Wine Quality Clustering

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Libraries

```r
library(readr)
library(stats)
library(tidyverse)
```

```
## -- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
## v dplyr     1.1.4     v purrr     1.0.2
## v forcats   1.0.0     v stringr   1.5.1
## v ggplot2   3.5.1     v tibble    3.2.1
## v lubridate 1.9.3     v tidyr     1.3.1
## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts
```

Reading in data set

```r
wine = read_delim("winequality-red.csv", delim = ";", escape_double = FALSE, trim_ws = T
```

```
## Rows: 1599 Columns: 12
## -- Column specification --------------------------------------------------------
## Delimiter: ";"
## dbl (12): fixed acidity, volatile acidity, citric acid, residual sugar, chlo...
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```r
head(wine, 5)
```

```
## # A tibble: 5 x 12
##   `fixed acidity` `volatile acidity` `citric acid` `residual sugar` chlorides
##             <dbl>              <dbl>         <dbl>            <dbl>     <dbl>
## 1             7.4               0.7          0                 1.9     0.076
## 2             7.8               0.88         0                 2.6     0.098
## 3             7.8               0.76         0.04              2.3     0.092
## 4            11.2               0.28         0.56              1.9     0.075
## 5             7.4               0.7          0                 1.9     0.076
## # i 7 more variables: `free sulfur dioxide` <dbl>,
## #   `total sulfur dioxide` <dbl>, density <dbl>, pH <dbl>, sulphates <dbl>,
## #   alcohol <dbl>, quality <dbl>
```

Looking at correlation matrix

```r
wine %>%
  select(-quality) %>%
  cor(use="pairwise.complete.obs") %>%
  round(2)
```

```
##                      fixed acidity volatile acidity citric acid residual sugar
## fixed acidity                 1.00            -0.26        0.67           0.11
## volatile acidity             -0.26             1.00       -0.55           0.00
## citric acid                   0.67            -0.55        1.00           0.14
## residual sugar                