INFS 692 Data Science Final Project Model 3

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Model 3

Without considering the *binary output* and *categorical variables* in the data set, compare the following clustering technique results:

Step 1: inport the data set and essential R libraries

```
# import libraries
##################
# Helper packages
library(dplyr)       # for data manipulation
```

```
##
## Attaching package: 'dplyr'
```

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

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

```
library(ggplot2)     # for data visualization
library(stringr)     # for string functionality
library(gridExtra)   # for manipulaiting the grid
```

```
##
## Attaching package: 'gridExtra'
```

```
## The following object is masked from 'package:dplyr':
##
##     combine
```

```
# Modeling packages
library(tidyverse)  # data manipulation
```

```
## ── Attaching packages ─────────────────────────────────────
## tidyverse 1.3.2 ──
```

```
## ✔ tibble  3.1.8     ✔ purrr   0.3.5
## ✔ tidyr   1.1.4     ✔ forcats 0.5.1
## ✔ readr   2.1.3
## ── Conflicts ────────────────────────────────────────── tidyverse_conflicts() ──
## ✖ gridExtra::combine() masks dplyr::combine()
## ✖ dplyr::filter()      masks stats::filter()
## ✖ dplyr::lag()         masks stats::lag()
```

```
library(cluster)     # for general clustering algorithms
library(factoextra)  # for visualizing cluster results
```

```
## Welcome! Want to learn more? See two factoextra-related books at https://goo.gl/ve3WB
a
```

```
# Modeling packages
library(mclust)   # for fitting clustering algorithms
```

```
## Package 'mclust' version 6.0.0
## Type 'citation("mclust")' for citing this R package in publications.
##
## Attaching package: 'mclust'
##
## The following object is masked from 'package:purrr':
##
##     map
```

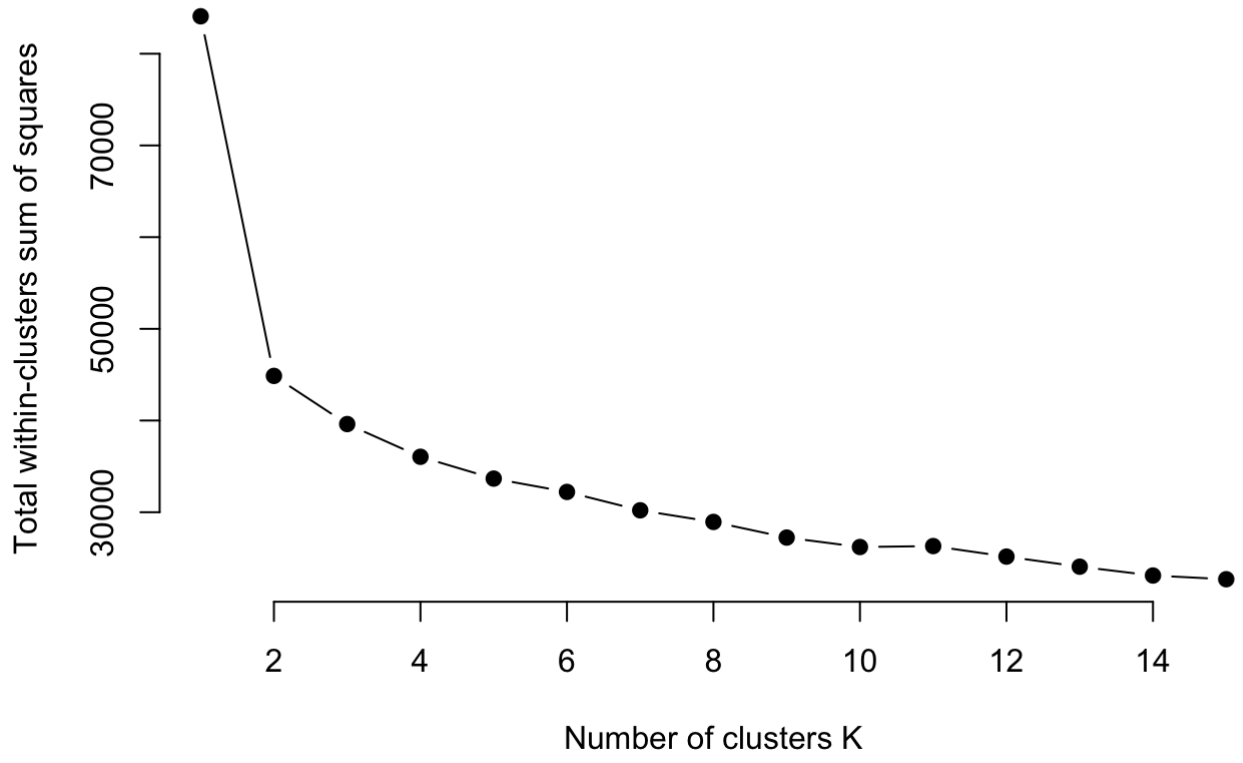
```
# load essential data frame
df_m3 <-  read.csv('./radiomics_completedata.csv')
```

Step 2: Conduct K-Means clustering

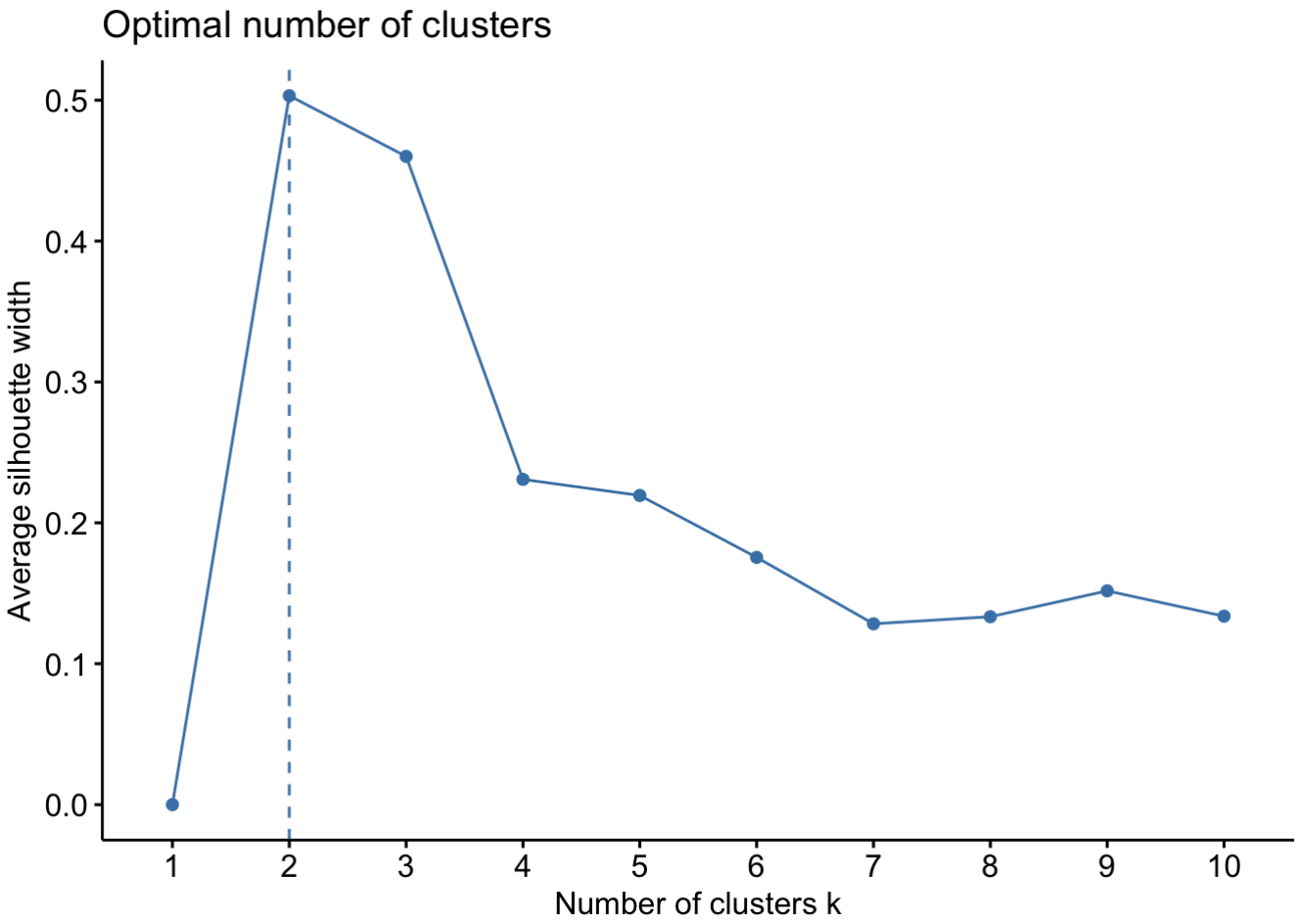
```
# remove categorical and binary columns from the data frame
i1_m3 <- sapply(df_m3, is.numeric)

df_m3 <- df_m3[i1_m3]

df_m3 <- Filter(function(x) !all(x %in% c(0, 1)), df_m3)

# Check if there's any null values
df_m3 <- na.omit(df_m3)

# scale the data
final_m3 <- scale(df_m3)

final_m3 <- as.data.frame(final_m3)
```

Start the Clustering process for K-Means

```
# Determining Optimal Number of Clusters
set.seed(123)

#function to compute total within-cluster sum of square
wss <- function(k) {
  kmeans(final_m3, k, nstart = 10)$tot.withinss
}

# Compute and plot wss for k = 1 to k = 15
k.values <- 1:15

# extract wss for 2-15 clusters
wss_values <- map_dbl(k.values, wss)

plot(k.values, wss_values,
     type="b", pch = 19, frame = FALSE,
     xlab="Number of clusters K",
     ylab="Total within-clusters sum of squares")
```



