0.5)
```



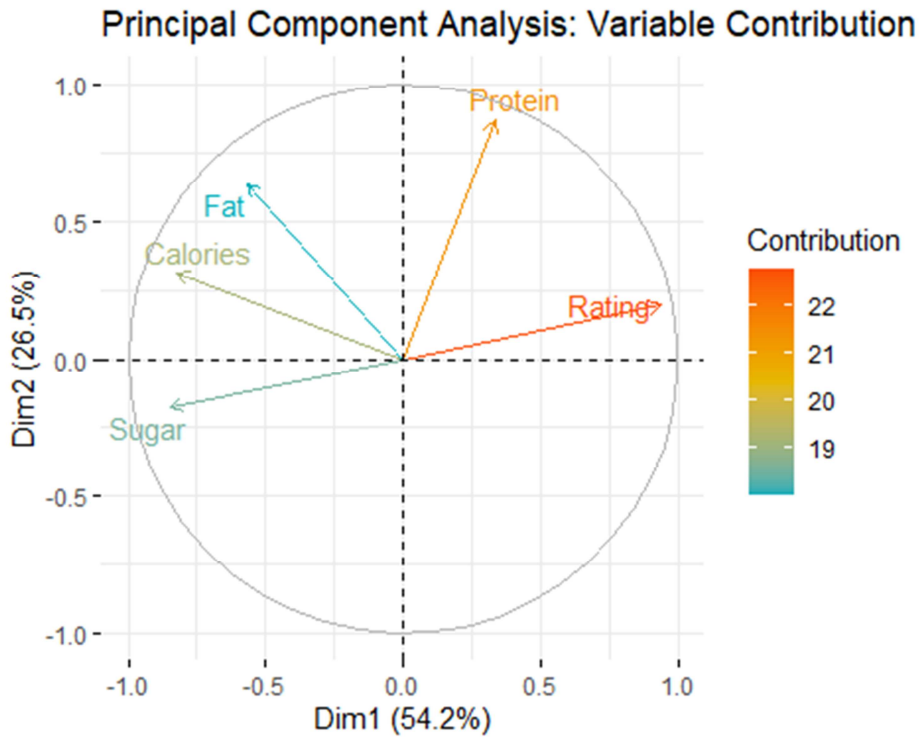

```
#-----Cluster Dendrogram--coloured---
fviz_dend(cereals_cluster3, k=4 ,cex=0.5 , k_colors =
c("#2E9FDF","#D95F02","#E7B800","#66A61E"),
          color_labels_by_k = TRUE,
          rect = TRUE)
```




```
#------Cut tree-----another way to represent cluster plot---
cereals_cluster4<- cutree(cereals_cluster3, k=4)
head(cereals_cluster4, n=4)

## 1 2 3 4
## 1 1 1 1

table(cereals_cluster4)

## cereals_cluster4
##  1  2  3  4
## 15 27 25 10

rownames(cereals_cluster2.scaled)[cereals_cluster4==1]

##  [1] "1"  "2"  "3"  "4"  "5"  "6"  "7"  "8"  "13" "14" "16" "20" "35" "52"
"62"

fviz_cluster(list(data = cereals_cluster2.scaled, cluster =
cereals_cluster4),
             palette = c("#2E9FDF","#D95F02","#E7B800","#66A61E"),
             ellipse = TRUE,
             ellipse.type = "convex",
             repel = TRUE,
             show.clust.cent = FALSE,
             ggtheme = theme_classic())
```




```
#-----Principal component analysis-PCA Plot----
PCA_data<-cereals_cluster1

PCA_cereals <- prcomp(PCA_data[], scale. = T)
summary(PCA_cereals)

## Importance of components:
##                           PC1    PC2    PC3    PC4    PC5
## Standard deviation     1.6458 1.1517 0.7078 0.5886 0.3428
## Proportion of Variance 0.5417 0.2653 0.1002 0.0693 0.0235
## Cumulative Proportion  0.5417 0.8070 0.9072 0.9765 1.0000

fviz_pca_var(PCA_cereals,
             col.var = "contrib",
             repel = T,
             gradient.cols = c("#00AFBB", "#E7B800", "#FC4E07"),
             title = "Principal Component Analysis: Variable Contribution",
             legend.title = "Contribution"
)
```




```
library(RColorBrewer)
library(wordcloud)
library(wordcloud2)
library(stringr)
library(stringi)
library(NLP)
library(tm)
library(qdap)
```

```
## Loading required package: qdapDictionaries
```

```
## Loading required package: qdapRegex
```

```
## Loading required package: qdapTools
```

```
##
## Attaching package: 'qdap'
```

```
## The following objects are masked from 'package:tm':
##
##     as.DocumentTermMatrix, as.TermDocumentMatrix
```

```
## The following object is masked from 'package:NLP':
##
##     ngrams
```

```
## The following object is masked from 'package:stringr':
##
##     %>%

## The following object is masked from 'package:base':
##
##     Filter

library(qdapDictionaries)

# install.packages("rlang")
x<-readLines("cereals_wordcloud_final.txt")
nchar(x)

##  [1] 459 301 290 318  69 185 167 160 186 151 142 160 112 141 310 187  83
143 143
## [20]   6 334  70  72  71  15  88  82  84  92  78  91  71  84  72  84  95
62  74
## [39]  78  82  86 150  94 105  81  88  87 110  96  97  76  48  58  48  35
134  60
## [58]  55  54  65  66 767 260  35   7  20  50  34  42  23  23  43  60  14
57   7
## [77]   5 112  55  71  59   5 281   0   0   0   0

x<-tolower(x)
#casefold(s,upper=T)
#S<-toupper(s)
#S
x<-paste(x,collapse = " ")
x