0.11             0.00        0.14           1.00
## chlorides                     0.09             0.06        0.20           0.06
## free sulfur dioxide          -0.15            -0.01       -0.06           0.19
## total sulfur dioxide         -0.11             0.08        0.04           0.20
## density                       0.67             0.02        0.36           0.36
## pH                           -0.68             0.23       -0.54          -0.09
## sulphates                     0.18            -0.26        0.31           0.01
## alcohol                      -0.06            -0.20        0.11           0.04
##                      chlorides free sulfur dioxide total sulfur dioxide density
## fixed acidity             0.09               -0.15                -0.11    0.67
## volatile acidity          0.06               -0.01                 0.08    0.02
## citric acid               0.20               -0.06                 0.04    0.36
## residual sugar            0.06                0.19                 0.20    0.36
## chlorides                 1.00                0.01                 0.05    0.20
## free sulfur dioxide       0.01                1.00                 0.67   -0.02
## total sulfur dioxide      0.05                0.67                 1.00    0.07
## density                   0.20               -0.02                 0.07    1.00
## pH                       -0.27                0.07                -0.07   -0.34
## sulphates                 0.37                0.05                 0.04    0.15
## alcohol                  -0.22               -0.07                -0.21   -0.50
##                         pH sulphates alcohol
```

```
## fixed acidity        -0.68      0.18   -0.06
## volatile acidity      0.23     -0.26   -0.20
## citric acid          -0.54      0.31    0.11
## residual sugar       -0.09      0.01    0.04
## chlorides            -0.27      0.37   -0.22
## free sulfur dioxide   0.07      0.05   -0.07
## total sulfur dioxide -0.07      0.04   -0.21
## density              -0.34      0.15   -0.50
## pH                    1.00     -0.20    0.21
## sulphates            -0.20      1.00    0.09
## alcohol               0.21      0.09    1.00
```