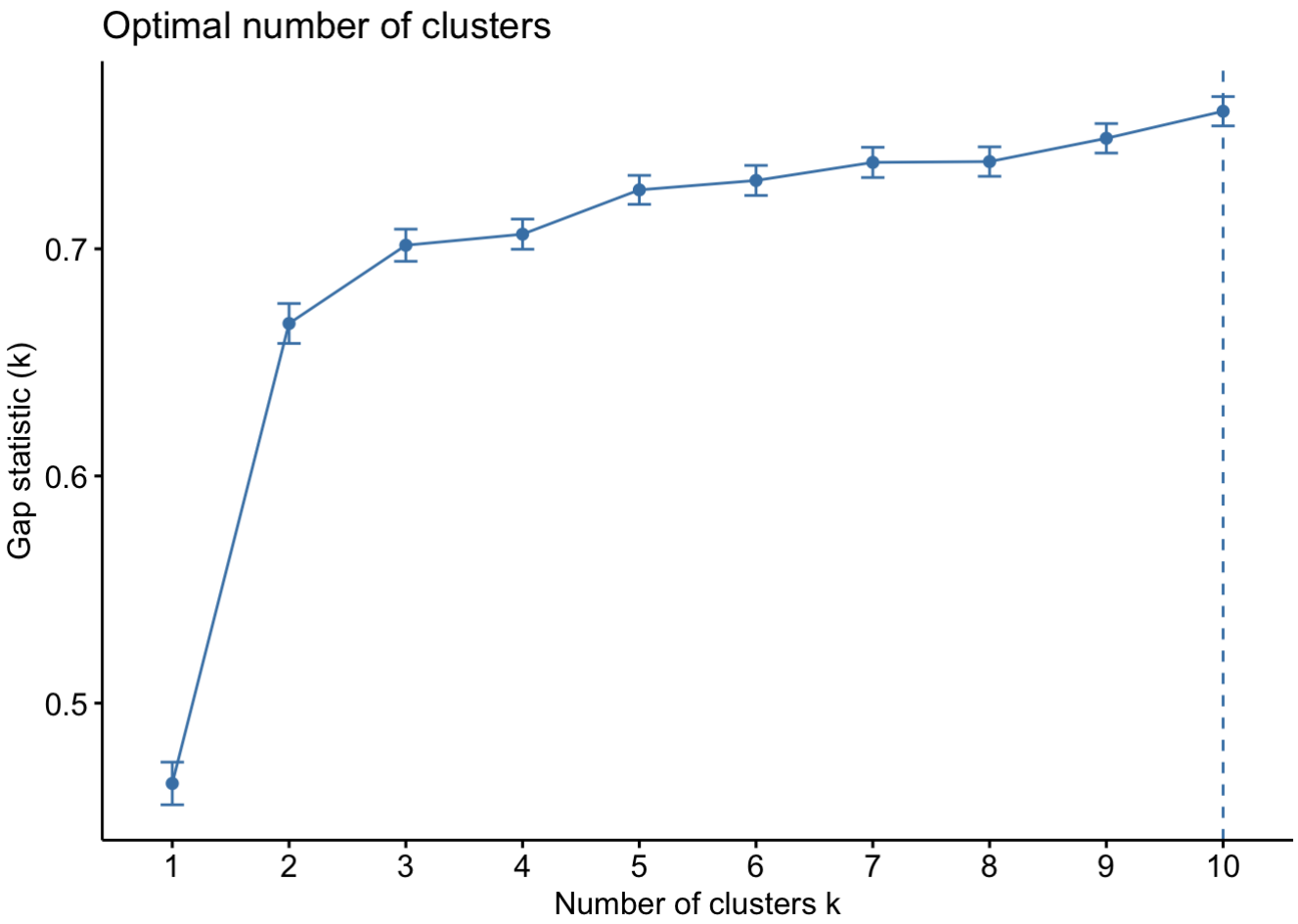

```
#or use this
fviz_nbclust(final_m3, kmeans, method = "silhouette")
```




```
# compute gap statistic
set.seed(123)
gap_stat <- clusGap(final_m3, FUN = kmeans, nstart = 25,
                    K.max = 10, B = 50)
# Print the result
print(gap_stat, method = "firstmax")
```

```
## Clustering Gap statistic ["clusGap"] from call:
## clusGap(x = final_m3, FUNcluster = kmeans, K.max = 10, B = 50, nstart = 25)
## B=50 simulated reference sets, k = 1..10; spaceH0="scaledPCA"
##  --> Number of clusters (method 'firstmax'): 10
##           logW   E.logW       gap      SE.sim
##  [1,] 7.171204 7.635853 0.4646496 0.009379996
##  [2,] 6.879524 7.546674 0.6671493 0.008786338
##  [3,] 6.798848 7.500436 0.7015873 0.007082545
##  [4,] 6.760004 7.466467 0.7064633 0.006632270
##  [5,] 6.715614 7.441579 0.7259645 0.006374244
##  [6,] 6.689522 7.419633 0.7301115 0.006603869
##  [7,] 6.661683 7.399745 0.7380616 0.006654018
##  [8,] 6.643211 7.381624 0.7384134 0.006480643
##  [9,] 6.616471 7.365139 0.7486677 0.006484664
## [10,] 6.588968 7.349544 0.7605765 0.006453097
```

```
fviz_gap_stat(gap_stat)
```




```
# Compute k-means clustering with k = 2
set.seed(123)
final <- kmeans(final_m3, 2, nstart = 25)
print(final)
```

```
## K-means clustering with 2 clusters of sizes 50, 147
##
## Cluster means:
##         Failure Entropy_cooc.W.ADC GLNU_align.H.PET Min_hist.PET Max_hist.PET
## 1 -0.0014733768         0.04845450      -0.07901100    0.9204612    0.9468341
## 2  0.0005011486        -0.01648112       0.02687449   -0.3130820   -0.3220524
##   Mean_hist.PET Variance_hist.PET Standard_Deviation_hist.PET Skewness_hist.PET
## 1     0.9216792         0.4594337                   0.9319222         0.9115602
## 2    -0.3134963        -0.1562700                  -0.3169804        -0.3100545
##   Kurtosis_hist.PET Energy_hist.PET Entropy_hist.PET AUC_hist.PET  H_suv.PET
## 1        0.25274217       0.6864958        1.5003007    1.6957546  0.9652219
## 2       -0.08596673      -0.2335020       -0.5103064   -0.5767873 -0.3283068
##   Volume.PET X3D_surface.PET ratio_3ds_vol.PET ratio_3ds_vol_norm.PET
## 1  0.5900077       0.3802612         0.9436984              0.9622506
## 2 -0.2006829      -0.1293406        -0.3209858             -0.3272961
##   irregularity.PET tumor_length.PET Compactness_v1.PET Compactness_v2.PET
## 1        1.6522842        1.0256292          0.8807232          0.4324058
## 2       -0.5620014       -0.3488535         -0.2995657         -0.1470768
##   Spherical_disproportion.PET Sphericity.PET Asphericity.PET Center_of_mass.PET
## 1                   0.9622506      0.4460709       0.9240341          0.6358358
## 2                  -0.3272961     -0.1517248      -0.3142973         -0.2162707
##   Max_3D_diam.PET Major_axis_length.PET Minor_axis_length.PET
## 1       0.8259982             0.8904297             1.1433164
## 2      -0.2809518            -0.3028672            -0.3888831
##   Least_axis_length.PET Elongation.PET Flatness.PET Max_cooc.L.PET
## 1             0.9772289      1.4563692    1.3553445      0.7290795
## 2            -0.3323908     -0.4953637   -0.4610015     -0.2479862
##   Average_cooc.L.PET Variance_cooc.L.PET Entropy_cooc.L.PET DAVE_cooc.L.PET
## 1           1.389215           1.1041050          1.6813985       1.2936781
## 2          -0.472522          -0.3755459         -0.5719043      -0.4400266
##   DVAR_cooc.L.PET DENT_cooc.L.PET SAVE_cooc.L.PET SVAR_cooc.L.PET
## 1       1.1366603       1.6603800       1.3889879       1.1209781
## 2      -0.3866192      -0.5647551      -0.4724449      -0.3812851
##   SENT_cooc.L.PET ASM_cooc.L.PET Contrast_cooc.L.PET Dissimilarity_cooc.L.PET
## 1       1.6614758      0.6775498           0.9285775                1.2936781
## 2      -0.5651278     -0.2304591          -0.3158427               -0.4400266
##   Inv_diff_cooc.L.PET Inv_diff_norm_cooc.L.PET IDM_cooc.L.PET
## 1            1.443028                1.6979660      1.2814891
## 2           -0.490826               -0.5775395     -0.4358807
##   IDM_norm_cooc.L.PET Inv_var_cooc.L.PET Correlation_cooc.L.PET
## 1           1.7046571          1.2896785               1.123648
## 2          -0.5798153         -0.4386661              -0.382193
##   Autocorrelation_cooc.L.PET Tendency_cooc.L.PET Shade_cooc.L.PET
## 1                  1.0338012           1.1209781        0.5578271
## 2                 -0.3516331          -0.3812851       -0.1897371
##   Prominence_cooc.L.PET IC1_.L.PET IC2_.L.PET Coarseness_vdif_.L.PET
## 1             0.7889007 -0.6341334  1.5273752              0.7537450
## 2            -0.2683336  0.2156916 -0.5195154             -0.2563758
##   Contrast_vdif_.L.PET Busyness_vdif_.L.PET Complexity_vdif_.L.PET
## 1            0.3878173            0.5565230              1.2153015
## 2           -0.1319107           -0.1892936             -0.4133678
##   Strength_vdif_.L.PET SRE_align.L.PET LRE_align.L.PET GLNU_align.L.PET
```

```
## 1            0.4934069        1.706523       1.6948229        0.4587983
## 2           -0.1678255       -0.580450      -0.5764704       -0.1560539
##   RLNU_align.L.PET RP_align.L.PET LGRE_align.L.PET HGRE_align.L.PET
## 1        0.4189336      1.7061400        1.0408063        1.0700373
## 2       -0.1424944     -0.5803197       -0.3540158       -0.3639583
##   LGSRE_align.L.PET HGSRE_align.L.PET LGHRE_align.L.PET HGLRE_align.L.PET
## 1          1.048281         1.0672364         1.0052958          1.078233
## 2         -0.356558        -0.3630056        -0.3419373         -0.366746
##   GLNU_norm_align.L.PET RLNU_norm_align.L.PET GLVAR_align.L.PET
## 1             1.1041018             1.7034139         1.1510468
## 2            -0.3755448            -0.5793925        -0.3915125
##   RLVAR_align.L.PET Entropy_align.L.PET SZSE.L.PET LZSE.L.PET LGLZE.L.PET
## 1         1.0474522           1.6880661  1.6676802  1.1852630   1.0601400
## 2        -0.3562762          -0.5741722 -0.5672382 -0.4031507  -0.3605919
##   HGLZE.L.PET SZLGE.L.PET SZHGE.L.PET LZLGE.L.PET LZHGE.L.PET GLNU_area.L.PET
## 1   1.0866745   1.0735299   1.0776043   0.8457163   0.8914749       0.4621309
## 2  -0.3696172  -0.3651462  -0.3665321  -0.2876586  -0.3032228      -0.1571874
##   ZSNU.L.PET ZSP.L.PET GLNU_norm.L.PET ZSNU_norm.L.PET GLVAR_area.L.PET
## 1  0.4218710  1.679008       1.1042309        1.681848        1.1694826
## 2 -0.1434935 -0.571091      -0.3755887       -0.572057       -0.3977832
##   ZSVAR.L.PET Entropy_area.L.PET Max_cooc.H.PET Average_cooc.H.PET
## 1   0.7548095          1.6893793      0.5052232          1.6652563
## 2  -0.2567379         -0.5746188     -0.1718446         -0.5664137
##   Variance_cooc.H.PET Entropy_cooc.H.PET DAVE_cooc.H.PET DVAR_cooc.H.PET
## 1           1.4721984          1.4404122       1.5079528       1.4645709
## 2          -0.5007478         -0.4899361      -0.5129091      -0.4981534
##   DENT_cooc.H.PET SAVE_cooc.H.PET SVAR_cooc.H.PET SENT_cooc.H.PET
## 1       1.3368883       1.6782221       1.4484331       1.1582831
## 2      -0.4547239      -0.5708239      -0.4926643      -0.3939739
##   ASM_cooc.H.PET Contrast_cooc.H.PET Dissimilarity_cooc.H.PET
## 1      0.4701159            1.344935                1.5079528
## 2     -0.1599034           -0.457461               -0.5129091
##   Inv_diff_cooc.H.PET Inv_diff_norm_cooc.H.PET IDM_cooc.H.PET
## 1           1.1377441                1.6996628      0.9576980
## 2          -0.3869878               -0.5781166     -0.3257476
##   IDM_norm_cooc.H.PET Inv_var_cooc_.H.PET Correlation_cooc.H.PET
## 1           1.7052806           0.9554037              1.1365587
## 2          -0.5800274          -0.3249672             -0.3865846
##   Autocorrelation_cooc.H.PET Tendency_cooc.H.PET Shade_cooc.H.PET
## 1                  1.5649714           1.4092944       -0.7124616
## 2                 -0.5323032          -0.4793518        0.2423339
##   Prominence_cooc.H.PET IC1_d.H.PET IC2_d.H.PET Coarseness_vdif.H.PET
## 1             1.0427158 -0.23095606   1.3345708             0.6663547
## 2            -0.3546653  0.07855648  -0.4539356            -0.2266512
##   Contrast_vdif.H.PET Busyness_vdif.H.PET Complexity_vdif.H.PET
## 1           0.4860224          0.25301766             1.0958360
## 2          -0.1653138         -0.08606043            -0.3727333
##   Strength_vdif.H.PET SRE_align.H.PET LRE_align.H.PET RLNU_align.H.PET
## 1          0.03112072       1.6638495       1.0890098        0.4166644
## 2         -0.01058528      -0.5659352      -0.3704115       -0.1417226
##   RP_align.H.PET LGRE_align.H.PET HGRE_align.H.PET LGSRE_align.H.PET
## 1      1.6436641        0.7082866        1.5743684         0.7040204
```

```
## 2     -0.5590694       -0.2409138       -0.5354994        -0.2394627
##   HGSRE_align.H.PET LGHRE_align.H.PET HGLRE_align.H.PET GLNU_norm_align.H.PET
## 1         1.6533952         0.7311054         0.7453460             0.8572435
## 2        -0.5623793        -0.2486753        -0.2535191            -0.2915794
##   RLNU_norm_align.H.PET GLVAR_align.H.PET RLVAR_align.H.PET Entropy_align.H.PET
## 1             1.5584253         1.4161797         0.4776867            1.550297
## 2            -0.5300766        -0.4816938        -0.1624785           -0.527312
##   SZSE.H.PET  LZSE.H.PET LGLZE.H.PET HGLZE.H.PET SZLGE.H.PET SZHGE.H.PET
## 1  1.4671263 -0.09759617   0.7096710   1.4890573   0.6984264   1.4294579
## 2 -0.4990226  0.03319598  -0.2413847  -0.5064821  -0.2375600  -0.4862102
##    LZLGE.H.PET LZHGE.H.PET GLNU_area.H.PET ZSNU.H.PET  ZSP.H.PET
## 1  0.001044652 -0.08592571       0.4835029  0.3648643  1.1565208
## 2 -0.000355324  0.02922643      -0.1644568 -0.1241035 -0.3933744
##   GLNU_norm.H.PET ZSNU_norm.H.PET GLVAR_area.H.PET ZSVAR_H.PET
## 1       0.8791603       1.2441418        1.3802703 -0.09449223
## 2      -0.2990341      -0.4231775       -0.4694797  0.03214021
##   Entropy_area.H.PET Max_cooc.W.PET Average_cooc.W.PET Variance_cooc.W.PET
## 1          1.6279234      0.5502762          0.9151412           0.4579807
## 2         -0.5537154     -0.1871688         -0.3112725          -0.1557757
##   Entropy_cooc.W.PET DAVE_cooc.W.PET DVAR_cooc.W.PET DENT_cooc.W.PET
## 1          1.4784780       0.9564701       0.5165571        1.450023
## 2         -0.5028837      -0.3253300      -0.1756997       -0.493205
##   SAVE_cooc.W.PET SVAR_cooc.W.PET SENT_cooc.W.PET ASM_cooc.W.PET
## 1       0.9140050       0.4135667       1.5336398      0.5955603
## 2      -0.3108861      -0.1406689      -0.5216462     -0.2025715
##   Contrast_cooc.W.PET Dissimilarity_cooc.W.PET Inv_diff_cooc.W.PET
## 1           0.5325478                0.9564701           1.2750883
## 2          -0.1811387               -0.3253300          -0.4337035
##   Inv_diff_norm_cooc.W.PET IDM_cooc.W.PET IDM_norm_cooc.W.PET
## 1                1.6983343       1.044167           1.7048157
## 2               -0.5776647      -0.355159          -0.5798693
##   Inv_var_cooc.W.PET Correlation_cooc.W.PET Autocorrelation_cooc.W.PET
## 1          1.1637708              1.1228422                  0.4576739
## 2         -0.3958404             -0.3819191                 -0.1556714
##   Tendency_cooc.W.PET Shade_cooc.W.PET Prominence_cooc.W.PET IC1_d.W.PET
## 1           0.4135667       0.07642004           0.022900737 -0.26887955
## 2          -0.1406689      -0.02599321          -0.007789366  0.09145563
##   IC2_d.W.PET Coarseness_vdif.W.PET Contrast_vdif.W.PET Busyness_vdif.W.PET
## 1   1.4455561             0.7071892           0.8252351           0.4153574
## 2  -0.4916858            -0.2405405          -0.2806922          -0.1412780
##   Complexity_vdif.W.PET Strength_vdif.W.PET SRE_align.W.PET LRE_align.W.PET
## 1             0.2991726           0.4249851        1.697315       1.4801473
## 2            -0.1017594          -0.1445527       -0.577318      -0.5034515
##   GLNU_align.W.PET RLNU_align.W.PET RP_align.W.PET LGRE_align.W.PET
## 1        0.4738278        0.4182280      1.6901986        0.8300003
## 2       -0.1611659       -0.1422544     -0.5748975       -0.2823130
##   HGRE_align.W.PET LGSRE_align.W.PET HGSRE_align.W.PET LGHRE_align.W.PET
## 1        0.4630749         0.8904857         0.4557129         0.5563026
## 2       -0.1575085        -0.3028863        -0.1550044        -0.1892186
##   HGLRE_align.W.PET GLNU_norm_align.W.PET RLNU_norm_align.W.PET
## 1         0.4921754             0.8494549              1.658483
## 2        -0.1674066            -0.2889302             -0.564110
```