## [1] "breakfast breakfast breakfast breakfast breakfast breakfast breakfast
breakfast breakfast breakfast breakfast breakfast breakfast breakfast
breakfast breakfast breakfast breakfast breakfast breakfast breakfast
breakfast breakfast breakfast breakfast breakfast breakfast breakfast
breakfast breakfast breakfast breakfast breakfast breakfast breakfast
breakfast breakfast breakfast breakfast breakfast breakfast breakfast
breakfast breakfast breakfast breakfast cereal cereal cereal  cereal  cereal
cereal  cereal  cereal  cereal  cereal  cereal  cereal  cereal  cereal
cereal  cereal  cereal  cereal  cereal  cereal  cereal cereal cereal cereal
cereal  cereal cereal  cereal  cereal cereal cereal cereal cereal cereal
cereal cereal cereal cereal cereal cereal delicious delicious delicious
delicious delicious delicious delicious delicious delicious delicious
delicious delicious delicious delicious delicious delicious delicious
delicious delicious delicious delicious delicious delicious delicious
delicious delicious delicious delicious delicious  nutritious nutritious
nutritious nutritious nutritious nutritious nutritious nutritious nutritious
nutritious nutritious nutritious nutritious nutritious nutritious nutritious
nutritious nutritious nutritious nutritious nutritious nutritious nutritious
nutritious nutritious nutritious nutritious nutritious nutritious  bowl
bowl   bowl   bowl   bowl   bowl   bowl   bowl   bowl   bowl  fitness fitness
```

fitness fitness fitness fitness fitness fitness fitness fitness fitness fitness fitness fitness fitness fitness fitness fitness fitness fitness fiber protein vitamins healthy lifestyle healthy lifestyle healthy lifestyle healthy lifestyle healthy lifestyle healthy lifestyle healthy lifestyle healthy lifestyle vegetarian vegetarian vegetarian vegetarian vegetarian vegetarian vegetarian vegetarian vegetarian vegetarian vegetarian vegetarian vegetarian vegetarian energy eating energy eating energy eating energy eating energy eating energy eating energy eating energy eating energy eating energy eating energy eating energy eating energy milk milk milk milk milk milk milk milk milk milk milk milk milk milk milk milk milk milk milk crunchy crunchy crunchy crunchy crunchy crispy,crispy,crispy,crispy,crispy,crispy, crispy,crispy,crispy,crispy,crispy,crispy,crispy,crispy, eating flakes freshness fruits grain eating flakes freshness fruits grain eating flakes freshness fruits grain eating flakes freshness fruits grain eating flakes freshness fruits grain eating flakes freshness fruits grain eating flakes freshness fruits grain natural fresh fresh fresh fresh fresh fresh fresh fresh fresh fresh fresh fresh fresh fresh variety variety variety variety variety variety variety variety variety variety variety variety variety variety variety variety variety meal organic meal organic meal organic meal organic meal organic meal organic meal organic meal organic meal organic meal organic meal organic meal organic muesli fruitss,flavours,strawberry,wheat,raisin,nuts,oats,rice,bran,honey,fruitss,flavours,strawberry,wheat,raisin,nuts,oats,rice,bran,honey,fruitss,flavours,strawberry,wheat,raisin,nuts,oats,rice,bran,honey,fruitss,flavours,strawberry,wheat,raisin,nuts,oats,rice,bran,honey,fruitss,flavours,strawberry,wheat,raisin,nuts,oats,rice,bran,honey snack snack snack snack snack snack snack snack snack snacksnack snack cereal is usually eat with milk, yogurt, fresh fruitss, nuts and seeds. cereal is made up from processed grain and is considered as a healthy early morning it is usually eat with milk, yogurt, fresh fruitss, nuts and seeds. you were unaware of this but cereal is often fortified with vitamins and minerals. this means that the nutritiouss are cereals to make it nutritious. cereals claim to be packed with essential vitamins and minerals. no doubt, they are a convenient option for both kids and adults. cereal are usually made up of corn, wheat, oats and rice. vitaamins, they healthy contain cereals nutritiouss like vitamins and minerals, salt, cereals sugar, preservatives, yeast, and some other flavorings to enhance the taste. some cereal healthy contains cereals nuts and dried fruitss, coated with chocolate. '' is one of the most important meals of the day. so your choice holds a lot of significerealce. must be a wholesome and balanced meal and should include all the important food

groups. we cereal include whole grains like wheat, millets, oats etc in our . not to forget, our must be freshly prepared from local and seasonal ingredients.'' she further adds, ''ready to eat cereals are laced with hidden sugars, chemical preservatives and various other additives. as a thumb rule, if the food comes from a plant, eat it; if it is manufactured in a plant, do not eat it! so ready to eat packaged cereals are best avoided. one cereal prepare one's own home - made muesli or granola.itâ\200\231s a well-known saying that is the most important meal of the day but, unlike many other sayings, this one is supported by scientific evidence. time and again, studies show that consumers are leaner, have lower cholesterol levels, and higher intakes of fibre, vitamins and minerals compared with people who do not consume . the reason is simple: the types of foods eat at time tend to be healthier and more nutritious-dense than foods eat at other times of the day. a great example of this is cereals. cereals are high carbohydrate, low fat foods that are often fortified with essential vitamins and minerals. with diets in europe still failing to meet targets for fibre and saturated fat, and certain groups of consumers, such as teenagers and young women, having inadequate intakes of some vitamins and minerals, cereals continue to play an important role in helping consumers of all ages move towards a healthy, balanced diet. eating contributes to cognitive performance â\200“ it improves concentration and fuels physical activity5,6,7 provides many nutritiousal and health benefits, eating a proper in the morning, cereals a healthy choice.cereals a healthy choice cereals a healthy choice cereals a healthy choice cereals a healthy choice they are made from grain; they are typically high in carbo - hydrates, low in fat, and often a good source of fibre. cereals are a â\200œnutritious denseâ\200\235 food, i.e. while supplying only a nutritious amount of energy (calories) they make a significerealt contribution to intakes of essential nutritiouss: carbohydrates, proteins, proteins, vitamins and minerals.carbohydrates, proteins, proteins, vitamins and minerals.carbohydrates, proteins, proteins, vitamins and minerals.carbohydrates, proteins, proteins, vitamins and minerals.carbohydrates, proteins, proteins, vitamins and minerals.carbohydrates, proteins, proteins, vitamins and minerals.carbohydrates, proteins, proteins, vitamins and minerals.carbohydrates, proteins, proteins, vitamins and minerals.carbohydrates, proteins, proteins, vitamins and minerals.carbohydrates, proteins, proteins, vitamins and minerals.carbohydrates, proteins, proteins, vitamins and minerals. essential nutritiouss essential nutritiouss essential nutritiouss essential nutritiouss essential nutritiouss essential nutritioussessential nutritioussessential nutritioussessential nutritiouss essential nutritioussessential nutritiouss essential nutritiouss maintain a healthy, balanced diet. cereal and oat variety of cereals, ranging from conventional cereals to oat flakes and varieties of mueslis. cereals cereal play an important diets and the nutritiousal status cereal consumers have , and are more likely to meet nutritiousal from nutritiouss such as vitamins , minerals and fibre than 1,2,3,23,24,29 more nutritious s, which

```
helps to develop good nutritious habits  24,26 cereal has always been part of
a healthy  and viewed as a nutritious morning food. after milling, cereal
grains, sugar and water are mixed together before being cooked. diet eating
flake food fresh freshness  fruits graing healthy lifestyle meal milk natural
nutritious oat organicvegetarian vitamins wheat bowl  cereal corn cornflakes
crisp crispy crunchy dairy delicious diet eating energy fitness flake flakes
food fresh freshness grain granola health healthy heap ingredient lifestyle
meal milk morning muesli natural nutritious organic snack spoon studio sweet
tasty vegetarian whole    "
```

```
nchar(x)
```

```
## [1] 9301
```

```
#library(tm)-text mining
#NLP-Natural language processing
stopwords()
```

```
##   [1] "i"          "me"         "my"         "myself"     "we"
##   [6] "our"        "ours"       "ourselves"  "you"        "your"
##  [11] "yours"      "yourself"   "yourselves" "he"         "him"
##  [16] "his"        "himself"    "she"        "her"        "hers"
##  [21] "herself"    "it"         "its"        "itself"     "they"
##  [26] "them"       "their"      "theirs"     "themselves" "what"
##  [31] "which"      "who"        "whom"       "this"       "that"
##  [36] "these"      "those"      "am"         "is"         "are"
##  [41] "was"        "were"       "be"         "been"       "being"
##  [46] "have"       "has"        "had"        "having"     "do"
##  [51] "does"       "did"        "doing"      "would"      "should"
##  [56] "could"      "ought"      "i'm"        "you're"     "he's"
##  [61] "she's"      "it's"       "we're"      "they're"    "i've"
##  [66] "you've"     "we've"      "they've"    "i'd"        "you'd"
##  [71] "he'd"       "she'd"      "we'd"       "they'd"     "i'll"
##  [76] "you'll"     "he'll"      "she'll"     "we'll"      "they'll"
##  [81] "isn't"      "aren't"     "wasn't"     "weren't"    "hasn't"
##  [86] "haven't"    "hadn't"     "doesn't"    "don't"      "didn't"
##  [91] "won't"      "wouldn't"   "shan't"     "shouldn't"  "can't"
##  [96] "cannot"     "couldn't"   "mustn't"    "let's"      "that's"
## [101] "who's"      "what's"     "here's"     "there's"    "when's"
## [106] "where's"    "why's"      "how's"      "a"          "an"
## [111] "the"        "and"        "but"        "if"         "or"
## [116] "because"    "as"         "until"      "while"      "of"
## [121] "at"         "by"         "for"        "with"       "about"
## [126] "against"    "between"    "into"       "through"    "during"
## [131] "before"     "after"      "above"      "below"      "to"
## [136] "from"       "up"         "down"       "in"         "out"
## [141] "on"         "off"        "over"       "under"      "again"
## [146] "further"    "then"       "once"       "here"       "there"
## [151] "when"       "where"      "why"        "how"        "all"
## [156] "any"        "both"       "each"       "few"        "more"
## [161] "most"       "other"      "some"       "such"       "no"
```