Normalizing the data

```
predictors = wine %>%
  select(-quality)

predictors[, c("fixed acidity", "volatile acidity", "citric acid", "residual sugar", "ch

head(predictors, 5)
```

```
## # A tibble: 5 x 11
##   `fixed acidity` `volatile acidity` `citric acid` `residual sugar` chlorides
##             <dbl>              <dbl>         <dbl>            <dbl>     <dbl>
## 1          -0.528              0.962         -1.39           -0.453    -0.244
## 2          -0.298              1.97          -1.39            0.0434    0.224
## 3          -0.298              1.30          -1.19           -0.169     0.0963
## 4           1.65              -1.38           1.48           -0.453    -0.265
## 5          -0.528              0.962         -1.39           -0.453    -0.244
## # i 6 more variables: `free sulfur dioxide` <dbl>,
## #   `total sulfur dioxide` <dbl>, density <dbl>, pH <dbl>, sulphates <dbl>,
## #   alcohol <dbl>
```

Fitting and Evaluating

```
kmodel = kmeans(predictors, centers = 3, nstart = 20)
kmodel
```

```
## K-means clustering with 3 clusters of sizes 724, 502, 373
##
## Cluster means:
```

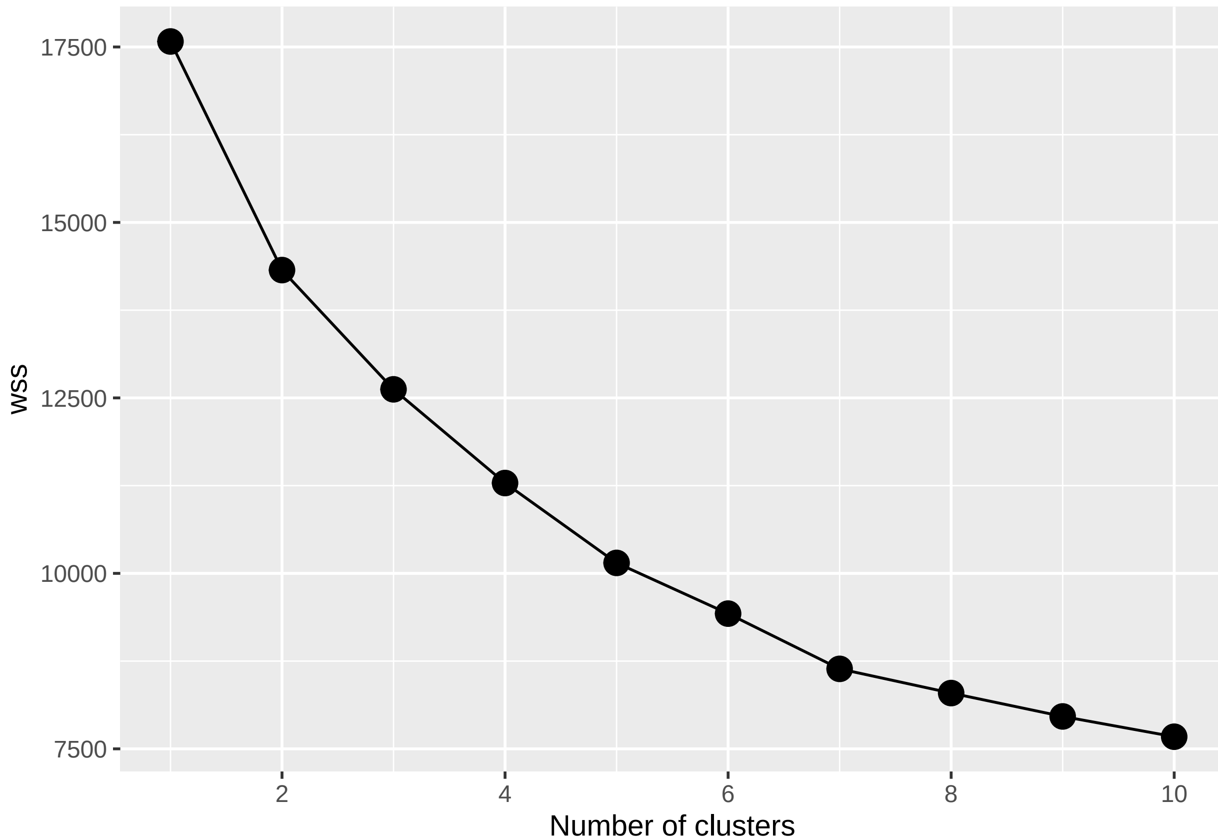
```
##   fixed acidity volatile acidity citric acid residual sugar    chlorides
## 1   -0.64949027       0.45482336  -0.7591418    -0.22780950 -0.188575893
## 2    1.00367463      -0.68547433   1.0204527     0.03104004  0.276076371
## 3   -0.09011718       0.03972118   0.1001378     0.40040745 -0.005526519
##   free sulfur dioxide total sulfur dioxide    density         pH  sulphates
## 1          -0.2216967           -0.3492025 -0.4505506  0.6139437 -0.2873116
## 2          -0.4767114           -0.4815366  0.4383036 -0.7518363  0.5544470
## 3           1.0718969            1.3258820  0.2846387 -0.1798214 -0.1885221
##       alcohol
## 1  0.06851232
## 2  0.28250279
## 3 -0.51318854
##
## Clustering vector:
##    [1] 1 3 1 2 1 1 1 1 1 3 1 3 1 2 3 3 3 2 1 2 3 3 2 3 1 1 1 2 1 1 1 1 3 3 1 1 1
##   [38] 2 1 3 3 3 2 2 1 1 3 2 1 3 2 1 1 