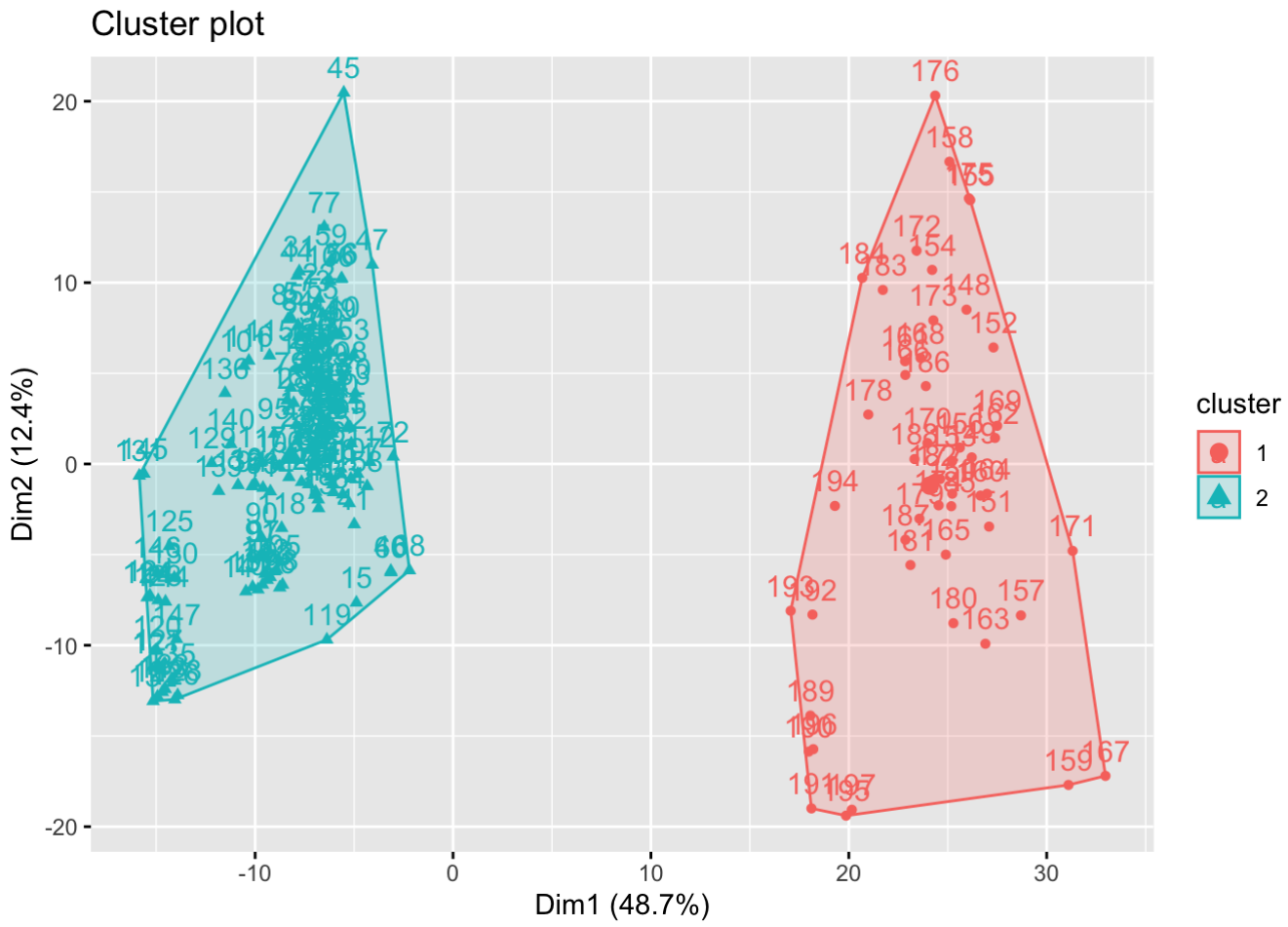
```
##   GLVAR_align.W.PET RLVAR_align.W.PET Entropy_align.W.PET SZSE.W.PET
## 1         0.4593218         0.5957178           1.5543465  1.6121174
## 2        -0.1562319        -0.2026251          -0.5286893 -0.5483392
##    LZSE.W.PET LGLZE.W.PET HGLZE.W.PET SZLGE.W.PET SZHGE.W.PET  LZLGE.W.PET
## 1  0.21517025   0.8709408   0.4690713   0.9938480   0.4481637 -0.004326372
## 2 -0.07318716  -0.2962384  -0.1595481  -0.3380435  -0.1524366  0.001471555
##   LZHGE.W.PET GLNU_area.W.PET ZSNU.W.PET  ZSP.W.PET GLNU_norm.W.PET
## 1   0.5263985       0.4910918  0.3971868  1.4948131       0.8826796
## 2  -0.1790471      -0.1670380 -0.1350976 -0.5084398      -0.3002311
##   ZSNU_norm.W.PET GLVAR_area.W.PET ZSVAR.W.PET Entropy_area.W.PET Min_hist.ADC
## 1       1.4869647        0.4655759  0.06408427          1.6167770    0.5724098
## 2      -0.5057703       -0.1583592 -0.02179737         -0.5499242   -0.1946972
##   Max_hist.ADC Mean_hist.ADC Variance_hist.ADC Standard_Deviation_hist.ADC
## 1    1.5075750     1.4864908         0.7599395                    1.2359485
## 2   -0.5127806    -0.5056091        -0.2584828                   -0.4203906
##   Skewness_hist.ADC Kurtosis_hist.ADC Energy_hist.ADC Entropy_hist.ADC
## 1         0.3899909         0.4662845       0.7015053        1.6284344
## 2        -0.1326500        -0.1586002      -0.2386073       -0.5538893
##   AUC_hist.ADC Volume.ADC X3D_surface.ADC ratio_3ds_vol.ADC
## 1    1.6655300  0.5687484       0.7349831         1.1042095
## 2   -0.5665068 -0.1934518      -0.2499942        -0.3755815
##   ratio_3ds_vol_norm.ADC irregularity.ADC Compactness_v1.ADC Compactness_v2.ADC
## 1              1.6106322        1.6397737          1.1221987          1.3007130
## 2             -0.5478341       -0.5577462         -0.3817002         -0.4424194
##   Spherical_disproportion.ADC Sphericity.ADC Asphericity.ADC Center_of_mass.ADC
## 1                   1.6106322      1.6242350       1.1989866          0.5373920
## 2                  -0.5478341     -0.5524609      -0.4078186         -0.1827864
##   Max_3D_diam.ADC Major_axis_length.ADC Minor_axis_length.ADC
## 1       1.0866100             1.2316275             1.1312333
## 2      -0.3695952            -0.4189209            -0.3847732
##   Least_axis_length.ADC Elongation.ADC Flatness.ADC Max_cooc.L.ADC
## 1             1.0417403      1.4824827    1.4052040      0.8250964
## 2            -0.3543334     -0.5042458   -0.4779606     -0.2806450
##   Average_cooc.L.ADC Variance_cooc.L.ADC Entropy_cooc.L.ADC DAVE_cooc.L.ADC
## 1           1.456079           0.9533869          1.6827114       1.2819538
## 2          -0.495265          -0.3242813         -0.5723508      -0.4360387
##   DVAR_cooc.L.ADC DENT_cooc.L.ADC SAVE_cooc.L.ADC SVAR_cooc.L.ADC
## 1       0.9295089       1.6521421       1.4558899       0.9317704
## 2      -0.3161595      -0.5619531      -0.4952006      -0.3169287
##   SENT_cooc.L.ADC ASM_cooc.L.ADC Contrast_cooc.L.ADC Dissimilarity_cooc.L.ADC
## 1       1.2584756      0.7127202           0.8811662                1.2819538
## 2      -0.4280529     -0.2424218          -0.2997164               -0.4360387
##   Inv_diff_cooc.L.ADC Inv_diff_norm_cooc.L.ADC IDM_cooc.L.ADC
## 1           1.5058302                1.7039344      1.3642322
## 2          -0.5121871               -0.5795695     -0.4640245
##   IDM_norm_cooc.L.ADC Inv_var_cooc.L.ADC Correlation_cooc.L.ADC
## 1           1.7073272           1.379898              1.2216811
## 2          -0.5807235          -0.469353             -0.4155378
##   Autocorrelation_.L.ADC Tendency_cooc.L.ADC Shade_.L.ADC Prominence_cooc.L.ADC
## 1              1.1050198           0.9317704   0.29259000             0.5515288
## 2             -0.3758571          -0.3169287  -0.09952041            -0.1875948
##   IC1_.L.ADC IC2_.L.ADC Coarseness_vdif_.L.ADC Contrast_vdif_.L.ADC
```

```
## 1 -0.6732168  1.5121032              0.6939723            0.6587722
## 2  0.2289853 -0.5143208             -0.2360450           -0.2240722
##   Busyness_vdif_.L.ADC Complexity_vdif_.L.ADC Strength_vdif_.L.ADC
## 1            0.6475886              1.2753146            0.4214397
## 2           -0.2202682             -0.4337805           -0.1433468
##   SRE_align.L.ADC LRE_align.L.ADC GLNU_align.L.ADC RLNU_align.L.ADC
## 1       1.7052408       1.6811893        0.5682374        0.5910147
## 2      -0.5800139      -0.5718331       -0.1932780       -0.2010254
##   RP_align.L.ADC LGRE_align.L.ADC HGRE_align.L.ADC LGSRE_align.L.ADC
## 1      1.7034645        0.7243458        1.2086645         0.7235521
## 2     -0.5794097       -0.2463761       -0.4111104        -0.2461061
##   HGSRE_align.L.ADC LGHRE_align.L.ADC HGLRE_align.L.ADC GLNU_norm_align.L.ADC
## 1         1.2124123         0.7234431         1.1801466             1.2291014
## 2        -0.4123852        -0.2460691        -0.4014104            -0.4180617
##   RLNU_norm_align.L.ADC GLVAR_align.L.ADC RLVAR_align.L.ADC Entropy_align.L.ADC
## 1             1.6955541         0.9930121         1.1385331           1.6982212
## 2            -0.5767191        -0.3377592        -0.3872562          -0.5776262
##   SZSE.L.ADC LZSE.L.ADC LGLZE.L.ADC HGLZE.L.ADC SZLGE.L.ADC SZHGE.L.ADC
## 1  1.6968578  1.3430968   0.7262967   1.2295659   0.7219542   1.2399482
## 2 -0.5771625 -0.4568356  -0.2470397  -0.4182197  -0.2455627  -0.4217511
##   LZLGE.L.ADC LZHGE.L.ADC GLNU_area.L.ADC ZSNU.L.ADC  ZSP.L.ADC GLNU_norm.L.ADC
## 1   0.6651854    1.077189       0.5782984  0.5919629  1.6748354       1.2251432
## 2  -0.2262535   -0.366391      -0.1967001 -0.2013479 -0.5696719      -0.4167154
##   ZSNU_norm.L.ADC GLVAR_area.L.ADC ZSVAR.L.ADC Entropy_area.L.ADC
## 1       1.6570978         1.012871   0.6758567          1.7010816
## 2      -0.5636387        -0.344514  -0.2298832         -0.5785992
##   Max_cooc.H.ADC Average_cooc.H.ADC Variance_cooc.H.ADC Entropy_cooc.H.ADC
## 1      0.7039103          1.6967547           1.7053247          1.7011475
## 2     -0.2394253         -0.5771274          -0.5800424         -0.5786216
##   DAVE_cooc.H.ADC DVAR_cooc.H.ADC DENT_cooc.H.ADC SAVE_cooc.H.ADC
## 1       1.5698813       1.4861394       1.7017575       1.6967573
## 2      -0.5339732      -0.5054896      -0.5788291      -0.5771283
##   SVAR_cooc.H.ADC SENT_cooc.H.ADC ASM_cooc.H.ADC Contrast_cooc.H.ADC
## 1       1.6206816       1.6803084      0.6607170           1.3858879
## 2      -0.5512522      -0.5715335     -0.2247337          -0.4713904
##   Dissimilarity_cooc.H.ADC Inv_diff_cooc.H.ADC Inv_diff_norm_cooc.H.ADC
## 1                1.5698813           1.5546888                1.7028145
## 2               -0.5339732          -0.5288057               -0.5791886
##   IDM_cooc.H.ADC IDM_norm_cooc.H.ADC Inv_var_cooc.H.ADC Correlation_cooc.H.ADC
## 1      1.4136874           1.7054539          1.4364367              1.1993586
## 2     -0.4808461          -0.5800864         -0.4885839             -0.4079451
##   Autocorrelation_cooc.H.ADC Tendency_cooc.H.ADC Shade_cooc.H.ADC
## 1                  1.6722184           1.6206816        0.3887230
## 2                 -0.5687818          -0.5512522       -0.1322187
##   Prominence_cooc.H.ADC IC1_d.H.ADC IC2_d.H.ADC Coarseness_vdif.H.ADC
## 1             1.5404751  -0.5455177   1.5085932             0.6780216
## 2            -0.5239711   0.1855502  -0.5131269            -0.2306196
##   Contrast_vdif.H.ADC Busyness_vdif.H.ADC Complexity_vdif.H.ADC
## 1           1.5316725           0.6153610              1.503704
## 2          -0.5209771          -0.2093065             -0.511464
##   Strength_vdif.H.ADC SRE_align.H.ADC LRE_align.H.ADC GLNU_align.H.ADC
## 1           0.3677298       1.7071497       1.7038845        0.5901231
```

```
## 2          -0.1250782      -0.5806632      -0.5795526       -0.2007222
##   RLNU_align.H.ADC RP_align.H.ADC LGRE_align.H.ADC HGRE_align.H.ADC
## 1        0.5924412       1.706814        1.0946139        1.7100780
## 2       -0.2015106      -0.580549       -0.3723177       -0.5816592
##   LGSRE_align.H.ADC HGSRE_align.H.ADC LGHRE_align.H.ADC HGLRE_align.H.ADC
## 1         1.0760014         1.7093907         1.1710039         1.7053139
## 2        -0.3659869        -0.5814254        -0.3983006        -0.5800387
##   GLNU_norm_align.H.ADC RLNU_norm_align.H.ADC GLVAR_align.H.ADC
## 1             0.9735389             1.7053279         1.7100152
## 2            -0.3311357            -0.5800435        -0.5816378
##   RLVAR_align.H.ADC Entropy_align.H.ADC SZSE.H.ADC LZSE.H.ADC LGLZE.H.ADC
## 1         1.0687509           1.7093530  1.7049082  1.6336887   1.0589022
## 2        -0.3635207          -0.5814126 -0.5799008 -0.5556764  -0.3601708
##   HGLZE.H.ADC SZLGE.H.ADC SZHGE.H.ADC LZLGE.H.ADC LZHGE.H.ADC GLNU_area.H.ADC
## 1    1.709075   1.0114862   1.7031396   1.0813161   1.5698347       0.5919958
## 2   -0.581318  -0.3440429  -0.5792992  -0.3677946  -0.5339574      -0.2013591
##   ZSNU.H.ADC  ZSP.H.ADC GLNU_norm.H.ADC ZSNU_norm.H.ADC GLVAR_area.H.ADC
## 1  0.5972096  1.7013318       0.9745507        1.692802        1.7072803
## 2 -0.2031325 -0.5786843      -0.3314798       -0.575783       -0.5807076
##   ZSVAR.H.ADC Entropy_area.H.ADC Max_cooc.W.ADC Average_cooc.W.ADC
## 1   0.8431301          1.7066118      0.6868122           1.199285
## 2  -0.2867790         -0.5804802     -0.2336096          -0.407920
##   Variance_cooc.W.ADC DAVE_cooc.W.ADC DVAR_cooc.W.ADC DENT_cooc.W.ADC
## 1           0.7283676       1.3033631       0.7679414       1.6768624
## 2          -0.2477441      -0.4433208      -0.2612045      -0.5703613
##   SAVE_cooc.W.ADC SVAR_cooc.W.ADC SENT_cooc.W.ADC ASM_cooc.W.ADC
## 1       1.1909017       0.6843706       1.2023295      0.6601442
## 2      -0.4050686      -0.2327791      -0.4089556     -0.2245389
##   Contrast_cooc.W.ADC Dissimilarity_cooc.W.ADC Inv_diff_cooc.W.ADC
## 1           0.7994120                1.3033631           1.3827605
## 2          -0.2719088               -0.4433208          -0.4703267
##   Inv_diff_norm_cooc.W.ADC IDM_cooc.W.ADC IDM_norm_cooc.W.ADC
## 1                1.7038802      1.3112119           1.7073083
## 2               -0.5795511     -0.4459904          -0.5807171
##   Inv_var_cooc.W.ADC Correlation_cooc.W.ADC Autocorrelation_cooc.W.ADC
## 1          1.3074526              1.2225367                  0.8447953
## 2         -0.4447118             -0.4158288                 -0.2873453
##   Tendency_cooc.W.ADC Shade_cooc.W.ADC Prominence_cooc.W.ADC IC1_d.W.ADC
## 1           0.6843706        0.2567335             0.3775512  -0.6756692
## 2          -0.2327791       -0.0873243            -0.1284188   0.2298194
##   IC2_d.W.ADC Coarseness_vdif.W.ADC Contrast_vdif.W.ADC Busyness_vdif.W.ADC
## 1   1.6012140             0.7114542           0.6249552           1.0116700
## 2  -0.5446306            -0.2419912          -0.2125698          -0.3441054
##   Complexity_vdif.W.ADC Strength_vdif.W.ADC SRE_align.W.ADC LRE_align.W.ADC
## 1             0.6003182           0.5784705       1.7073214       1.7065667
## 2            -0.2041899          -0.1967587      -0.5807216      -0.5804649
##   GLNU_align.W.ADC RLNU_align.W.ADC RP_align.W.ADC LGRE_align.W.ADC
## 1        0.6326468        0.5857336      1.7071535        0.6918953
## 2       -0.2151860       -0.1992291     -0.5806645       -0.2353386
##   HGRE_align.W.ADC LGSRE_align.W.ADC HGSRE_align.W.ADC LGHRE_align.W.ADC
## 1        0.8626770         0.6918084         0.8616174         0.6894568
## 2       -0.2934276        -0.2353090        -0.2930672        -0.2345091
```

```
##   HGLRE_align.W.ADC GLNU_norm_align.W.ADC RLNU_norm_align.W.ADC
## 1          0.866512             0.9154487             1.7063312
## 2         -0.294732            -0.3113771            -0.5803848
##   GLVAR_align.W.ADC RLVAR_align.W.ADC Entropy_align.W.ADC SZSE.W.ADC LZSE.W.ADC
## 1         0.7640782         0.9834635            1.661714  1.7066974  1.6823970
## 2        -0.2598905        -0.3345114           -0.565209 -0.5805093 -0.5722439
##   LGLZE.W.ADC HGLZE.W.ADC SZLGE.W.ADC SZHGE.W.ADC LZLGE.W.ADC LZHGE.W.ADC
## 1   0.6918923   0.8639228   0.6899145   0.8602645   0.6450074   0.8755515
## 2  -0.2353375  -0.2938513  -0.2346648  -0.2926070  -0.2193903  -0.2978066
##   GLNU_area.W.ADC ZSNU.W.ADC  ZSP.W.ADC GLNU_norm.W.ADC ZSNU_norm.W.ADC
## 1       0.6327545  0.5822861  1.7050925       0.9137899        1.699026
## 2      -0.2152226 -0.1980565 -0.5799634      -0.3108129       -0.577900
##   GLVAR_area.W.ADC ZSVAR.W.ADC Entropy_area.W.ADC
## 1        0.7713592   1.0785430           1.672228
## 2       -0.2623671  -0.3668514          -0.568785
##
## Clustering vector:
##   1   2   3   4   5   6   7   8   9  10  11  12  13  14  15  16  17  18  19  20
##   2   2   2   2   2   2   2   2   2   2   2   2   2   2   2   2   2   2   2   2
##  21  22  23  24  25  26  27  28  29  30  31  32  33  34  35  36  37  38  39  40
##   2   2   2   2   2   2   2   2   2   2   2   2   2   2   2   2   2   2   2   2
##  41  42  43  44  45  46  47  48  49  50  51  52  53  54  55  56  57  58  59  60
##   2   2   2   2   2   2   2   2   2   2   2   2   2   2   2   2   2   2   2   2
##  61  62  63  64  65  66  67  68  69  70  71  72  73  74  75  76  77  78  79  80
##   2   2   2   2   2   2   2   2   2   2   2   2   2   2   2   2   2   2   2   2
##  81  82  83  84  85  86  87  88  89  90  91  92  93  94  95  96  97  98  99 100
##   2   2   2   2   2   2   2   2   2   2   2   2   2   2   2   2   2   2   2   2
## 101 102 103 104 105 106 107 108 109 110 111 112 113 114 115 116 117 118 119 120
##   2   2   2   2   2   2   2   2   2   2   2   2   2   2   2   2   2   2   2   2
## 121 122 123 124 125 126 127 128 129 130 131 132 133 134 135 136 137 138 139 140
##   2   2   2   2   2   2   2   2   2   2   2   2   2   2   2   2   2   2   2   2
## 141 142 143 144 145 146 147 148 149 150 151 152 153 154 155 156 157 158 159 160
##   2   2   2   2   2   2   2   1   1   1   1   1   1   1   1   1   1   1   1   1
## 161 162 163 164 165 166 167 168 169 170 171 172 173 174 175 176 177 178 179 180
##   1   1   1   1   1   1   1   1   1   1   1   1   1   1   1   1   1   1   1   1
## 181 182 183 184 185 186 187 188 189 190 191 192 193 194 195 196 197
##   1   1   1   1   1   1   1   1   1   1   1   1   1   1   1   1   1
##
## Within cluster sum of squares by cluster:
## [1] 21058.70 23808.27
##  (between_SS / total_SS =  46.6 %)
##
## Available components:
##
## [1] "cluster"      "centers"      "totss"        "withinss"     "tot.withinss"
## [6] "betweenss"    "size"         "iter"         "ifault"
```