```
## [166] "nor"        "not"        "only"       "own"        "same"
## [171] "so"         "than"       "too"        "very"
```

```
sort(stopwords())
```

```
##   [1] "a"          "about"      "above"      "after"      "again"
##   [6] "against"    "all"        "am"         "an"         "and"
##  [11] "any"        "are"        "aren't"     "as"         "at"
##  [16] "be"         "because"    "been"       "before"     "being"
##  [21] "below"      "between"    "both"       "but"        "by"
##  [26] "can't"      "cannot"     "could"      "couldn't"   "did"
##  [31] "didn't"     "do"         "does"       "doesn't"    "doing"
##  [36] "don't"      "down"       "during"     "each"       "few"
##  [41] "for"        "from"       "further"    "had"        "hadn't"
##  [46] "has"        "hasn't"     "have"       "haven't"    "having"
##  [51] "he"         "he'd"       "he'll"      "he's"       "her"
##  [56] "here"       "here's"     "hers"       "herself"    "him"
##  [61] "himself"    "his"        "how"        "how's"      "i"
##  [66] "i'd"        "i'll"       "i'm"        "i've"       "if"
##  [71] "in"         "into"       "is"         "isn't"      "it"
##  [76] "it's"       "its"        "itself"     "let's"      "me"
##  [81] "more"       "most"       "mustn't"    "my"         "myself"
##  [86] "no"         "nor"        "not"        "of"         "off"
##  [91] "on"         "once"       "only"       "or"         "other"
##  [96] "ought"      "our"        "ours"       "ourselves"  "out"
## [101] "over"       "own"        "same"       "shan't"     "she"
## [106] "she'd"      "she'll"     "she's"      "should"     "shouldn't"
## [111] "so"         "some"       "such"       "than"       "that"
## [116] "that's"     "the"        "their"      "theirs"     "them"
## [121] "themselves" "then"       "there"      "there's"    "these"
## [126] "they"       "they'd"     "they'll"    "they're"    "they've"
## [131] "this"       "those"      "through"    "to"         "too"
## [136] "under"      "until"      "up"         "very"       "was"
## [141] "wasn't"     "we"         "we'd"       "we'll"      "we're"
## [146] "we've"      "were"       "weren't"    "what"       "what's"
## [151] "when"       "when's"     "where"      "where's"    "which"
## [156] "while"      "who"        "who's"      "whom"       "why"
## [161] "why's"      "with"       "won't"      "would"      "wouldn't"
## [166] "you"        "you'd"      "you'll"     "you're"     "you've"
## [171] "your"       "yours"      "yourself"   "yourselves"
```

```
Top200Words
```

```
##   [1] "the"       "of"        "and"       "a"         "to"        "in"
##   [7] "is"        "you"       "that"      "it"        "he"        "was"
##  [13] "for"       "on"        "are"       "as"        "with"      "his"
##  [19] "they"      "I"         "at"        "be"        "this"      "have"
##  [25] "from"      "or"        "one"       "had"       "by"        "word"
##  [31] "but"       "not"       "what"      "all"       "were"      "we"
##  [37] "when"      "your"      "can"       "said"      "there"     "use"
##  [43] "an"        "each"      "which"     "she"       "do"        "how"
```

```
##  [49] "their"     "if"        "will"      "up"        "other"     "about"
##  [55] "out"       "many"      "then"      "them"      "these"     "so"
##  [61] "some"      "her"       "would"     "make"      "like"      "him"
##  [67] "into"      "time"      "has"       "look"      "two"       "more"
##  [73] "write"     "go"        "see"       "number"    "no"        "way"
##  [79] "could"     "people"    "my"        "than"      "first"     "water"
##  [85] "been"      "call"      "who"       "oil"       "its"       "now"
##  [91] "find"      "long"      "down"      "day"       "did"       "get"
##  [97] "come"      "made"      "may"       "part"      "over"      "new"
## [103] "sound"     "take"      "only"      "little"    "work"      "know"
## [109] "place"     "year"      "live"      "me"        "back"      "give"
## [115] "most"      "very"      "after"     "thing"     "our"       "just"
## [121] "name"      "good"      "sentence"  "man"       "think"     "say"
## [127] "great"     "where"     "help"      "through"   "much"      "before"
## [133] "line"      "right"     "too"       "mean"      "old"       "any"
## [139] "same"      "tell"      "boy"       "follow"    "came"      "want"
## [145] "show"      "also"      "around"    "form"      "three"     "small"
## [151] "set"       "put"       "end"       "does"      "another"   "well"
## [157] "large"     "must"      "big"       "even"      "such"
"because"
## [163] "turn"      "here"      "why"       "ask"       "went"      "men"
## [169] "read"      "need"      "land"      "different" "home"      "us"
## [175] "move"      "try"       "kind"      "hand"      "picture"   "again"
## [181] "change"    "off"       "play"      "spell"     "air"       "away"
## [187] "animal"    "house"     "point"     "page"      "letter"    "mother"
## [193] "answer"    "found"     "study"     "still"     "learn"     "should"
## [199] "America"   "world"
```

```
sort(Top200Words)
```

```
##   [1] "a"         "about"     "after"     "again"     "air"       "all"
##   [7] "also"      "America"   "an"        "and"       "animal"
"another"
##  [13] "answer"    "any"       "are"       "around"    "as"        "ask"
##  [19] "at"        "away"      "back"      "be"        "because"   "been"
##  [25] "before"    "big"       "boy"       "but"       "by"        "call"
##  [31] "came"      "can"       "change"    "come"      "could"     "day"
##  [37] "did"       "different" "do"        "does"      "down"      "each"
##  [43] "end"       "even"      "find"      "first"     "follow"    "for"
##  [49] "form"      "found"     "from"      "get"       "give"      "go"
##  [55] "good"      "great"     "had"       "hand"      "has"       "have"
##  [61] "he"        "help"      "her"       "here"      "him"       "his"
##  [67] "home"      "house"     "how"       "I"         "if"        "in"
##  [73] "into"      "is"        "it"        "its"       "just"      "kind"
##  [79] "know"      "land"      "large"     "learn"     "letter"    "like"
##  [85] "line"      "little"    "live"      "long"      "look"      "made"
##  [91] "make"      "man"       "many"      "may"       "me"        "mean"
##  [97] "men"       "more"      "most"      "mother"    "move"      "much"
## [103] "must"      "my"        "name"      "need"      "new"       "no"
## [109] "not"       "now"       "number"    "of"        "off"       "oil"
```