3 3 3 2 3 1 1 3 3 1 1 1 1 1 1 2 1 1 3 3 1
##   [75] 3 2 2 1 1 3 1 2 3 2 1 1 2 1 3 1 3 2 2 1 1 1 1 1 1 1 1 1 1 1 1 1 2 1 3 3 1
##  [112] 3 3 2 1 2 1 1 1 3 1 1 1 1 3 3 1 1 1 1 3 1 1 1 1 1 1 1 3 3 1 1 1 1 1 3 1 3
##  [149] 1 1 2 2 3 3 3 3 3 3 1 1 1 1 1 3 3 3 3 1 1 2 1 1 1 1 1 1 1 1 1 1 1 3 1 1 1
##  [186] 3 3 1 3 3 3 1 3 1 1 3 1 2 1 1 2 3 1 1 1 2 2 3 3 2 2 1 2 3 1 3 1 1 1 3 3 3
##  [223] 1 1 1 3 2 1 3 1 1 1 3 1 1 1 1 1 1 1 2 2 3 2 2 1 1 3 1 1 2 1 2 3 1 3 2 1 2
##  [260] 2 1 1 1 3 2 2 1 2 1 2 3 2 2 1 3 3 1 2 2 2 2 2 1 2 3 3 2 3 1 3 1 2 2 1 2 2
##  [297] 3 1 1 1 1 2 1 1 3 2 1 2 2 1 2 3 3 3 3 1 3 3 3 3 3 3 1 3 3 3 2 2 2 2 2 2 3
##  [334] 1 1 2 2 3 2 2 2 2 2 2 2 3 1 2 2 1 2 1 1 2 3 1 2 2 2 2 3 3 2 2 2 2 2 2 2 2
##  [371] 1 2 2 3 2 2 2 2 2 3 2 2 2 2 3 1 3 1 3 2 1 2 2 3 2 2 3 2 2 1 3 1 2 2 1 2 2
##  [408] 2 2 2 3 3 1 2 3 3 2 3 2 1 3 1 1 2 1 1 1 1 2 2 2 3 2 2 2 2 3 2 2 1 2 2 2 2
##  [445] 1 1 2 2 1 2 2 2 1 2 1 2 2 3 2 2 2 1 2 3 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 1 2
##  [482] 2 2 2 2 2 2 2 2 3 2 2 3 3 2 1 3 2 3 1 2 2 2 2 2 2 2 3 2 2 3 2 2 2 2 3 2 2
##  [519] 2 3 2 3 3 3 3 3 3 3 3 2 2 2 2 2 2 2 2 1 2 2 3 2 1 2 2 3 1 2 2 2 1 2 2 1 2
##  [556] 2 2 2 2 2 2 3 3 3 2 2 2 2 2 1 2 1 2 2 2 2 2 3 3 2 2 2 2 2 2 3 1 2 3 1 2 3 3
##  [593] 3 2 1 3 2 2 1 2 1 2 1 2 3 1 2 3 2 1 3 2 1 2 2 3 3 2 2 2 3 3 2 1 3 3 1 1 1
##  [630] 3 1 2 1 3 3 1 3 3 1 2 2 3 2 3 2 1 1 1 1 3 2 3 2 2 2 3 2 2 1 1 1 1 1 2 2 3
##  [667] 2 2 2 2 3 1 3 1 2 2 2 1 3 2 2 1 3 1 3 1 1 3 1 2 1 3 2 3 3 1 1 1 3 2 3 1 1
##  [704] 3 1 1 1 1 1 2 3 3 1 1 3 1 1 1 1 1 1 3 1 3 1 1 1 1 1 1 2 1 1 3 1 1 1 1 3 1
##  [741] 1 3 1 3 3 1 3 3 1 1 1 1 3 1 2 1 1 1 1 3 3 1 1 1 1 1 3 3 3 1 3 3 3 2 2 1 1
##  [778] 1 2 3 1 1 3 1 1 2 2 3 3 3 3 3 1 1 2 2 3 2 2 2 3 1 1 1 1 2 2 2 1 1 1 2 2 1
##  [815] 2 2 2 2 1 3 1 1 1 1 1 1 1 1 1 1 1 1 2 2 1 1 3 3 2 1 2 1 3 3 2 1 1 1 1 1 2
##  [852] 2 3 3 3 1 3 2 2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 2 1 1 3 1 1 1 2 1 3 1 1 2
##  [889] 1 3 3 1 2 1 1 1 2 1 2 1 2 1 1 1 1 3 1 1 1 1 2 2 2 2 1 2 1 3 3 1 2 3 1 3 2
##  [926] 3 3 3 2 2 1 1 3 1 1 2 2 2 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 