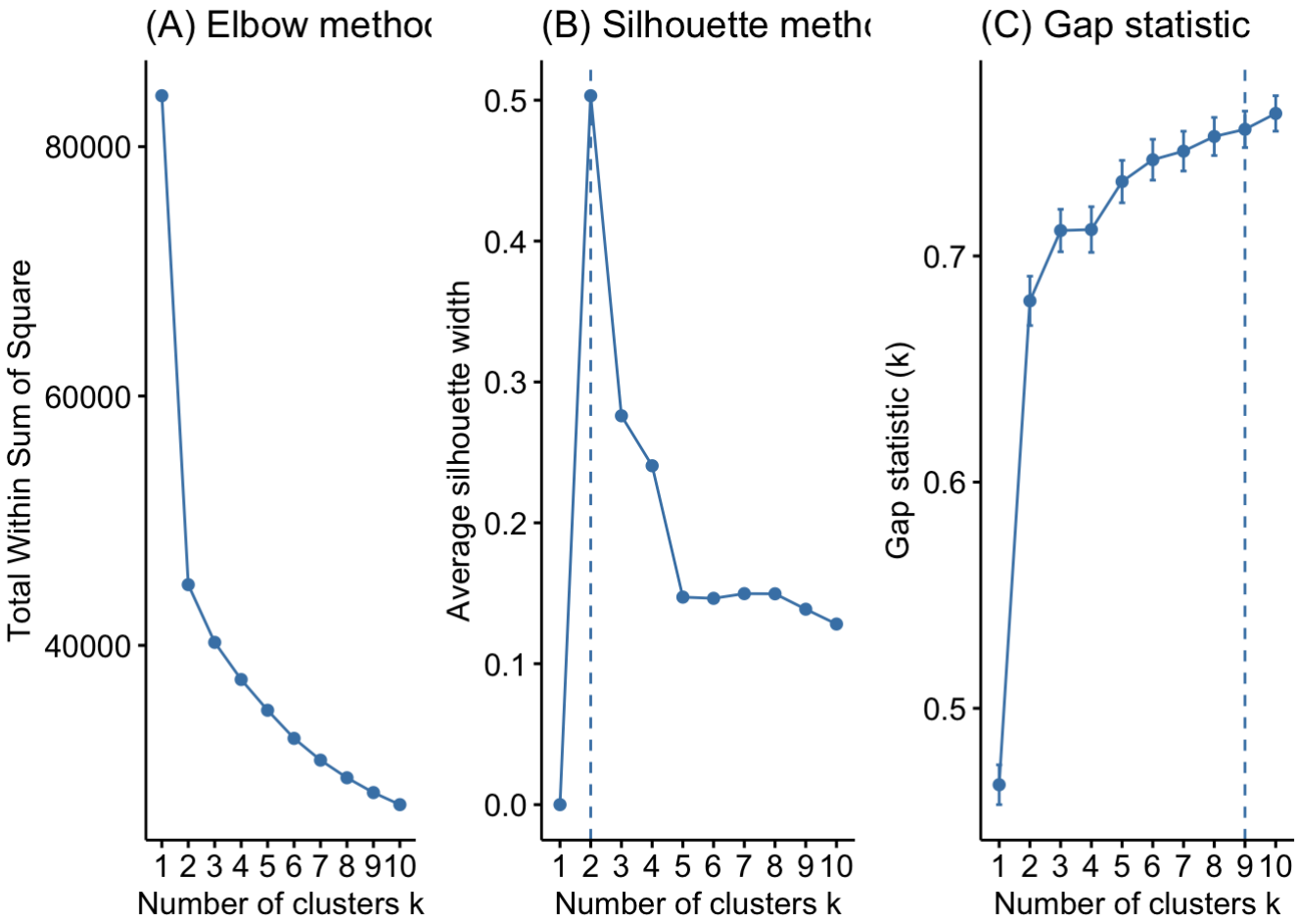
```
#final data
fviz_cluster(final, data = final_m3)
```