```
## [115] "old"       "on"        "one"       "only"      "or"        "other"
## [121] "our"       "out"       "over"      "page"      "part"      "people"
## [127] "picture"   "place"     "play"      "point"     "put"       "read"
## [133] "right"     "said"      "same"      "say"       "see"
"sentence"
## [139] "set"       "she"       "should"    "show"      "small"     "so"
## [145] "some"      "sound"     "spell"     "still"     "study"     "such"
## [151] "take"      "tell"      "than"      "that"      "the"       "their"
## [157] "them"      "then"      "there"     "these"     "they"      "thing"
## [163] "think"     "this"      "three"     "through"   "time"      "to"
## [169] "too"       "try"       "turn"      "two"       "up"        "us"
## [175] "use"       "very"      "want"      "was"       "water"     "way"
## [181] "we"        "well"      "went"      "were"      "what"      "when"
## [187] "where"     "which"     "who"       "why"       "will"      "with"
## [193] "word"      "work"      "world"     "would"     "write"     "year"
## [199] "you"       "your"
```

```
x<-removeWords(x,stopwords())
nchar(x)
```

```
## [1] 8591
```

```
x<-gsub(pattern = "\\W", replace = " ",x)
x
```

```
## [1] "breakfast breakfast breakfast breakfast breakfast breakfast breakfast
breakfast breakfast breakfast breakfast breakfast breakfast breakfast breakfast
breakfast breakfast breakfast breakfast breakfast breakfast breakfast breakfast
breakfast breakfast breakfast breakfast breakfast breakfast breakfast breakfast
breakfast breakfast breakfast breakfast breakfast breakfast breakfast breakfast
breakfast breakfast breakfast breakfast breakfast breakfast breakfast breakfast
breakfast breakfast breakfast breakfast cereal cereal cereal  cereal  cereal
cereal  cereal  cereal  cereal  cereal  cereal  cereal  cereal  cereal  cereal
cereal  cereal  cereal  cereal  cereal  cereal  cereal cereal cereal cereal
cereal  cereal cereal  cereal  cereal cereal cereal cereal cereal cereal
cereal cereal cereal cereal cereal cereal delicious delicious delicious
delicious delicious delicious delicious delicious delicious delicious
delicious delicious delicious delicious delicious delicious delicious
delicious delicious delicious delicious delicious delicious delicious
delicious delicious delicious delicious delicious  nutritious nutritious
nutritious nutritious nutritious nutritious nutritious nutritious nutritious
nutritious nutritious nutritious nutritious nutritious nutritious nutritious
nutritious nutritious nutritious nutritious nutritious nutritious nutritious
nutritious nutritious nutritious nutritious nutritious nutritious  bowl
bowl   bowl   bowl   bowl   bowl   bowl   bowl   bowl   bowl  fitness fitness
fitness fitness fitness fitness fitness fitness fitness fitness fitness
fitness fitness fitness fitness fitness  fitness fitness fitness fitness
fitness fitness fitness  fiber fiber fiber fiber fiber fiber fiber fiber
fiber fiber fiber fiber fiber fiber fiber fiber fiber fiber fiber fiber fiber
fiber fiber fiber fiber fiber fiber fiber protein protein protein protein
protein protein protein protein protein protein protein protein protein
```

protein protein protein protein protein protein protein vitamins vitamins vitamins vitamins vitamins vitamins vitamins vitamins vitamins vitamins vitamins vitamins vitamins vitamins vitamins vitamins vitamins vitamins healthy lifestyle healthy lifestyle healthy lifestyle healthy lifestyle healthy lifestyle healthy lifestyle healthy lifestyle healthy lifestyle vegetarian vegetarian vegetarian vegetarian vegetarian vegetarian vegetarian vegetarian vegetarian vegetarian vegetarian vegetarian vegetarian vegetarian energy eating energy eating energy eating energy eating energy eating energy eating energy eating energy eating energy eating energy eating energy eating energy eating energy eating energy milk milk milk milk milk milk milk milk milk milk milk milk milk milk milk milk milk milk milk crunchy crunchy crunchy crunchy crunchy crispy crispy crispy crispy crispy crispy crispy crispy crispy crispy crispy crispy crispy crispy crispy crispy crispy eating flakes freshness fruits grain eating flakes freshness fruits grain eating flakes freshness fruits grain eating flakes freshness fruits grain eating flakes freshness fruits grain eating flakes freshness fruits grain eating flakes freshness fruits grain eating flakes freshness fruits grain natural fresh fresh fresh fresh fresh fresh fresh fresh fresh fresh fresh fresh fresh fresh fresh fresh fresh variety meal organic meal organic meal organic meal organic meal organic meal organic meal organic meal organic meal organic meal organic meal organic meal organic meal organic meal organic meal organic meal organic muesli fruitss flavours strawberry wheat raisin nuts oats rice bran honey fruitss flavours strawberry wheat raisin nuts oats rice bran honey fruitss flavours strawberry wheat raisin nuts oats rice bran honey fruitss flavours strawberry wheat raisin nuts oats rice bran honey fruitss flavours strawberry wheat raisin nuts oats rice bran honey snack snack snack snack snack snack snack snack snack snacksnack snack cereal usually eat milk yogurt fresh fruitss nuts seeds cereal made processed grain considered healthy early morning usually eat milk yogurt fresh fruitss nuts seeds unaware cereal often fortified vitamins minerals means nutritiouss cereals make nutritious cereals claim packed essential vitamins minerals doubt convenient option kids adults cereal usually made corn wheat oats rice vitaamins healthy contain cereals nutritiouss like vitamins minerals salt cereals sugar preservatives yeast flavorings enhance taste cereal healthy contains cereals nuts dried fruitss coated chocolate one important meals day choice holds lot significerealce must wholesome balanced meal include important food groups cereal include whole grains like wheat millets oats etc forget must freshly prepared local seasonal ingredients adds ready eat cereals laced hidden sugars chemical preservatives various additives thumb rule food comes plant eat manufactured plant eat ready eat packaged cereals best avoided one cereal prepare one s home made muesli granola itâ s well known saying important meal day unlike many sayings one supported scientific evidence time studies show consumers leaner lower cholesterol levels higher intakes fibre vitamins minerals compared people consume reason simple types foods eat time tend

```
healthier   nutritious dense  foods eat   times   day   great example
cereals   cereals  high carbohydrate  low fat foods   often fortified
essential vitamins    minerals   diets  europe still failing  meet targets
fibre  saturated fat   certain groups  consumers    teenagers  young women
inadequate intakes   vitamins    minerals   cereals continue  play  important
role  helping consumers   ages move towards  healthy  balanced diet  eating
contributes  cognitive performance â    improves concentration  fuels
physical activity5 6 7  provides many nutritiousal  health benefits  eating
proper    morning   cereals   healthy  choice cereals   healthy  choice
cereals   healthy  choice cereals   healthy  choice cereals   healthy  choice
made  grain    typically high  carbo   hydrates  low  fat   often  good
source  fibre   cereals   â  nutritious denseâ   food   e   supplying
nutritious amount  energy  calories   make  significerealt contribution
intakes  essential nutritiouss  carbohydrates  proteins  proteins  vitamins
minerals carbohydrates  proteins  proteins  vitamins    minerals
carbohydrates  proteins  proteins  vitamins    minerals carbohydrates
proteins  proteins  vitamins    minerals carbohydrates  proteins  proteins
vitamins    minerals carbohydrates  proteins  proteins  vitamins    minerals
carbohydrates  proteins  proteins  vitamins    minerals carbohydrates
proteins  proteins  vitamins    minerals carbohydrates  proteins  proteins
vitamins    minerals carbohydrates  proteins  proteins  vitamins    minerals
carbohydrates  proteins  proteins  vitamins    minerals carbohydrates
proteins  proteins  vitamins    minerals carbohydrates  proteins  proteins
vitamins    minerals  essential nutritiouss essential nutritiouss essential
nutritiouss essential nutritiouss essential nutritiouss essential
nutritioussessential nutritioussessential nutritioussessential nutritiouss
essential nutritioussessential nutritiouss essential nutritiouss  maintain
healthy  balanced diet    cereal  oat  variety   cereals  ranging
conventional  cereals  oat flakes  varieties  mueslis    cereals cereal play
important diets   nutritiousal status  cereal consumers        likely  meet
nutritiousal   nutritiouss   vitamins    minerals  fibre  1 2 3 23 24 29
nutritious s   helps  develop good nutritious habits  24 26 cereal  always
part   healthy   viewed   nutritious morning food   milling  cereal grains
sugar  water  mixed together   cooked  diet eating flake food fresh freshness
fruits graing healthy lifestyle meal milk natural nutritious oat
organicvegetarian vitamins wheat bowl  cereal corn cornflakes crisp crispy
crunchy dairy delicious diet eating energy fitness flake flakes food fresh
freshness grain granola health healthy heap ingredient lifestyle meal milk
morning muesli natural nutritious organic snack spoon studio sweet tasty
vegetarian whole    "

x<-gsub(pattern = "\\d", replace = " ",x)
#initiate library(qdap) ; replace_number(x) in case we donot want to delete
numbers.
x