1 1 2 1
##  [963] 1 2 2 2 2 3 2 1 2 2 2 1 2 3 3 3 1 2 2 1 3 2 2 1 2 3 1 2 1 3 1 3 3 1 1 1 1
## [1000] 1 1 2 2 1 3 1 2 2 2 2 2 2 1 1 1 2 2 3 3 1 2 2 1 2 1 1 1 1 3 1 1 1 1 1 1 2
## [1037] 1 1 2 1 1 1 1 2 1 1 1 1 2 2 1 2 1 2 3 3 2 3 2 2 2 2 2 2 1 1 1 2 2 3 2 3 3
## [1074] 1 3 3 2 2 2 3 2 3 3 3 3 3 2 2 2 2 3 2 1 2 1 2 1 2 2 2 2 1 1 1 1 1 2 2 1 2
## [1111] 1 1 2 2 1 1 1 1 1 1 1 1 1 2 1 2 1 1 3 3 1 3 1 1 2 1 2 2 3 3 3 3 1 1 3 3 1
```

```
## [1148] 2 1 2 2 1 1 2 1 1 3 1 2 2 2 2 2 1 1 2 2 2 1 1 2 1 2 3 3 1 1 1 1 2 2 2 3 1
## [1185] 3 1 1 1 3 1 2 1 1 1 1 1 3 1 3 3 1 1 2 3 1 1 1 2 1 1 1 1 1 2 2 2 3 3 2 2 2
## [1222] 2 3 2 2 3 3 2 1 3 2 3 3 2 1 3 1 1 1 1 3 3 2 3 3 1 1 1 1 1 1 3 1 1 1 1 3 1
## [1259] 1 1 2 1 3 1 1 1 1 2 1 1 1 1 1 3 1 3 2 1 3 2 1 1 1 3 1 2 1 1 3 3 1 1 1 1 1
## [1296] 3 3 1 1 1 1 1 2 3 3 3 3 1 3 3 3 1 1 1 3 3 1 2 3 2 3 1 2 2 1 1 1 1 1 3 3 3
## [1333] 1 1 1 1 1 1 1 1 1 1 1 2 1 1 1 1 1 3 1 1 1 1 1 1 1 3 2 2 1 2 1 1 1 1 1 3 3
## [1370] 1 2 2 2 3 1 3 1 1 1 1 1 1 3 3 3 3 1 1 1 3 1 1 1 1 3 1 1 3 1 1 3 3 2 2 1 2
## [1407] 2 1 2 1 1 1 2 2 2 1 2 1 1 3 1 3 1 1 2 2 2 1 1 3 1 3 1 1 3 3 3 1 1 3 1 3 1
## [1444] 1 3 3 1 1 3 1 1 2 1 3 2 1 3 3 2 2 3 1 1 1 1 1 3 1 3 1 2 1 2 1 3 1 3 1 1 2
## [1481] 1 2 2 2 1 1 1 1 1 1 1 1 1 3 1 1 3 1 1 1 1 3 1 1 2 1 1 2 2 2 1 1 1 1 1 1 1
## [1518] 1 2 1 1 1 1 3 1 1 1 1 3 3 1 1 1 3 1 1 1 1 1 3 1 1 1 2 2 1 1 1 2 1 1 1 1 1
## [1555] 1 1 1 1 3 3 3 3 1 1 1 1 2 1 1 1 2 1 3 1 3 1 2 1 1 1 1 1 1 3 2 2 3 1 3 3 1
## [1592] 1 1 1 1 1 1 1 1
##
## Within cluster sum of squares by cluster:
## [1] 4195.309 5040.596 3386.103
##  (between_SS / total_SS =  28.2 %)
##
## Available components:
##
## [1] "cluster"      "centers"      "totss"        "withinss"     "tot.withinss"
## [6] "betweenss"    "size"         "iter"         "ifault"
```

The SS proportion is not very great, now its time to test different possible cluster amounts:

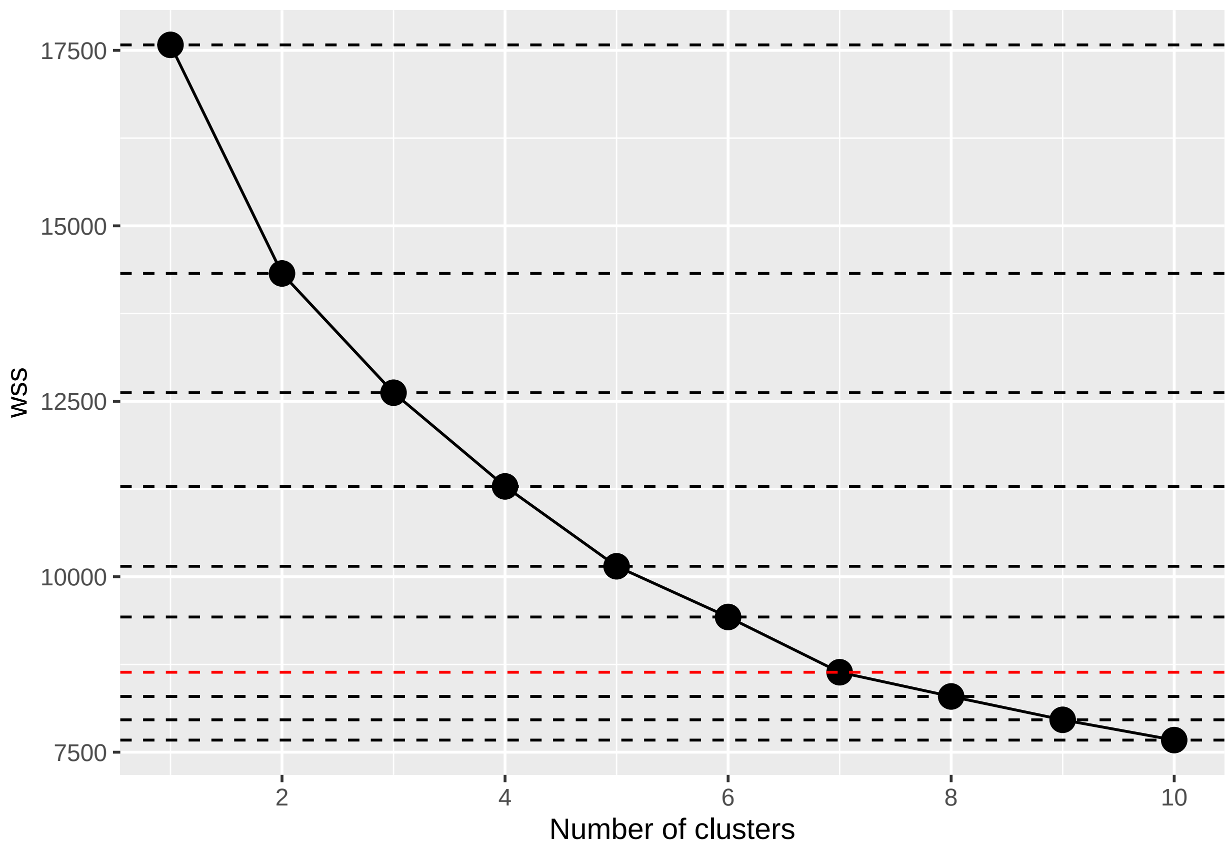
```r
max_clusters = 10

# Within sum of squares
wss = numeric(max_clusters)

# Reproducibility
set.seed(321)

# Look over 1 -> n clusters
for (i in 1:max_clusters) {
  km = kmeans(predictors, centers = i, nstart = 20)