Step 3: Hierarchical

Now that we have done the K-Means clustering, we are aiming for unsupervised learning using hierarchical model

```
# Dissimilarity matrix
d <- dist(final_m3, method = "euclidean")

# Plot cluster results
p1 <- fviz_nbclust(final_m3, FUN = hcut, method = "wss",
                   k.max = 10) +
  ggtitle("(A) Elbow method")
p2 <- fviz_nbclust(final_m3, FUN = hcut, method = "silhouette",
                   k.max = 10) +
  ggtitle("(B) Silhouette method")
p3 <- fviz_nbclust(final_m3, FUN = hcut, method = "gap_stat",
                   k.max = 10) +
  ggtitle("(C) Gap statistic")

# Display plots side by side
gridExtra::grid.arrange(p1, p2, p3, nrow = 1)
```




```
# Construct dendorgram for the given data
hc5 <- hclust(d, method = "ward.D2" )
dend_plot <- fviz_dend(hc5)
```

```
## Warning: The `<scale>` argument of `guides()` cannot be `FALSE`. Use "none" instead a
s
## of ggplot2 3.3.4.
## ℹ The deprecated feature was likely used in the factoextra package.
##   Please report the issue at < ]8;;https://github.com/kassambara/factoextra/issues htt
ps://github.com/kassambara/factoextra/issues ]8;; >.
```

```
dend_data <- attr(dend_plot, "dendrogram")
dend_cuts <- cut(dend_data, h = 2)
dend_cuts
```

```
## $upper
## 'dendrogram' with 2 branches and 187 members total, at height 280.0608
##
## $lower
## $lower[[1]]
## 'dendrogram' leaf '169', at height 0
##
## $lower[[2]]
## 'dendrogram' leaf '155', at height 0
##
## $lower[[3]]
## 'dendrogram' leaf '175', at height 0
##
## $lower[[4]]
## 'dendrogram' leaf '148', at height 0
##
## $lower[[5]]
## 'dendrogram' leaf '188', at height 0
##
## $lower[[6]]
## 'dendrogram' leaf '154', at height 0
##
## $lower[[7]]
## 'dendrogram' leaf '158', at height 0
##
## $lower[[8]]
## 'dendrogram' leaf '176', at height 0
##
## $lower[[9]]
## 'dendrogram' leaf '183', at height 0
##
## $lower[[10]]
## 'dendrogram' leaf '184', at height 0
##
## $lower[[11]]
## 'dendrogram' leaf '193', at height 0
##
## $lower[[12]]
## 'dendrogram' leaf '194', at height 0
##
## $lower[[13]]
## 'dendrogram' with 2 branches and 2 members total, at height 1.053377
##
## $lower[[14]]
## 'dendrogram' leaf '191', at height 0
##
## $lower[[15]]
## 'dendrogram' leaf '196', at height 0
##
## $lower[[16]]
## 'dendrogram' leaf '189', at height 0
##
```

```
## $lower[[17]]
## 'dendrogram' leaf '190', at height 0
##
## $lower[[18]]
## 'dendrogram' leaf '167', at height 0
##
## $lower[[19]]
## 'dendrogram' leaf '159', at height 0
##
## $lower[[20]]
## 'dendrogram' leaf '171', at height 0
##
## $lower[[21]]
## 'dendrogram' leaf '180', at height 0
##
## $lower[[22]]
## 'dendrogram' leaf '157', at height 0
##
## $lower[[23]]
## 'dendrogram' leaf '150', at height 0
##
## $lower[[24]]
## 'dendrogram' leaf '149', at height 0
##
## $lower[[25]]
## 'dendrogram' leaf '151', at height 0
##
## $lower[[26]]
## 'dendrogram' leaf '192', at height 0
##
## $lower[[27]]
## 'dendrogram' leaf '170', at height 0
##
## $lower[[28]]
## 'dendrogram' leaf '177', at height 0
##
## $lower[[29]]
## 'dendrogram' leaf '182', at height 0
##
## $lower[[30]]
## 'dendrogram' leaf '153', at height 0
##
## $lower[[31]]
## 'dendrogram' leaf '164', at height 0
##
## $lower[[32]]
## 'dendrogram' leaf '162', at height 0
##
## $lower[[33]]
## 'dendrogram' leaf '152', at height 0
##
## $lower[[34]]
```

```
## 'dendrogram' leaf '160', at height 0
##
## $lower[[35]]
## 'dendrogram' leaf '163', at height 0
##
## $lower[[36]]
## 'dendrogram' leaf '156', at height 0
##
## $lower[[37]]
## 'dendrogram' leaf '179', at height 0
##
## $lower[[38]]
## 'dendrogram' leaf '181', at height 0
##
## $lower[[39]]
## 'dendrogram' leaf '165', at height 0
##
## $lower[[40]]
## 'dendrogram' leaf '174', at height 0
##
## $lower[[41]]
## 'dendrogram' leaf '185', at height 0
##
## $lower[[42]]
## 'dendrogram' leaf '186', at height 0
##
## $lower[[43]]
## 'dendrogram' leaf '173', at height 0
##
## $lower[[44]]
## 'dendrogram' leaf '187', at height 0
##
## $lower[[45]]
## 'dendrogram' leaf '172', at height 0
##
## $lower[[46]]
## 'dendrogram' leaf '168', at height 0
##
## $lower[[47]]
## 'dendrogram' leaf '178', at height 0
##
## $lower[[48]]
## 'dendrogram' leaf '161', at height 0
##
## $lower[[49]]
## 'dendrogram' leaf '166', at height 0
##
## $lower[[50]]
## 'dendrogram' leaf '126', at height 0
##
## $lower[[51]]
## 'dendrogram' leaf '128', at height 0
```

```
##
## $lower[[52]]
## 'dendrogram' leaf '125', at height 0
##
## $lower[[53]]
## 'dendrogram' with 2 branches and 2 members total, at height 1.598802
##
## $lower[[54]]
## 'dendrogram' leaf '146', at height 0
##
## $lower[[55]]
## 'dendrogram' leaf '147', at height 0
##
## $lower[[56]]
## 'dendrogram' with 2 branches and 3 members total, at height 1.798135
##
## $lower[[57]]
## 'dendrogram' leaf '132', at height 0
##
## $lower[[58]]
## 'dendrogram' leaf '135', at height 0
##
## $lower[[59]]
## 'dendrogram' leaf '142', at height 0
##
## $lower[[60]]
## 'dendrogram' leaf '137', at height 0
##
## $lower[[61]]
## 'dendrogram' leaf '141', at height 0
##
## $lower[[62]]
## 'dendrogram' leaf '123', at height 0
##
## $lower[[63]]
## 'dendrogram' leaf '130', at height 0
##
## $lower[[64]]
## 'dendrogram' leaf '127', at height 0
##
## $lower[[65]]
## 'dendrogram' leaf '144', at height 0
##
## $lower[[66]]
## 'dendrogram' leaf '120', at height 0
##
## $lower[[67]]
## 'dendrogram' leaf '121', at height 0
##
## $lower[[68]]
## 'dendrogram' leaf '46', at height 0
##
```

```
## $lower[[69]]
## 'dendrogram' leaf '119', at height 0
##
## $lower[[70]]
## 'dendrogram' leaf '17', at height 0
##
## $lower[[71]]
## 'dendrogram' leaf '117', at height 0
##
## $lower[[72]]
## 'dendrogram' leaf '88', at height 0
##
## $lower[[73]]
## 'dendrogram' leaf '114', at height 0
##
## $lower[[74]]
## 'dendrogram' leaf '97', at height 0
##
## $lower[[75]]
## 'dendrogram' leaf '90', at height 0
##
## $lower[[76]]
## 'dendrogram' leaf '91', at height 0
##
## $lower[[77]]
## 'dendrogram' with 2 branches and 2 members total, at height 0.385378
##
## $lower[[78]]
## 'dendrogram' with 2 branches and 2 members total, at height 0.7506009
##
## $lower[[79]]
## 'dendrogram' leaf '64', at height 0
##
## $lower[[80]]
## 'dendrogram' leaf '75', at height 0
##
## $lower[[81]]
## 'dendrogram' leaf '48', at height 0
##
## $lower[[82]]
## 'dendrogram' leaf '66', at height 0
##
## $lower[[83]]
## 'dendrogram' leaf '68', at height 0
##
## $lower[[84]]
## 'dendrogram' leaf '11', at height 0
##
## $lower[[85]]
## 'dendrogram' leaf '118', at height 0
##
## $lower[[86]]
```

```
## 'dendrogram' leaf '21', at height 0
##
## $lower[[87]]
## 'dendrogram' leaf '24', at height 0
##
## $lower[[88]]
## 'dendrogram' leaf '19', at height 0
##
## $lower[[89]]
## 'dendrogram' leaf '39', at height 0
##
## $lower[[90]]
## 'dendrogram' leaf '32', at height 0
##
## $lower[[91]]
## 'dendrogram' leaf '82', at height 0
##
## $lower[[92]]
## 'dendrogram' leaf '4', at height 0
##
## $lower[[93]]
## 'dendrogram' leaf '18', at height 0
##
## $lower[[94]]
## 'dendrogram' leaf '61', at height 0
##
## $lower[[95]]
## 'dendrogram' leaf '20', at height 0
##
## $lower[[96]]
## 'dendrogram' leaf '33', at height 0
##
## $lower[[97]]
## 'dendrogram' leaf '60', at height 0
##
## $lower[[98]]
## 'dendrogram' leaf '15', at height 0
##
## $lower[[99]]
## 'dendrogram' leaf '41', at height 0
##
## $lower[[100]]
## 'dendrogram' leaf '72', at height 0
##
## $lower[[101]]
## 'dendrogram' leaf '81', at height 0
##
## $lower[[102]]
## 'dendrogram' with 2 branches and 2 members total, at height 0.6585336
##
## $lower[[103]]
## 'dendrogram' with 2 branches and 3 members total, at height 1.235516
```

```
##
## $lower[[104]]
## 'dendrogram' leaf '70', at height 0
##
## $lower[[105]]
## 'dendrogram' leaf '112', at height 0
##
## $lower[[106]]
## 'dendrogram' leaf '2', at height 0
##
## $lower[[107]]
## 'dendrogram' leaf '7', at height 0
##
## $lower[[108]]
## 'dendrogram' leaf '27', at height 0
##
## $lower[[109]]
## 'dendrogram' leaf '38', at height 0
##
## $lower[[110]]
## 'dendrogram' leaf '1', at height 0
##
## $lower[[111]]
## 'dendrogram' leaf '28', at height 0
##
## $lower[[112]]
## 'dendrogram' leaf '89', at height 0
##
## $lower[[113]]
## 'dendrogram' leaf '34', at height 0
##
## $lower[[114]]
## 'dendrogram' leaf '35', at height 0
##
## $lower[[115]]
## 'dendrogram' leaf '50', at height 0
##
## $lower[[116]]
## 'dendrogram' leaf '51', at height 0
##
## $lower[[117]]
## 'dendrogram' leaf '52', at height 0
##
## $lower[[118]]
## 'dendrogram' leaf '58', at height 0
##
## $lower[[119]]
## 'dendrogram' leaf '107', at height 0
##
## $lower[[120]]
## 'dendrogram' leaf '13', at height 0
##
```

```
## $lower[[121]]
## 'dendrogram' leaf '111', at height 0
##
## $lower[[122]]
## 'dendrogram' leaf '83', at height 0
##
## $lower[[123]]
## 'dendrogram' leaf '100', at height 0
##
## $lower[[124]]
## 'dendrogram' leaf '65', at height 0
##
## $lower[[125]]
## 'dendrogram' leaf '42', at height 0
##
## $lower[[126]]
## 'dendrogram' leaf '54', at height 0
##
## $lower[[127]]
## 'dendrogram' leaf '71', at height 0
##
## $lower[[128]]
## 'dendrogram' leaf '78', at height 0
##
## $lower[[129]]
## 'dendrogram' leaf '93', at height 0
##
## $lower[[130]]
## 'dendrogram' leaf '40', at height 0
##
## $lower[[131]]
## 'dendrogram' leaf '23', at height 0
##
## $lower[[132]]
## 'dendrogram' leaf '30', at height 0
##
## $lower[[133]]
## 'dendrogram' leaf '45', at height 0
##
## $lower[[134]]
## 'dendrogram' leaf '106', at height 0
##
## $lower[[135]]
## 'dendrogram' leaf '136', at height 0
##
## $lower[[136]]
## 'dendrogram' leaf '85', at height 0
##
## $lower[[137]]
## 'dendrogram' with 2 branches and 2 members total, at height 0.5735473
##
## $lower[[138]]
```

```
## 'dendrogram' leaf '129', at height 0
##
## $lower[[139]]
## 'dendrogram' leaf '140', at height 0
##
## $lower[[140]]
## 'dendrogram' leaf '131', at height 0
##
## $lower[[141]]
## 'dendrogram' leaf '145', at height 0
##
## $lower[[142]]
## 'dendrogram' leaf '138', at height 0
##
## $lower[[143]]
## 'dendrogram' leaf '139', at height 0
##
## $lower[[144]]
## 'dendrogram' leaf '22', at height 0
##
## $lower[[145]]
## 'dendrogram' leaf '49', at height 0
##
## $lower[[146]]
## 'dendrogram' leaf '59', at height 0
##
## $lower[[147]]
## 'dendrogram' leaf '31', at height 0
##
## $lower[[148]]
## 'dendrogram' leaf '44', at height 0
##
## $lower[[149]]
## 'dendrogram' leaf '56', at height 0
##
## $lower[[150]]
## 'dendrogram' leaf '77', at height 0
##
## $lower[[151]]
## 'dendrogram' leaf '76', at height 0
##
## $lower[[152]]
## 'dendrogram' leaf '115', at height 0
##
## $lower[[153]]
## 'dendrogram' leaf '14', at height 0
##
## $lower[[154]]
## 'dendrogram' leaf '36', at height 0
##
## $lower[[155]]
## 'dendrogram' leaf '110', at height 0
```