## [1] "breakfast breakfast breakfast breakfast breakfast breakfast breakfast
breakfast breakfast breakfast breakfast breakfast breakfast breakfast
breakfast breakfast breakfast breakfast breakfast breakfast breakfast
breakfast breakfast breakfast breakfast breakfast breakfast breakfast
```

breakfast breakfast breakfast breakfast breakfast breakfast breakfast breakfast breakfast breakfast breakfast breakfast breakfast breakfast breakfast breakfast breakfast breakfast cereal delicious nutritious bowl bowl bowl bowl bowl bowl bowl bowl bowl bowl fitness fiber protein vitamins vitamins vitamins vitamins vitamins vitamins vitamins vitamins vitamins vitamins vitamins vitamins vitamins vitamins vitamins vitamins vitamins healthy lifestyle healthy lifestyle healthy lifestyle healthy lifestyle healthy lifestyle healthy lifestyle healthy lifestyle healthy lifestyle vegetarian vegetarian vegetarian vegetarian vegetarian vegetarian vegetarian vegetarian vegetarian vegetarian vegetarian vegetarian vegetarian energy eating energy eating energy eating energy eating energy eating energy eating energy eating energy eating energy eating energy eating energy eating energy milk milk milk milk milk milk milk milk milk milk milk milk milk milk milk milk milk milk milk crunchy crunchy crunchy crunchy crunchy crispy crispy crispy crispy crispy crispy crispy crispy crispy crispy crispy crispy crispy crispy eating flakes freshness fruits grain eating flakes freshness fruits grain eating flakes freshness fruits grain eating flakes freshness fruits grain eating flakes freshness fruits grain eating flakes freshness fruits grain eating flakes freshness fruits grain eating flakes freshness fruits grain natural fresh fresh fresh fresh fresh fresh fresh fresh fresh fresh fresh fresh fresh fresh variety variety variety variety variety variety variety variety variety variety variety variety variety variety variety variety variety variety meal organic meal organic meal organic meal organic meal organic meal organic meal organic meal organic meal organic meal organic meal organic muesli fruitss flavours strawberry wheat raisin nuts oats rice bran honey fruitss flavours strawberry wheat raisin nuts oats rice bran honey fruitss flavours strawberry wheat raisin nuts oats rice bran honey fruitss flavours strawberry wheat raisin nuts oats rice bran honey fruitss flavours

strawberry wheat raisin nuts oats rice bran honey snack snack snack snack snack snack snack snack snack snacksnack snack cereal usually eat milk yogurt fresh fruitss nuts seeds cereal made processed grain considered healthy early morning usually eat milk yogurt fresh fruitss nuts seeds unaware cereal often fortified vitamins minerals means nutritiouss cereals make nutritious cereals claim packed essential vitamins minerals doubt convenient option kids adults cereal usually made corn wheat oats rice vitaamins healthy contain cereals nutritiouss like vitamins minerals salt cereals sugar preservatives yeast flavorings enhance taste cereal healthy contains cereals nuts dried fruitss coated chocolate one important meals day choice holds lot significerealce must wholesome balanced meal include important food groups cereal include whole grains like wheat millets oats etc forget must freshly prepared local seasonal ingredients adds ready eat cereals laced hidden sugars chemical preservatives various additives thumb rule food comes plant eat manufactured plant eat ready eat packaged cereals best avoided one cereal prepare one s home made muesli granola itâ s well known saying important meal day unlike many sayings one supported scientific evidence time studies show consumers leaner lower cholesterol levels higher intakes fibre vitamins minerals compared people consume reason simple types foods eat time tend healthier nutritious dense foods eat times day great example cereals cereals high carbohydrate low fat foods often fortified essential vitamins minerals diets europe still failing meet targets fibre saturated fat certain groups consumers teenagers young women inadequate intakes vitamins minerals cereals continue play important role helping consumers ages move towards healthy balanced diet eating contributes cognitive performance â improves concentration fuels physical activity provides many nutritiousal health benefits eating proper morning cereals healthy choice cereals healthy choice cereals healthy choice cereals healthy choice made grain typically high carbo hydrates low fat often good source fibre cereals â nutritious denseâ food e supplying nutritious amount energy calories make significerealt contribution intakes essential nutritiouss carbohydrates proteins proteins vitamins minerals carbohydrates proteins proteins vitamins minerals carbohydrates proteins proteins vitamins minerals carbohydrates proteins proteins vitamins minerals carbohydrates proteins proteins vitamins minerals carbohydrates proteins proteins vitamins minerals carbohydrates proteins proteins vitamins minerals carbohydrates proteins proteins vitamins minerals carbohydrates proteins proteins vitamins minerals carbohydrates proteins proteins vitamins minerals carbohydrates proteins proteins vitamins minerals essential nutritiouss essential nutritiouss essential nutritiouss essential nutritiouss essential nutritiouss essential nutritioussessential nutritioussessential nutritioussessential nutritiouss essential nutritioussessential nutritiouss essential nutritiouss maintain healthy balanced diet cereal oat variety cereals ranging

```
conventional  cereals  oat flakes  varieties  mueslis    cereals cereal play
important diets   nutritiousal status  cereal consumers        likely  meet
nutritiousal   nutritiouss   vitamins    minerals  fibre
nutritious s   helps  develop good nutritious habits        cereal  always
part   healthy   viewed   nutritious morning food   milling  cereal grains
sugar  water  mixed together   cooked  diet eating flake food fresh freshness
fruits graing healthy lifestyle meal milk natural nutritious oat
organicvegetarian vitamins wheat bowl  cereal corn cornflakes crisp crispy
crunchy dairy delicious diet eating energy fitness flake flakes food fresh
freshness grain granola health healthy heap ingredient lifestyle meal milk
morning muesli natural nutritious organic snack spoon studio sweet tasty
vegetarian whole    "

#\\b is boundary and b{1} is single character
x<-gsub(pattern = "\\b[a-z]\\b{1}", replace = " ",x)
x