  wss[i] = km$tot.withinss
}

# Produce a scree plot to visualize wss vs clusters
wss_df = tibble(clusters = 1:max_clusters, wss = wss)

scree_plot = ggplot(wss_df, aes(x = clusters, y = wss, group = 1)) +
  geom_point(size = 4) +
```

```r
  geom_line() +
  scale_x_continuous(breaks = c(2, 4, 6, 8, 10)) +
  xlab("Number of clusters")
scree_plot
```



It's hard to tell where the drop off happens so I'll add lines in the graph.

```r
scree_plot +
  geom_hline(
    yintercept = wss,
    linetype = "dashed",
    col = c(rep("#000000", 6), "#FF0000", rep("#000000", 3))
  )
```



There is a significant reduction in model improvement after the 7th cluster, so we'll build a model based on this result.

```
k = 7
set.seed(321)

km = kmeans(predictors, centers = k, nstart = 20)
km
```

```
## K-means clustering with 7 clusters of sizes 335, 34, 246, 497, 29, 267, 191
##
## Cluster means:
##   fixed acidity volatile acidity citric acid residual sugar   chlorides
## 1   -0.10300336       0.05409899  0.05352831    -0.01164417 -0.03293559
## 2   -0.08560643      -0.03464133  0.41472600     4.96021580  0.29629520
## 3    0.05035896      -1.03768918  0.70824781    -0.18148350 -0.28949306
## 4   -0.40951062       0.63621199 -0.78204789    -0.20640683 -0.03782882
## 5    0.08180575       0.01794915  1.14382029    -0.39927103  5.60297844
## 6    1.64680959      -0.60790045  1.23778419     0.14965815  0.03321812
## 7   -1.11788120       0.43935979 -0.94891620    -0.24029985 -0.42083775
##   free sulfur dioxide total sulfur dioxide     density         pH   sulphates
## 1          0.99407806            1.2318849  0.22367883 -0.1077529 -0.18807595
```

```
## 2          1.74964380            1.6953018  1.22461740 -0.3253578 -0.02378189
## 3         -0.26318636           -0.5055549 -0.68017199 -0.1230637  0.39462568
## 4         -0.48364728           -0.4113709  0.02578926  0.3178251 -0.38981527
## 5         -0.07045695            0.4742672  0.18574466 -1.6868288  3.71944476
## 6         -0.52906451           -0.4704402  1.08624118 -0.9962650  0.29506721
## 7          