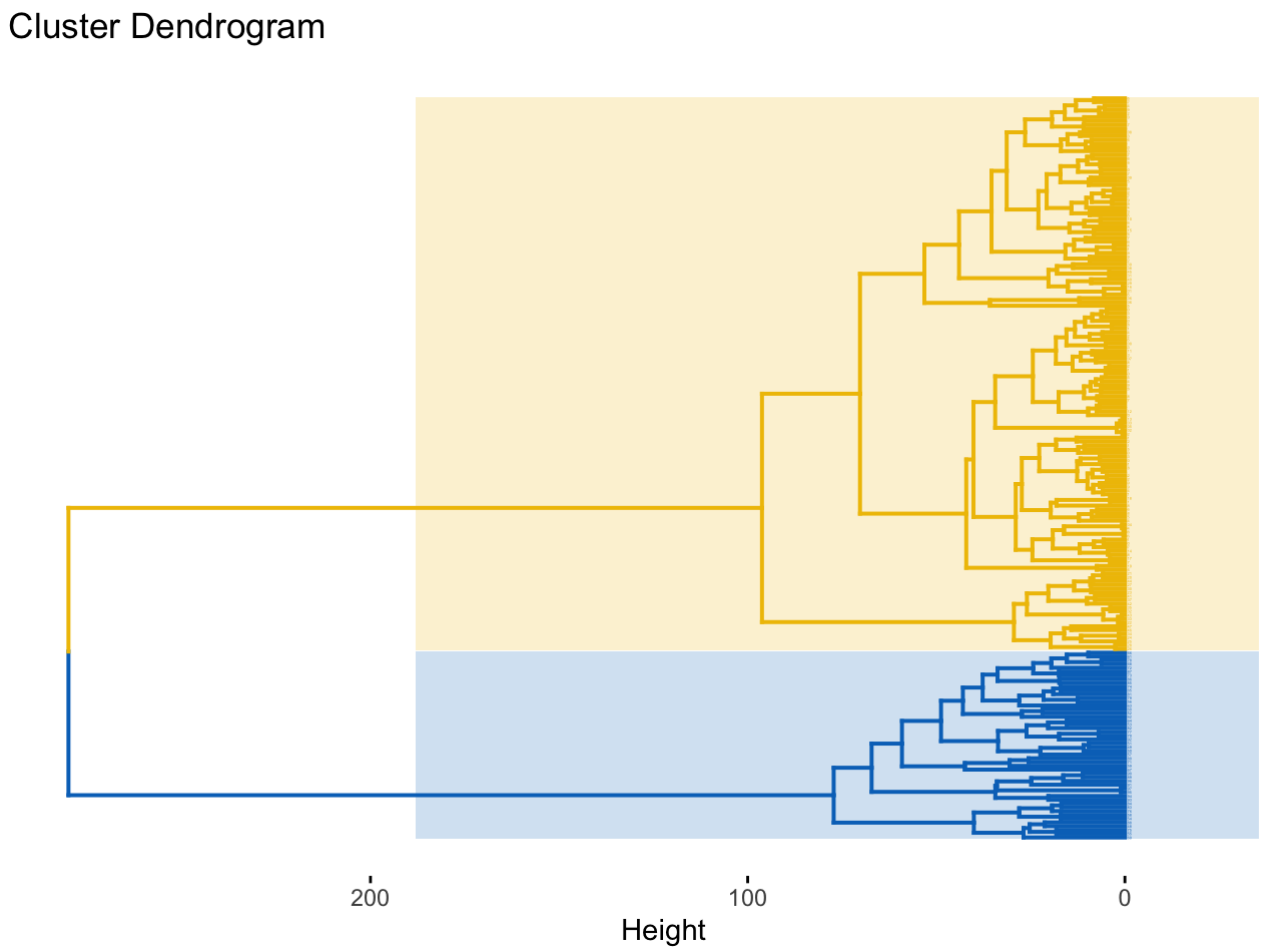
```
##
## $lower[[156]]
## 'dendrogram' leaf '55', at height 0
##
## $lower[[157]]
## 'dendrogram' leaf '73', at height 0
##
## $lower[[158]]
## 'dendrogram' leaf '74', at height 0
##
## $lower[[159]]
## 'dendrogram' leaf '69', at height 0
##
## $lower[[160]]
## 'dendrogram' leaf '79', at height 0
##
## $lower[[161]]
## 'dendrogram' leaf '67', at height 0
##
## $lower[[162]]
## 'dendrogram' leaf '62', at height 0
##
## $lower[[163]]
## 'dendrogram' leaf '99', at height 0
##
## $lower[[164]]
## 'dendrogram' leaf '9', at height 0
##
## $lower[[165]]
## 'dendrogram' leaf '25', at height 0
##
## $lower[[166]]
## 'dendrogram' leaf '109', at height 0
##
## $lower[[167]]
## 'dendrogram' leaf '57', at height 0
##
## $lower[[168]]
## 'dendrogram' leaf '80', at height 0
##
## $lower[[169]]
## 'dendrogram' leaf '8', at height 0
##
## $lower[[170]]
## 'dendrogram' leaf '16', at height 0
##
## $lower[[171]]
## 'dendrogram' leaf '86', at height 0
##
## $lower[[172]]
## 'dendrogram' leaf '87', at height 0
##
```

```
## $lower[[173]]
## 'dendrogram' leaf '63', at height 0
##
## $lower[[174]]
## 'dendrogram' leaf '53', at height 0
##
## $lower[[175]]
## 'dendrogram' leaf '5', at height 0
##
## $lower[[176]]
## 'dendrogram' leaf '26', at height 0
##
## $lower[[177]]
## 'dendrogram' leaf '43', at height 0
##
## $lower[[178]]
## 'dendrogram' leaf '108', at height 0
##
## $lower[[179]]
## 'dendrogram' leaf '6', at height 0
##
## $lower[[180]]
## 'dendrogram' leaf '47', at height 0
##
## $lower[[181]]
## 'dendrogram' leaf '3', at height 0
##
## $lower[[182]]
## 'dendrogram' leaf '10', at height 0
##
## $lower[[183]]
## 'dendrogram' leaf '12', at height 0
##
## $lower[[184]]
## 'dendrogram' leaf '29', at height 0
##
## $lower[[185]]
## 'dendrogram' leaf '84', at height 0
##
## $lower[[186]]
## 'dendrogram' leaf '37', at height 0
##
## $lower[[187]]
## 'dendrogram' leaf '95', at height 0
```

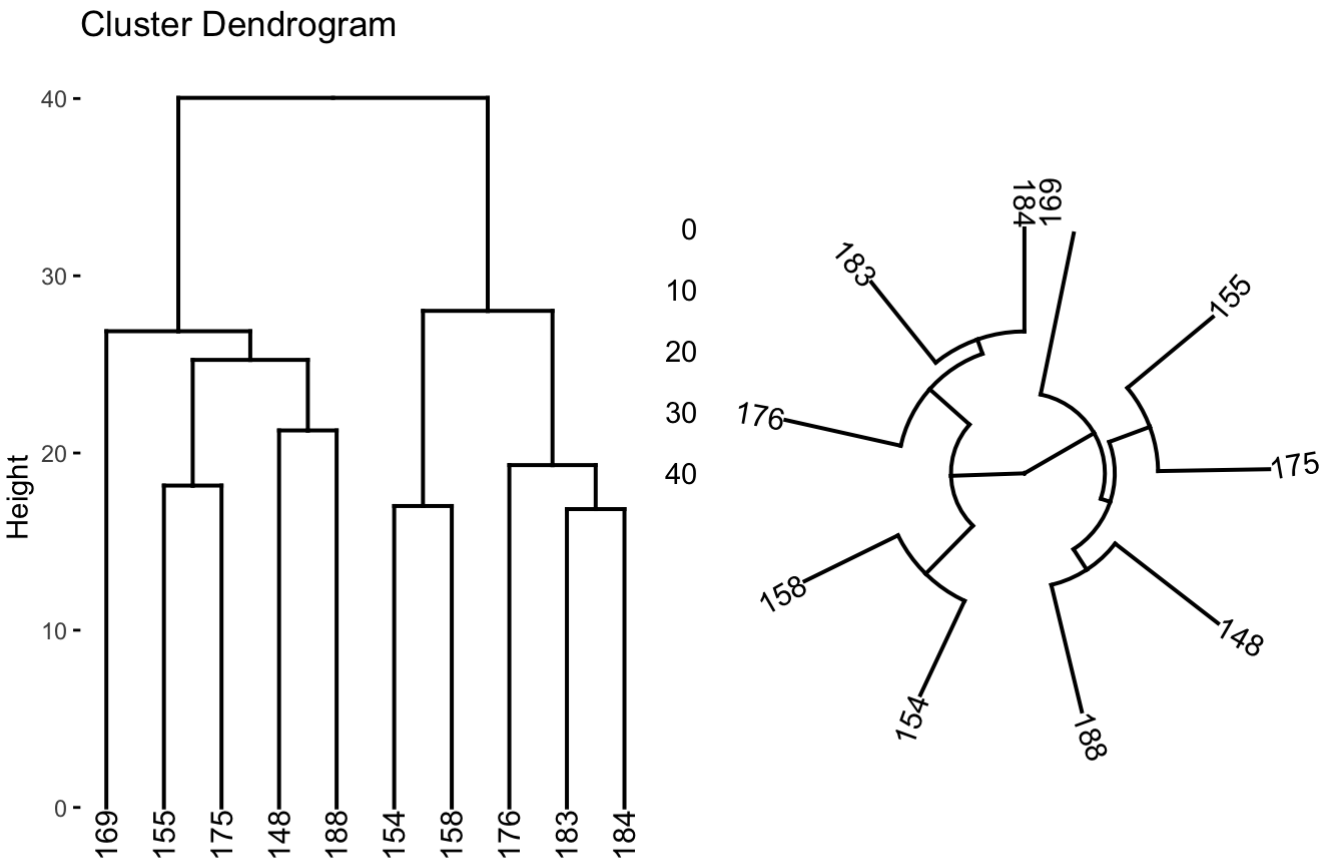
```
#fviz_dend(dend_cuts$lower[[3]])

# Ward's method
hc5 <- hclust(d, method = "ward.D2" )

# Cut tree into 4 groups
sub_grp <- cutree(hc5, k = 2)

# Number of members in each cluster
table(sub_grp)
```

```
## sub_grp
##   1   2
## 147  50
```

```
# Plot full dendogram
fviz_dend(
  hc5,
  k = 2,
  horiz = TRUE,
  rect = TRUE,
  rect_fill = TRUE,
  rect_border = "jco",
  k_colors = "jco",
  cex = 0.1
)
```




```
dend_plot <- fviz_dend(hc5)                # create full dendogram
dend_data <- attr(dend_plot, "dendrogram") # extract plot info
dend_cuts <- cut(dend_data, h = 70.5)      # cut the dendogram at
# designated height

# Create sub dendrogram plots
p1 <- fviz_dend(dend_cuts$lower[[1]])
p2 <- fviz_dend(dend_cuts$lower[[1]], type = 'circular')

# Side by side plots
gridExtra::grid.arrange(p1, p2, nrow = 1)
```