## [1] "breakfast breakfast breakfast breakfast breakfast breakfast breakfast
breakfast breakfast breakfast breakfast breakfast breakfast breakfast breakfast
breakfast breakfast breakfast breakfast breakfast breakfast breakfast
breakfast breakfast breakfast breakfast breakfast breakfast breakfast
breakfast breakfast breakfast breakfast breakfast breakfast breakfast
breakfast breakfast breakfast breakfast breakfast breakfast breakfast
breakfast breakfast breakfast breakfast cereal cereal cereal  cereal  cereal
cereal  cereal  cereal  cereal  cereal  cereal  cereal  cereal  cereal  cereal
cereal  cereal  cereal  cereal  cereal  cereal  cereal cereal cereal cereal
cereal  cereal cereal  cereal  cereal cereal cereal cereal cereal cereal
cereal cereal cereal cereal cereal cereal delicious delicious delicious
delicious delicious delicious delicious delicious delicious delicious
delicious delicious delicious delicious delicious delicious delicious
delicious delicious delicious delicious delicious delicious delicious
delicious delicious delicious delicious delicious  nutritious nutritious
nutritious nutritious nutritious nutritious nutritious nutritious nutritious
nutritious nutritious nutritious nutritious nutritious nutritious nutritious
nutritious nutritious nutritious nutritious nutritious nutritious nutritious
nutritious nutritious nutritious nutritious nutritious nutritious  bowl
bowl   bowl   bowl   bowl   bowl   bowl   bowl   bowl   bowl  fitness fitness
fitness fitness fitness fitness fitness fitness fitness fitness fitness
fitness fitness fitness fitness fitness  fitness fitness fitness fitness
fitness fitness fitness  fiber fiber fiber fiber fiber fiber fiber fiber
fiber fiber fiber fiber fiber fiber fiber fiber fiber fiber fiber fiber fiber
fiber fiber fiber fiber fiber fiber fiber protein protein protein protein
protein protein protein protein protein protein protein protein protein
protein protein protein protein protein protein protein  vitamins   vitamins
vitamins   vitamins   vitamins   vitamins   vitamins   vitamins   vitamins
vitamins   vitamins   vitamins   vitamins   vitamins   vitamins   vitamins
vitamins   healthy  lifestyle healthy  lifestyle healthy  lifestyle healthy
lifestyle healthy  lifestyle healthy  lifestyle healthy  lifestyle healthy
lifestyle vegetarian vegetarian vegetarian vegetarian vegetarian vegetarian
vegetarian vegetarian vegetarian vegetarian vegetarian vegetarian vegetarian
```

energy eating energy eating energy eating energy eating energy eating energy eating energy eating energy eating energy eating energy eating energy eating energy milk milk milk milk milk milk milk milk milk milk milk milk milk milk milk milk milk milk crunchy crunchy crunchy crunchy crunchy crispy crispy crispy crispy crispy crispy crispy crispy crispy crispy crispy crispy crispy crispy crispy crispy eating flakes freshness fruits grain eating flakes freshness fruits grain eating flakes freshness fruits grain eating flakes freshness fruits grain eating flakes freshness fruits grain eating flakes freshness fruits grain eating flakes freshness fruits grain eating flakes freshness fruits grain natural fresh fresh fresh fresh fresh fresh fresh fresh fresh fresh fresh fresh fresh fresh fresh fresh fresh variety meal organic meal organic meal organic meal organic meal organic meal organic meal organic meal organic meal organic meal organic meal organic meal organic meal organic meal organic meal organic meal organic muesli fruitss flavours strawberry wheat raisin nuts oats rice bran honey fruitss flavours strawberry wheat raisin nuts oats rice bran honey fruitss flavours strawberry wheat raisin nuts oats rice bran honey fruitss flavours strawberry wheat raisin nuts oats rice bran honey fruitss flavours strawberry wheat raisin nuts oats rice bran honey snack snack snack snack snack snack snack snack snack snacksnack snack cereal usually eat milk yogurt fresh fruitss nuts seeds cereal made processed grain considered healthy early morning usually eat milk yogurt fresh fruitss nuts seeds unaware cereal often fortified vitamins minerals means nutritiouss cereals make nutritious cereals claim packed essential vitamins minerals doubt convenient option kids adults cereal usually made corn wheat oats rice vitaamins healthy contain cereals nutritiouss like vitamins minerals salt cereals sugar preservatives yeast flavorings enhance taste cereal healthy contains cereals nuts dried fruitss coated chocolate one important meals day choice holds lot significerealce must wholesome balanced meal include important food groups cereal include whole grains like wheat millets oats etc forget must freshly prepared local seasonal ingredients adds ready eat cereals laced hidden sugars chemical preservatives various additives thumb rule food comes plant eat manufactured plant eat ready eat packaged cereals best avoided one cereal prepare one home made muesli granola itâ well known saying important meal day unlike many sayings one supported scientific evidence time studies show consumers leaner lower cholesterol levels higher intakes fibre vitamins minerals compared people consume reason simple types foods eat time tend healthier nutritious dense foods eat times day great example cereals cereals high carbohydrate low fat foods often fortified essential vitamins minerals diets europe still failing meet targets fibre saturated fat certain groups consumers teenagers young women inadequate intakes vitamins minerals cereals continue play important role helping consumers ages move towards healthy balanced diet eating contributes cognitive performance â improves concentration fuels

```
physical activity       provides many nutritiousal  health benefits  eating
proper    morning   cereals   healthy  choice cereals   healthy  choice
cereals   healthy  choice cereals   healthy  choice cereals   healthy  choice
made  grain    typically high  carbo   hydrates  low  fat   often  good
source  fibre   cereals   â  nutritious denseâ   food       supplying
nutritious amount  energy  calories   make  significerealt contribution
intakes  essential nutritiouss  carbohydrates  proteins  proteins  vitamins
minerals carbohydrates  proteins  proteins  vitamins    minerals
carbohydrates  proteins  proteins  vitamins    minerals carbohydrates
proteins  proteins  vitamins    minerals carbohydrates  proteins  proteins
vitamins    minerals carbohydrates  proteins  proteins  vitamins    minerals
carbohydrates  proteins  proteins  vitamins    minerals carbohydrates
proteins  proteins  vitamins    minerals carbohydrates  proteins  proteins
vitamins    minerals carbohydrates  proteins  proteins  vitamins    minerals
carbohydrates  proteins  proteins  vitamins    minerals carbohydrates
proteins  proteins  vitamins    minerals carbohydrates  proteins  proteins
vitamins    minerals  essential nutritiouss essential nutritiouss essential
nutritiouss essential nutritiouss essential nutritiouss essential
nutritioussessential nutritioussessential nutritioussessential nutritiouss
essential nutritioussessential nutritiouss essential nutritiouss  maintain
healthy  balanced diet    cereal  oat  variety   cereals  ranging
conventional  cereals  oat flakes  varieties  mueslis    cereals cereal play
important diets   nutritiousal status  cereal consumers        likely  meet
nutritiousal   nutritiouss   vitamins    minerals  fibre
nutritious     helps  develop good nutritious habits        cereal  always
part   healthy   viewed   nutritious morning food   milling  cereal grains
sugar  water  mixed together   cooked  diet eating flake food fresh freshness
fruits graing healthy lifestyle meal milk natural nutritious oat
organicvegetarian vitamins wheat bowl  cereal corn cornflakes crisp crispy
crunchy dairy delicious diet eating energy fitness flake flakes food fresh
freshness grain granola health healthy heap ingredient lifestyle meal milk
morning muesli natural nutritious organic snack spoon studio sweet tasty
vegetarian whole    "
```