0.29275382           -0.1552359 -1.34804889  1.2271977 -0.13702903
##       alcohol
## 1 -0.57245599
## 2 -0.36379918
## 3  1.01179431
## 4 -0.51438888
## 5 -0.88228685
## 6  0.02435629
## 7  1.20405754
##
## Clustering vector:
##    [1] 4 4 4 6 4 4 4 4 4 1 4 1 7 5 1 1 1 5 4 5 1 1 4 4 4 4 4 4 4 4 4 4 1 2 4 4 4
##   [38] 3 4 1 1 4 5 4 4 7 1 6 4 1 4 4 4 1 1 4 6 1 4 4 1 1 4 4 4 4 4 4 3 4 4 1 1 4
##   [75] 1 3 3 4 4 1 4 5 1 5 3 4 5 4 1 4 1 5 5 4 7 7 4 4 4 4 4 4 4 4 4 4 5 4 1 1 4
##  [112] 1 1 6 4 6 4 4 4 1 4 4 4 4 1 1 4 4 4 4 1 7 7 4 4 4 4 4 1 1 4 4 7 4 7 1 7 1
##  [149] 4 3 3 5 1 1 1 1 1 1 4 1 4 4 4 2 2 1 1 4 4 5 4 4 4 7 4 4 4 4 4 4 4 5 4 4 4
##  [186] 1 1 4 1 1 1 4 1 4 4 1 4 6 7 7 3 1 4 4 4 6 6 1 1 6 3 4 6 1 4 1 4 4 4 1 1 1
##  [223] 4 4 4 1 5 4 1 4 7 4 1 4 4 4 4 4 4 4 5 6 1 6 6 4 4 4 4 4 6 4 6 1 4 1 6 4 5
##  [260] 6 1 4 4 1 6 6 4 3 4 6 1 6 6 4 2 1 4 6 6 6 6 5 4 6 1 1 6 1 4 6 4 5 6 4 6 6
##  [297] 1 4 4 4 4 6 4 4 1 6 4 6 6 4 6 1 1 1 1 3 1 1 1 1 1 1 4 1 2 2 6 6 6 6 6 6 1
##  [334] 4 7 6 3 1 6 6 6 6 6 6 6 1 7 6 6 4 6 4 4 6 1 7 6 6 6 6 1 1 6 6 6 6 6 6 6 3
##  [371] 1 3 3 1 6 6 6 3 6 1 3 6 3 3 1 4 1 4 1 6 7 6 6 1 6 6 2 6 6 4 2 3 6 6 4 3 6
##  [408] 6 6 6 1 1 4 6 1 2 6 1 6 4 1 7 4 6 4 7 7 4 4 6 6 1 6 6 6 6 1 6 6 4 6 6 6 3
##  [445] 7 4 6 3 4 6 6 5 4 6 3 6 4 1 6 6 3 4 6 1 6 6 6 3 6 1 6 3 6 6 6 4 6 6 4 4 2
##  [482] 3 6 6 6 6 6 6 6 6 1 3 3 1 2 6 4 1 6 1 4 2 2 6 6 3 6 6 1 6 6 1 6 6 6 2 6 6
##  [519] 6 1 6 1 1 1 1 1 1 1 1 4 3 6 6 3 6 3 4 4 6 6 1 6 4 6 6 1 4 6 6 6 4 6 6 7 6
##  [556] 6 6 6 6 6 6 1 1 1 6 6 4 4 6 7 6 7 6 6 6 6 4 1 1 6 6 6 6 6 1 4 6 1 7 6 1 1
##  [593] 1 6 4 2 6 6 4 6 4 6 4 6 1 4 3 1 6 7 1 6 4 3 5 1 1 6 6 6 1 1 4 3 4 4 4 4 4
##  [630] 1 4 6 4 4 1 4 1 1 4 3 6 1 6 1 6 4 4 4 3 2 6 1 6 6 6 1 6 6 4 4 4 4 4 6 6 1
##  [667] 4 6 6 6 1 4 1 4 6 6 6 4 1 6 6 4 1 4 1 4 4 4 4 6 4 4 5 1 1 7 4 4 1 6 1 4 4
##  [704] 1 4 4 4 4 4 6 1 1 4 4 1 4 4 4 4 4 4 1 4 1 4 4 4 4 4 7 5 4 4 1 4 4 4 4 1 4
##  [741] 4 1 4 6 6 4 1 1 4 4 4 4 1 4 5 7 7 4 4 1 1 4 4 4 4 4 1 1 1 4 1 1 1 4 4 4 4
##  [778] 4 4 1 4 4 1 4 4 6 6 1 1 1 1 1 4 4 3 6 1 3 6 6 1 4 7 4 4 3 3 3 4 4 4 6 6 3
##  [815] 6 6 4 3 4 4 4 7 4 4 4 