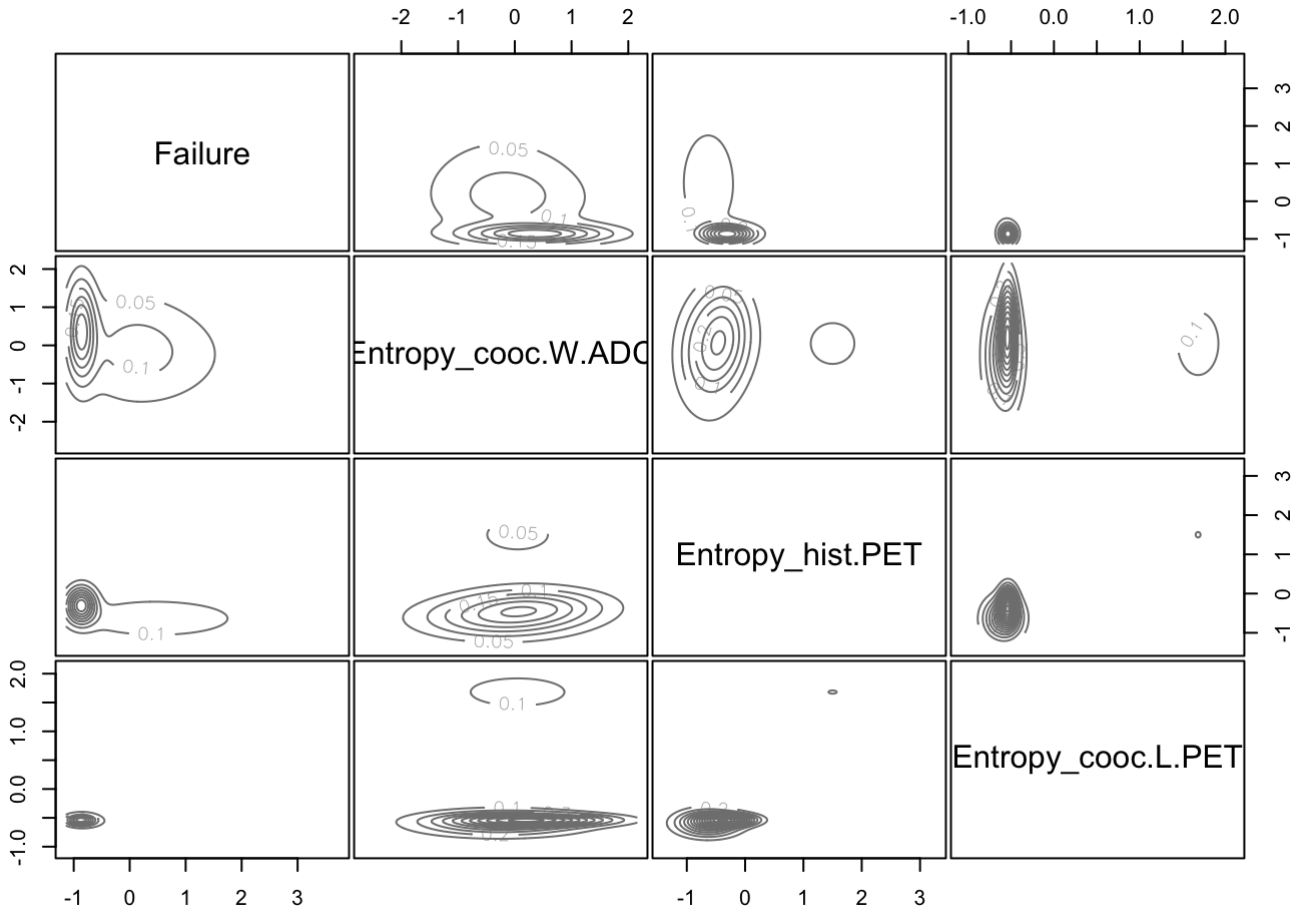


Step4: model-based

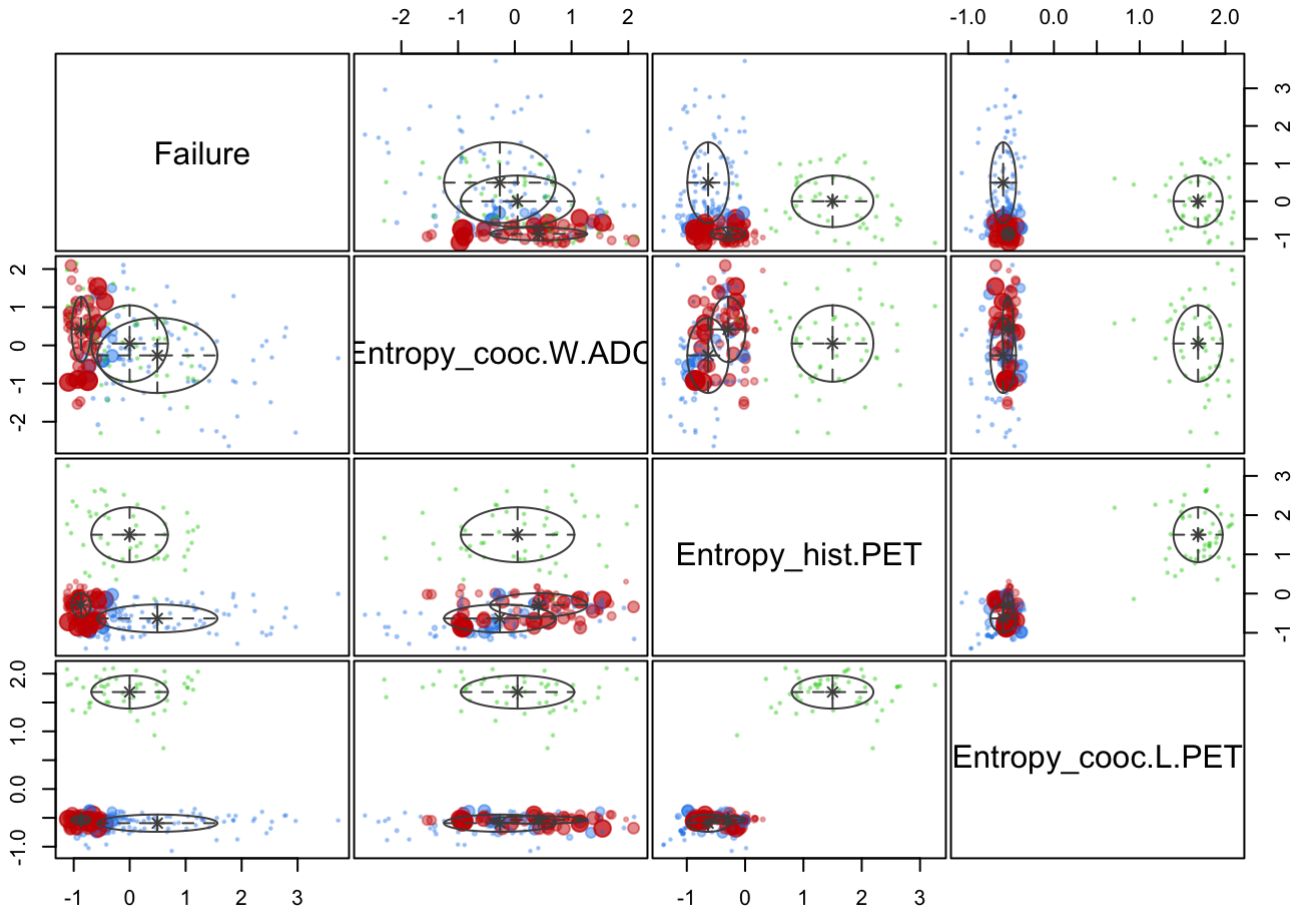
There is one problem for the model-based clustering techniques. In the model based clustering techniques since we have too much data, the plot would not be able to generate correctly. An Error for plot.new() indicating `figure margin is too large` will always occur even if we set the margin to `c(1,1,1,1)`.

Therefore, to apply GMM model with 3 components and plot the results correctly, I only chose four columns from the original data frame: `Failure`, `Entropy_cooc.W.ADC`, `Entropy_hist.PET` and `Entropy_cooc.L.PET`.

```
# Apply GMM model with 3 components
df_failure <- select(final_m3, Failure, Entropy_cooc.W.ADC, Entropy_hist.PET, Entropy_co
oc.L.PET)
arrest_mc <- Mclust(df_failure, G = 3)

# Plot results
par(mar=c(1,1,1,1))
plot(arrest_mc, what = "density")
```




```
plot(arrest_mc, what = "uncertainty")
```




```
# Observations with high uncertainty
sort(arrest_mc$uncertainty, decreasing = TRUE) %>% head()
```

```
##       116       101        79        43         4       139
## 0.4391194 0.3439769 0.3436707 0.3222617 0.3128399 0.3021089
```

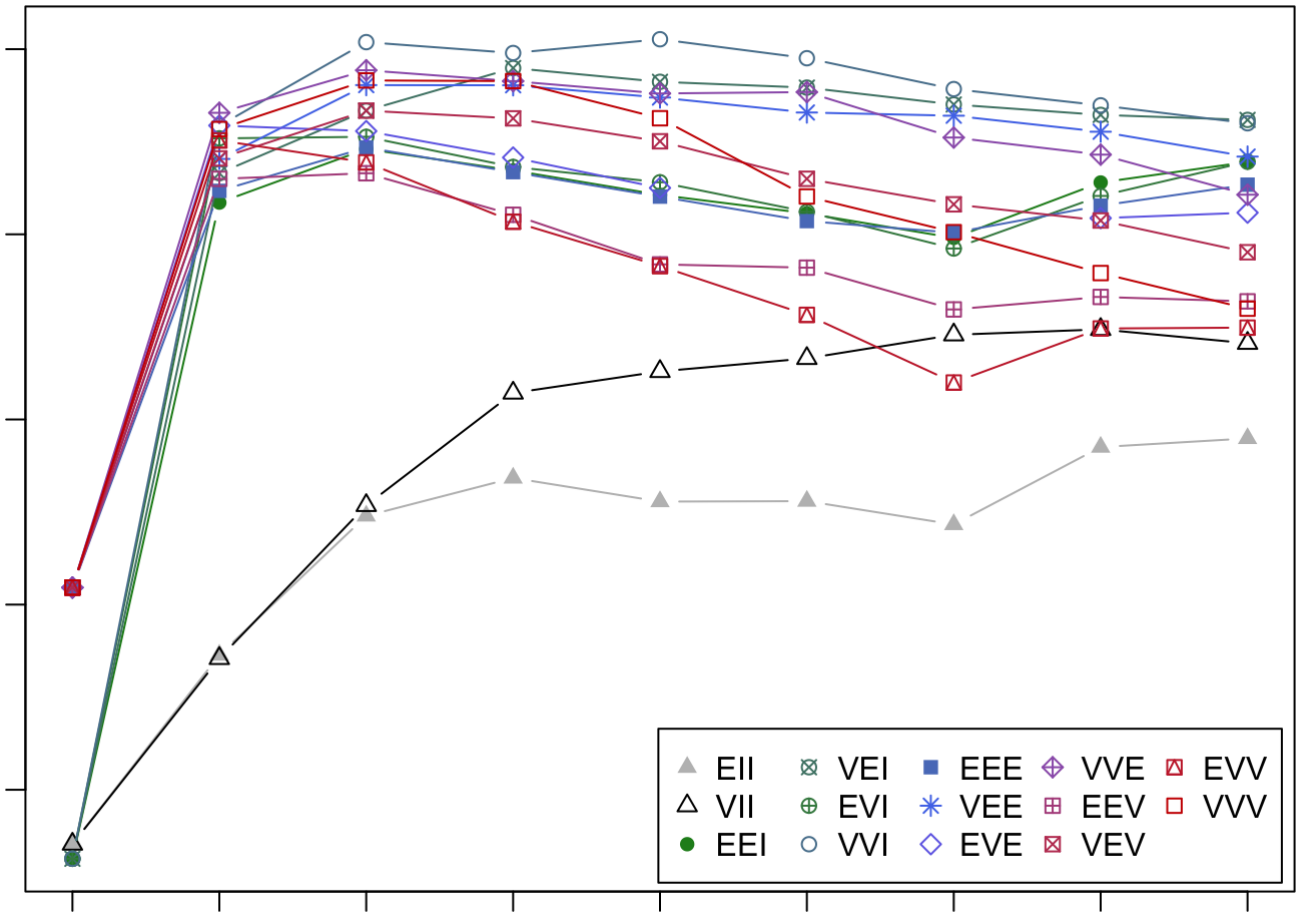
```
summary(arrest_mc)
```

```
## ----------------------------------------------------
## Gaussian finite mixture model fitted by EM algorithm
## ----------------------------------------------------
##
## Mclust VVI (diagonal, varying volume and shape) model with 3 components:
##
##  log-likelihood   n df       BIC       ICL
##       -627.5309 197 26 -1392.425 -1407.834
##
## Clustering table:
##  1  2  3
## 89 58 50
```

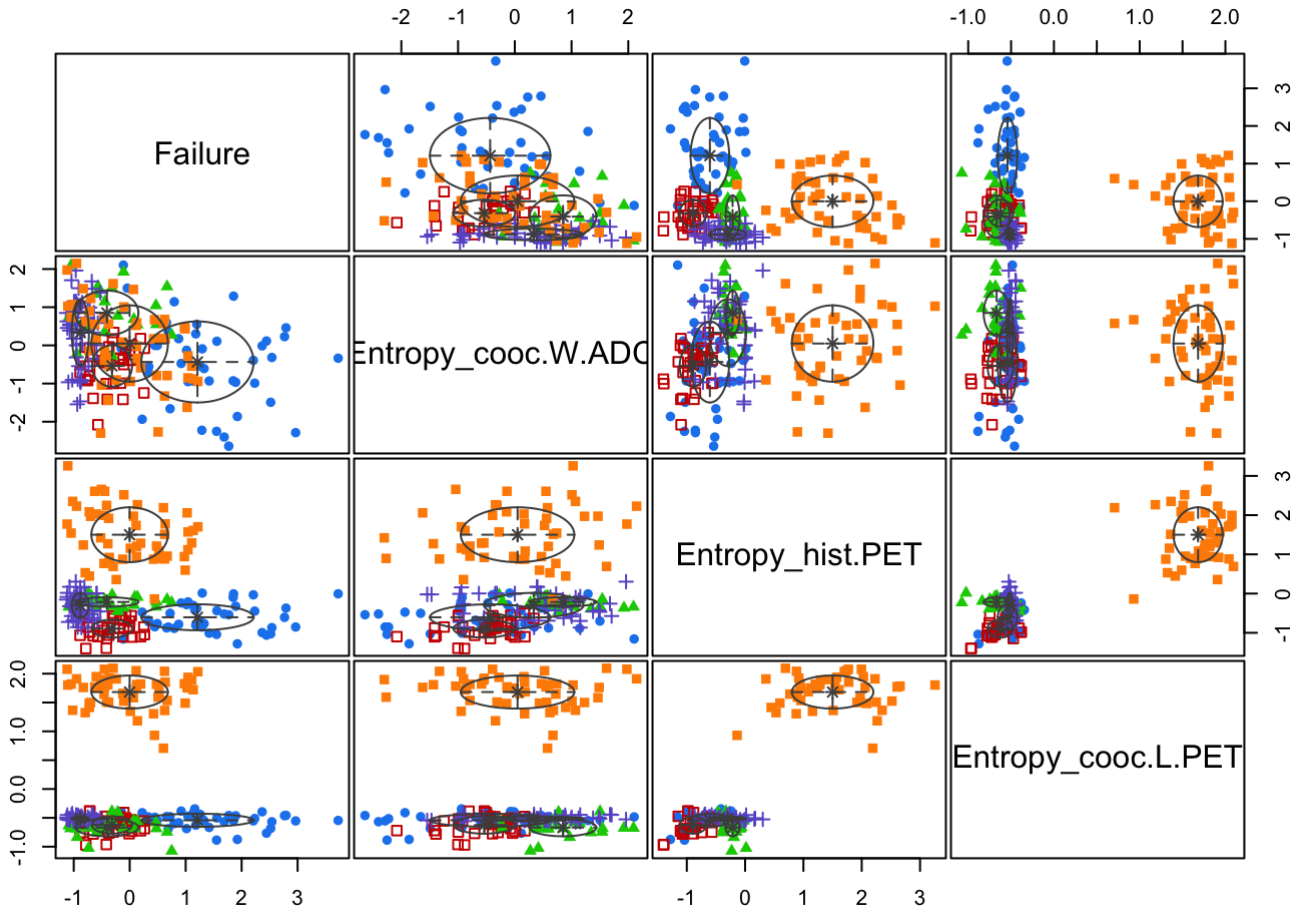
```
arrest_optimal_mc <- Mclust(df_failure)

summary(arrest_optimal_mc)
```

```
## ----------------------------------------------------
## Gaussian finite mixture model fitted by EM algorithm
## ----------------------------------------------------
##
## Mclust VVI (diagonal, varying volume and shape) model with 5 components:
##
##  log-likelihood   n df       BIC       ICL
##       -578.4222 197 44 -1389.305 -1422.034
##
## Clustering table:
##  1  2  3  4  5
## 43 33 24 47 50
```