```
t=Top200Words
x<-removeWords(x,t)
nchar(x)
```

```
## [1] 8457
```

```
x<-stripWhitespace(x)
x
```

```
## [1] "breakfast breakfast breakfast breakfast breakfast breakfast breakfast
breakfast breakfast breakfast breakfast breakfast breakfast breakfast breakfast
breakfast breakfast breakfast breakfast breakfast breakfast breakfast breakfast
breakfast breakfast breakfast breakfast breakfast breakfast breakfast breakfast
breakfast breakfast breakfast breakfast breakfast breakfast breakfast breakfast
breakfast breakfast breakfast breakfast breakfast breakfast breakfast breakfast
breakfast breakfast breakfast breakfast cereal cereal cereal cereal cereal
cereal cereal cereal cereal cereal cereal cereal cereal cereal cereal cereal
```

cereal delicious nutritious bowl bowl bowl bowl bowl bowl bowl bowl bowl bowl fitness fiber protein protein protein protein protein protein protein protein protein protein protein protein protein protein protein protein protein protein protein vitamins vitamins vitamins vitamins vitamins vitamins vitamins vitamins vitamins vitamins vitamins vitamins vitamins vitamins vitamins vitamins vitamins vitamins healthy lifestyle healthy lifestyle healthy lifestyle healthy lifestyle healthy lifestyle healthy lifestyle healthy lifestyle healthy lifestyle vegetarian vegetarian vegetarian vegetarian vegetarian vegetarian vegetarian vegetarian vegetarian vegetarian vegetarian vegetarian vegetarian energy eating energy eating energy eating energy eating energy eating energy eating energy eating energy eating energy eating energy eating energy eating energy milk milk milk milk milk milk milk milk milk milk milk milk milk milk milk milk milk milk milk crunchy crunchy crunchy crunchy crunchy crispy crispy crispy crispy crispy crispy crispy crispy crispy crispy crispy crispy crispy crispy eating flakes freshness fruits grain eating flakes freshness fruits grain eating flakes freshness fruits grain eating flakes freshness fruits grain eating flakes freshness fruits grain eating flakes freshness fruits grain eating flakes freshness fruits grain eating flakes freshness fruits grain natural fresh fresh fresh fresh fresh fresh fresh fresh fresh fresh fresh fresh fresh fresh variety variety variety variety variety variety variety variety variety variety variety variety variety variety variety variety variety variety meal organic meal organic meal organic meal organic meal organic meal organic meal organic meal organic meal organic meal organic meal organic muesli fruitss flavours strawberry wheat raisin nuts oats rice bran honey fruitss flavours strawberry wheat raisin nuts oats rice bran honey fruitss flavours strawberry wheat raisin nuts oats rice bran honey fruitss flavours strawberry wheat raisin nuts oats rice bran honey fruitss flavours strawberry wheat raisin nuts oats rice bran honey snack snack snack snack snack snack snack snack snack snacksnack snack cereal usually eat milk yogurt fresh fruitss nuts seeds cereal processed grain considered healthy early morning usually eat milk yogurt fresh fruitss nuts seeds unaware cereal often fortified vitamins minerals means nutritiouss cereals nutritious cereals claim packed essential vitamins minerals doubt convenient option kids adults

```
cereal usually corn wheat oats rice vitaamins healthy contain cereals
nutritiouss vitamins minerals salt cereals sugar preservatives yeast
flavorings enhance taste cereal healthy contains cereals nuts dried fruitss
coated chocolate important meals choice holds lot significerealce wholesome
balanced meal include important food groups cereal include whole grains wheat
millets oats etc forget freshly prepared local seasonal ingredients adds
ready eat cereals laced hidden sugars chemical preservatives various
additives thumb rule food comes plant eat manufactured plant eat ready eat
packaged cereals best avoided cereal prepare muesli granola itâ known saying
important meal unlike sayings supported scientific evidence studies consumers
leaner lower cholesterol levels higher intakes fibre vitamins minerals
compared consume reason simple types foods eat tend healthier nutritious
dense foods eat times example cereals cereals high carbohydrate low fat foods
often fortified essential vitamins minerals diets europe failing meet targets
fibre saturated fat certain groups consumers teenagers young women inadequate
intakes vitamins minerals cereals continue important role helping consumers
ages towards healthy balanced diet eating contributes cognitive performance â
improves concentration fuels physical activity provides nutritiousal health
benefits eating proper morning cereals healthy choice cereals healthy choice
cereals healthy choice cereals healthy choice cereals healthy choice grain
typically high carbo hydrates low fat often source fibre cereals â nutritious
denseâ food supplying nutritious amount energy calories significerealt
contribution intakes essential nutritiouss carbohydrates proteins proteins
vitamins minerals carbohydrates proteins proteins vitamins minerals
carbohydrates proteins proteins vitamins minerals carbohydrates proteins
proteins vitamins minerals carbohydrates proteins proteins vitamins minerals
carbohydrates proteins proteins vitamins minerals carbohydrates proteins
proteins vitamins minerals carbohydrates proteins proteins vitamins minerals
carbohydrates proteins proteins vitamins minerals carbohydrates proteins
proteins vitamins minerals carbohydrates proteins proteins vitamins minerals
carbohydrates proteins proteins vitamins minerals carbohydrates proteins
proteins vitamins minerals essential nutritiouss essential nutritiouss
essential nutritiouss essential nutritiouss essential nutritiouss essential
nutritioussessential nutritioussessential nutritioussessential nutritiouss
essential nutritioussessential nutritiouss essential nutritiouss maintain
healthy balanced diet cereal oat variety cereals ranging conventional cereals
oat flakes varieties mueslis cereals cereal important diets nutritiousal
status cereal consumers likely meet nutritiousal nutritiouss vitamins
minerals fibre nutritious helps develop nutritious habits cereal always
healthy viewed nutritious morning food milling cereal grains sugar mixed
together cooked diet eating flake food fresh freshness fruits graing healthy
lifestyle meal milk natural nutritious oat organicvegetarian vitamins wheat
bowl cereal corn cornflakes crisp crispy crunchy dairy delicious diet eating
energy fitness flake flakes food fresh freshness grain granola health healthy
heap ingredient lifestyle meal milk morning muesli natural nutritious organic
snack spoon studio sweet tasty vegetarian whole "
```

```
nchar(x)
```

```
## [1] 7737
```

```r
freq_terms(x,top = 100)
```

```
##     WORD                FREQ
## 1   cereal                53
## 2   breakfast             46
## 3   nutritious            38
## 4   vitamins              38
## 5   delicious             30
## 6   fiber                 28
## 7   proteins              26
## 8   fitness               24
## 9   eating                23
## 10  milk                  23
## 11  natural               23
## 12  healthy               21
## 13  minerals              20
## 14  protein               20
## 15  cereals               19
## 16  variety               19
## 17  fresh                 18
## 18  crispy                15
## 19  meal                  15
## 20  energy                14
## 21  vegetarian            14
## 22  carbohydrates         13
## 23  nutritiouss           12
## 24  organic               12
## 25  bowl                  11
## 26  essential             11
## 27  grain                 11
## 28  snack                 11
## 29  flakes                10
## 30  freshness             10
## 31  lifestyle             10
## 32  fruits                 9
## 33  eat                    8
## 34  fruitss                8
## 35  nuts                   8
## 36  wheat                  8
## 37  oats                   7
## 38  choice                 6
## 39  crunchy                6
## 40  food                   6
## 41  rice                   6
## 42  bran                   5
## 43  flavours               5
## 44  honey                  5
## 45  important              5
## 46  raisin                 5
## 47  strawberry             5
```