4 3 4 7 7 4 7 1 1 4 4 7 7 3 4 6 4 1 1 3 4 4 4 4 4 6
##  [852] 6 1 1 1 7 1 3 6 7 4 7 4 4 4 4 7 7 7 7 7 7 1 3 6 3 4 7 1 4 4 7 3 4 1 4 4 3
##  [889] 7 2 1 4 6 4 4 7 3 7 3 4 3 4 4 4 4 1 1 7 7 3 3 2 3 3 3 3 7 2 1 7 6 1 7 2 3
##  [926] 1 1 4 3 3 4 4 1 4 4 3 3 6 3 7 3 3 6 6 3 3 6 3 3 3 3 3 3 3 3 3 3 3 7 4 3 4
##  [963] 4 3 3 3 3 1 3 4 3 3 3 3 3 1 1 1 3 6 4 4 7 4 6 7 3 1 4 3 4 1 1 1 1 4 7 7 4
## [1000] 7 3 3 3 3 1 3 3 3 3 1 3 3 4 4 4 3 3 3 3 4 6 6 4 3 4 4 3 7 1 4 7 4 4 4 4 6
## [1037] 3 4 3 3 4 4 3 2 3 7 4 1 3 3 1 5 7 3 4 4 3 1 3 3 6 3 3 3 7 4 7 6 6 1 3 2 1
```

```
## [1074] 4 2 1 3 6 6 2 3 2 1 3 1 1 3 3 6 6 3 3 7 3 4 6 4 4 3 4 3 3 7 3 3 7 3 3 4 6
## [1111] 4 7 3 6 7 7 7 7 7 7 3 7 7 6 7 3 7 7 1 1 4 1 3 4 3 3 6 6 1 1 1 3 7 3 1 3 4
## [1148] 6 3 3 3 7 4 3 7 4 3 7 3 6 6 3 3 4 4 5 6 3 3 3 3 7 3 1 1 7 7 7 7 3 3 3 1 4
## [1185] 1 3 7 3 1 4 3 4 3 4 4 4 1 4 3 1 4 3 3 1 3 3 3 1 3 3 4 1 4 3 6 3 1 3 3 3 6
## [1222] 6 1 3 6 1 1 4 7 1 3 1 1 6 7 2 4 7 4 7 1 1 3 1 2 4 4 4 3 7 7 1 4 4 4 7 1 1
## [1259] 7 7 5 7 1 4 3 4 4 3 1 7 7 7 7 1 4 1 3 4 1 3 1 1 4 1 7 6 3 7 1 1 4 1 7 4 1
## [1296] 1 1 7 7 4 7 7 3 3 1 1 1 7 1 1 1 7 4 1 1 1 7 3 1 5 1 7 3 3 7 7 7 7 4 1 1 1
## [1333] 4 4 4 7 4 4 4 4 4 4 4 4 6 4 7 4 4 7 1 7 4 4 4 4 4 7 1 6 4 4 6 4 7 4 4 1 1
## [1370] 4 5 3 5 1 4 1 4 7 4 4 4 4 1 1 1 1 4 4 4 1 7 4 4 1 1 4 4 1 4 7 1 1 3 3 4 3
## [1407] 3 7 3 7 7 3 3 1 6 4 6 3 4 1 4 1 7 4 3 3 3 3 4 3 3 1 7 4 2 2 1 7 4 1 3 1 4
## [1444] 7 1 1 4 4 1 3 3 3 7 1 6 7 7 1 3 3 1 4 4 4 1 1 1 7 1 4 4 7 3 7 2 7 2 7 4 3
## [1481] 7 3 4 3 4 4 4 7 7 7 3 7 7 1 7 7 1 7 4 7 4 1 4 3 3 4 4 3 3 3 1 4 4 7 4 4 3
## [1518] 7 3 4 7 4 3 1 7 4 4 4 1 1 7 4 4 1 7 4 7 7 7 1 7 3 7 6 3 4 4 7 6 3 4 4 7 4
## [1555] 7 7 4 7 2 1 1 1 4 4 4 7 3 4 4 7 3 7 1 7 2 3 3 7 7 7 3 7 7 1 3 3 3 7 7 2 7
## [1592] 7 7 4 7 7 7 7 3
##
## Within cluster sum of squares by cluster:
## [1] 1853.1985  627.7512 1111.1525 2013.9315  462.0344 1502.8903 1068.2468
##  (between_SS / total_SS =  50.9 %)
##
## Available components:
##
## [1] "cluster"      "centers"      "totss"        "withinss"     "tot.withinss"
## [6] "betweenss"    "size"         "iter"         "ifault"
```