```
## 48  consumers               4
## 49  diet                    4
## 50  fibre                   4
## 51  morning                 4
## 52  nutritioussessential    4
## 53  balanced                3
## 54  fat                     3
## 55  foods                   3
## 56  intakes                 3
## 57  muesli                  3
## 58  nutritiousal            3
## 59  oat                     3
## 60  often                   3
## 61  usually                 3
## 62  â                       2
## 63  corn                    2
## 64  diets                   2
## 65  flake                   2
## 66  fortified               2
## 67  grains                  2
## 68  granola                 2
## 69  groups                  2
## 70  health                  2
## 71  high                    2
## 72  include                 2
## 73  low                     2
## 74  meet                    2
## 75  plant                   2
## 76  preservatives           2
## 77  ready                   2
## 78  seeds                   2
## 79  sugar                   2
## 80  whole                   2
## 81  yogurt                  2
## 82  activity                1
## 83  additives               1
## 84  adds                    1
## 85  adults                  1
## 86  ages                    1
## 87  always                  1
## 88  amount                  1
## 89  avoided                 1
## 90  benefits                1
## 91  best                    1
## 92  calories                1
## 93  carbo                   1
## 94  carbohydrate            1
## 95  certain                 1
## 96  chemical                1
## 97  chocolate               1
```

```
## 98  cholesterol             1
## 99  claim                   1
## 100 coated                  1
## 101 cognitive               1
## 102 comes                   1
## 103 compared                1
## 104 concentration           1
## 105 considered              1
## 106 consume                 1
## 107 contain                 1
## 108 contains                1
## 109 continue                1
## 110 contributes             1
## 111 contribution            1
## 112 convenient              1
## 113 conventional            1
## 114 cooked                  1
## 115 cornflakes              1
## 116 crisp                   1
## 117 dairy                   1
## 118 dense                   1
## 119 denseâ                  1
## 120 develop                 1
## 121 doubt                   1
## 122 dried                   1
## 123 early                   1
## 124 enhance                 1
## 125 etc                     1
## 126 europe                  1
## 127 evidence                1
## 128 example                 1
## 129 failing                 1
## 130 flavorings              1
## 131 forget                  1
## 132 freshly                 1
## 133 fuels                   1
## 134 graing                  1
## 135 habits                  1
## 136 healthier               1
## 137 heap                    1
## 138 helping                 1
## 139 helps                   1
## 140 hidden                  1
## 141 higher                  1
## 142 holds                   1
## 143 hydrates                1
## 144 improves                1
## 145 inadequate              1
## 146 ingredient              1
## 147 ingredients             1
```

```
## 148 itâ                    1
## 149 kids                   1
## 150 known                  1
## 151 laced                  1
## 152 leaner                 1
## 153 levels                 1
## 154 likely                 1
## 155 local                  1
## 156 lot                    1
## 157 lower                  1
## 158 maintain               1
## 159 manufactured           1
## 160 meals                  1
## 161 means                  1
## 162 millets                1
## 163 milling                1
## 164 mixed                  1
## 165 mueslis                1
## 166 option                 1
## 167 organicvegetarian      1
## 168 packaged               1
## 169 packed                 1
## 170 performance            1
## 171 physical               1
## 172 prepare                1
## 173 prepared               1
## 174 processed              1
## 175 proper                 1
## 176 provides               1
## 177 ranging                1
## 178 reason                 1
## 179 role                   1
## 180 rule                   1
## 181 salt                   1
## 182 saturated              1
## 183 saying                 1
## 184 sayings                1
## 185 scientific             1
## 186 seasonal               1
## 187 significerealce        1
## 188 significerealt         1
## 189 simple                 1
## 190 snacksnack             1
## 191 source                 1
## 192 spoon                  1
## 193 status                 1
## 194 studies                1
## 195 studio                 1
## 196 sugars                 1
## 197 supplying              1
```

```
## 198 supported               1
## 199 sweet                   1
## 200 targets                 1
## 201 taste                   1
## 202 tasty                   1
## 203 teenagers               1
## 204 tend                    1
## 205 thumb                   1
## 206 times                   1
## 207 together                1
## 208 towards                 1
## 209 types                   1
## 210 typically               1
## 211 unaware                 1
## 212 unlike                  1
## 213 varieties               1
## 214 various                 1
## 215 viewed                  1
## 216 vitaamins               1
## 217 wholesome               1
## 218 women                   1
## 219 yeast                   1
## 220 young                   1
```

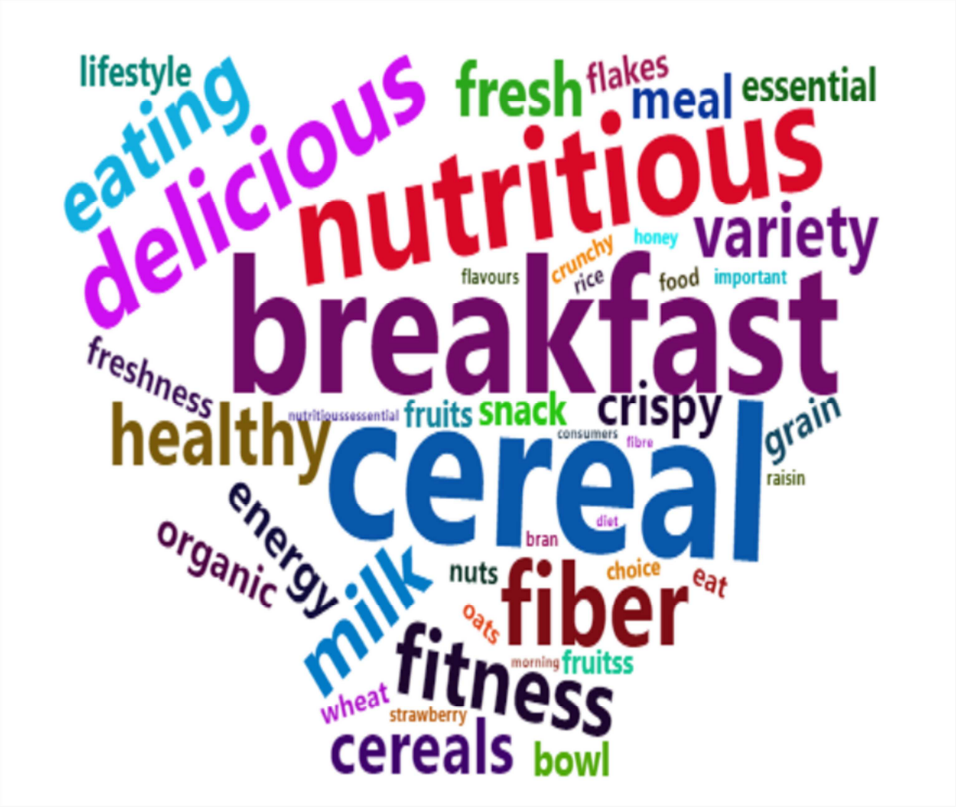
```
xx<-freq_terms(x,last = 30, at.least = 3, extend = TRUE)
xxx<-freq_terms(x,top = 50 , at.least =1, extend = TRUE)

wordcloud2(data = xx, figPath = "spoon.png", size =0.25,minSize =0,shuffle =
FALSE,ellipticity=0.7, color = "random-dark", backgroundColor="white")
```

```
wordcloud2(data = xxx, figPath = "bbboowl.png", size =0.55,minSize
=0.55,shuffle = FALSE,ellipticity=1, color = "random-dark",
backgroundColor="white")
```

R Markdown

This is an R Markdown document. Markdown is a simple formatting syntax for authoring HTML, PDF, and MS Word documents. For more details on using R Markdown see http://rmarkdown.rstudio.com.

When you click the **Knit** button a document will be generated that includes both content as well as the output of any embedded R code chunks within the document. You can embed an R code chunk like this:


lifestyle
eating
delicious
fresh
flakes
meal
essential
nutritious
variety
honey
crunchy
flavours
rice
food
important
breakfast
freshness
healthy
nutritioussessential
fruits
snack
crispy
consumers
fibre
grain
cereal
raisin
energy
diet
bran
organic
milk
nuts
choice
eat
fiber
oats
morning
fruitss
fitness
wheat
strawberry
cereals
bowl