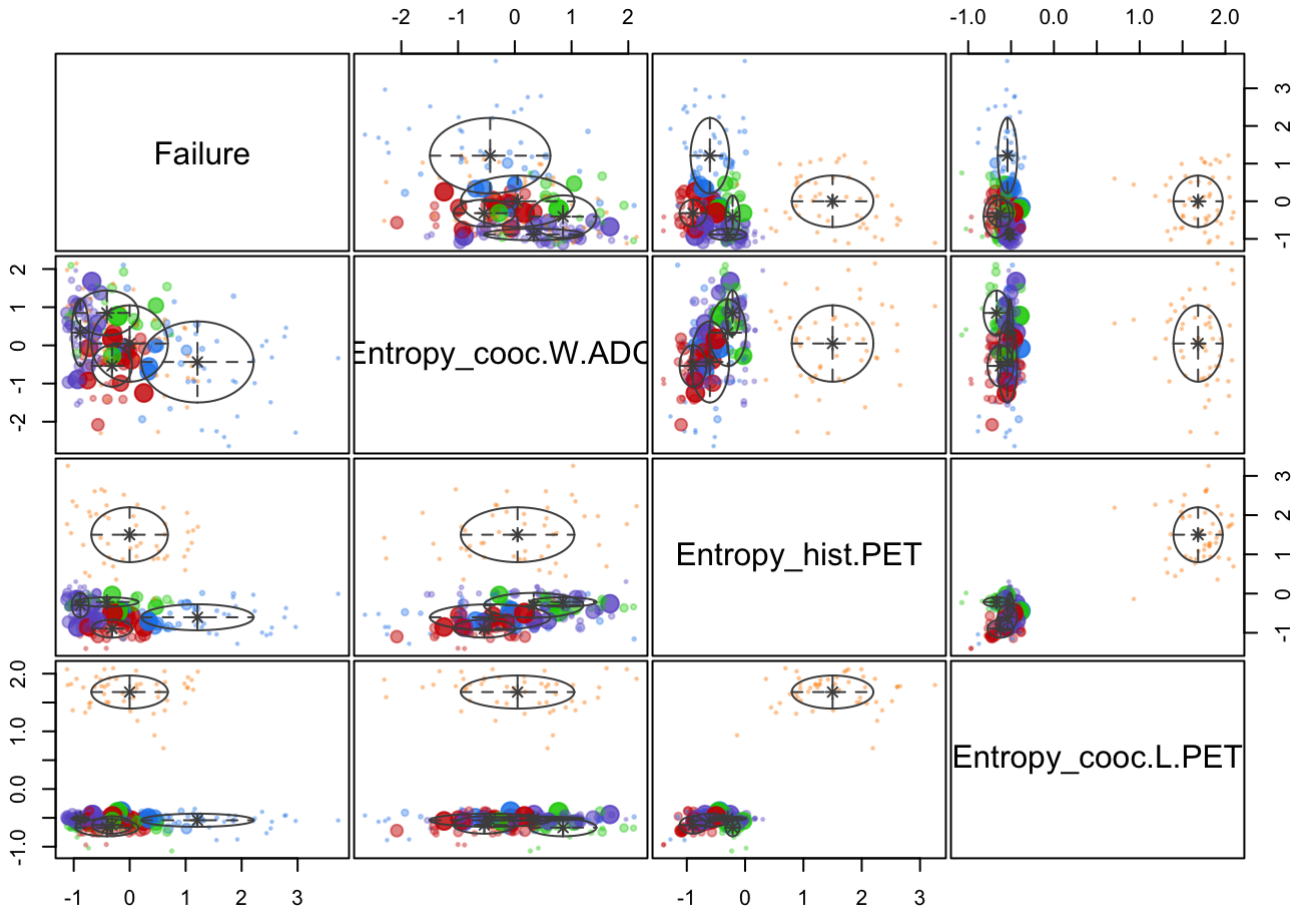
```
legend_args <- list(x = "bottomright", ncol = 5)
plot(arrest_optimal_mc, what = 'BIC', legendArgs = legend_args)
```




```
plot(arrest_optimal_mc, what = 'classification')
```



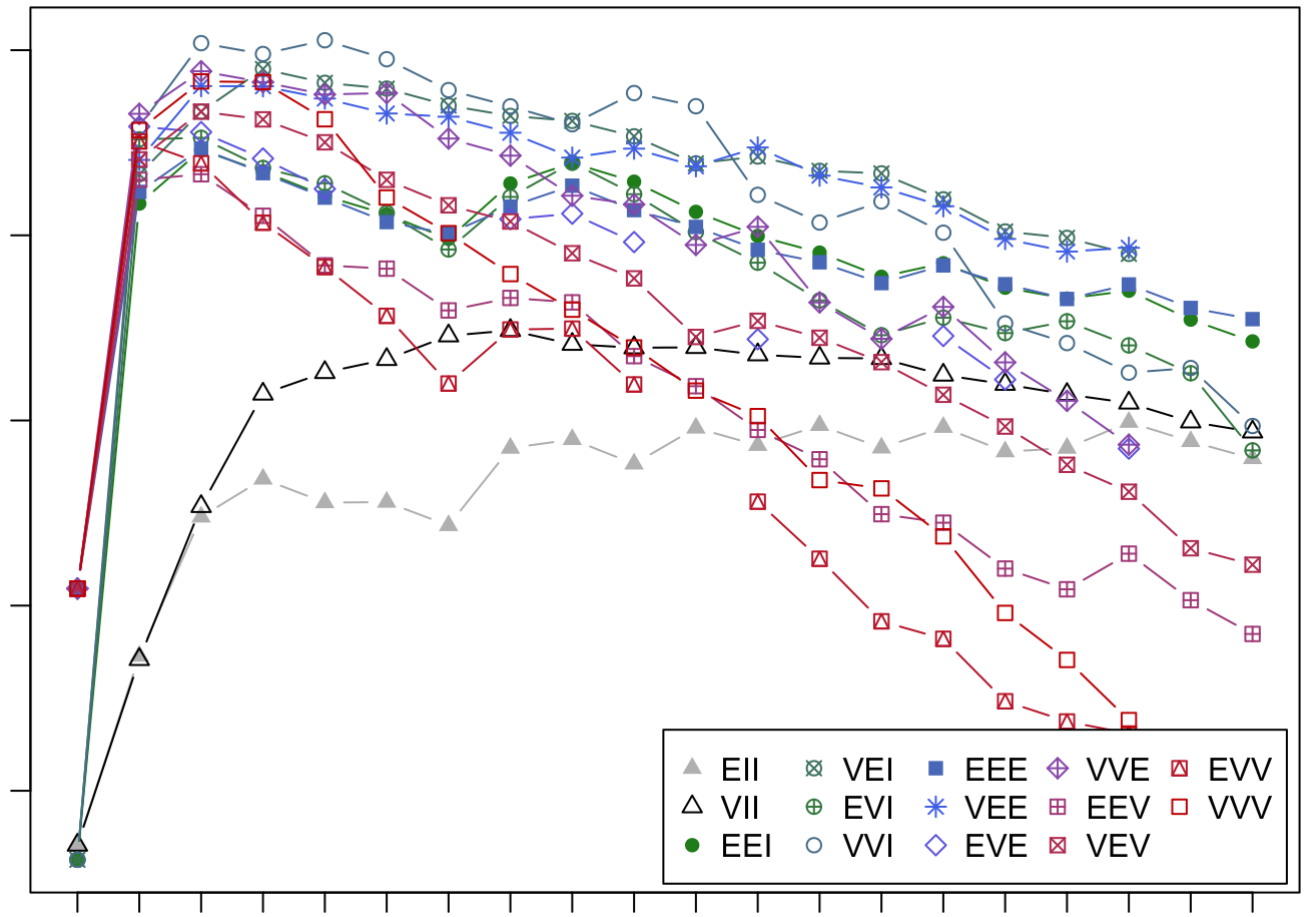

```
plot(arrest_optimal_mc, what = 'uncertainty')
```




```
df_mc <- Mclust(df_failure, 1:20)

summary(df_mc)
```

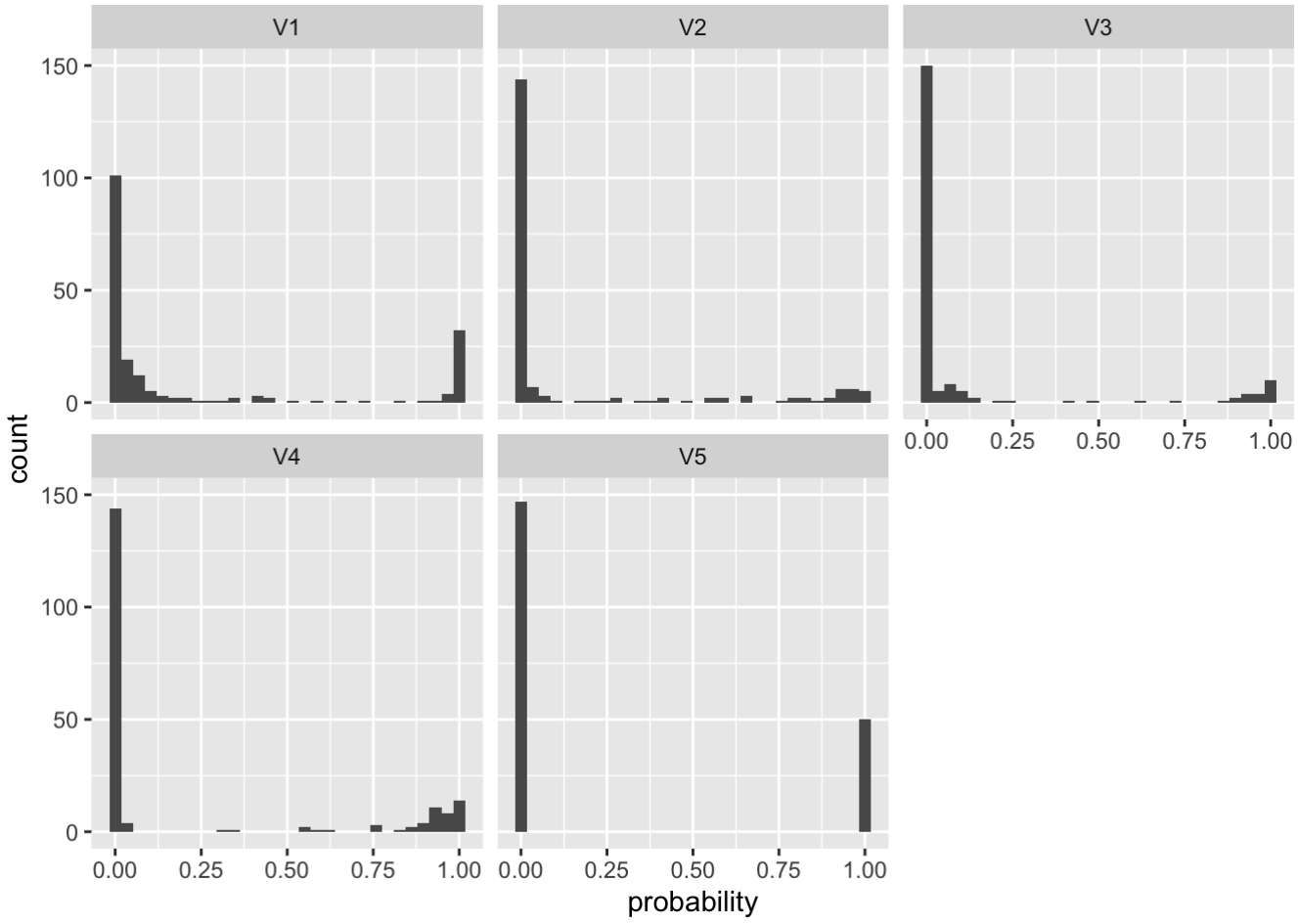
```
## ----------------------------------------------------
## Gaussian finite mixture model fitted by EM algorithm
## ----------------------------------------------------
##
## Mclust VVI (diagonal, varying volume and shape) model with 5 components:
##
##  log-likelihood   n df       BIC       ICL
##       -578.4222 197 44 -1389.305 -1422.034
##
## Clustering table:
##  1  2  3  4  5
## 43 33 24 47 50
```

```
plot(df_mc, what = 'BIC',
     legendArgs = list(x = "bottomright", ncol = 5))
```

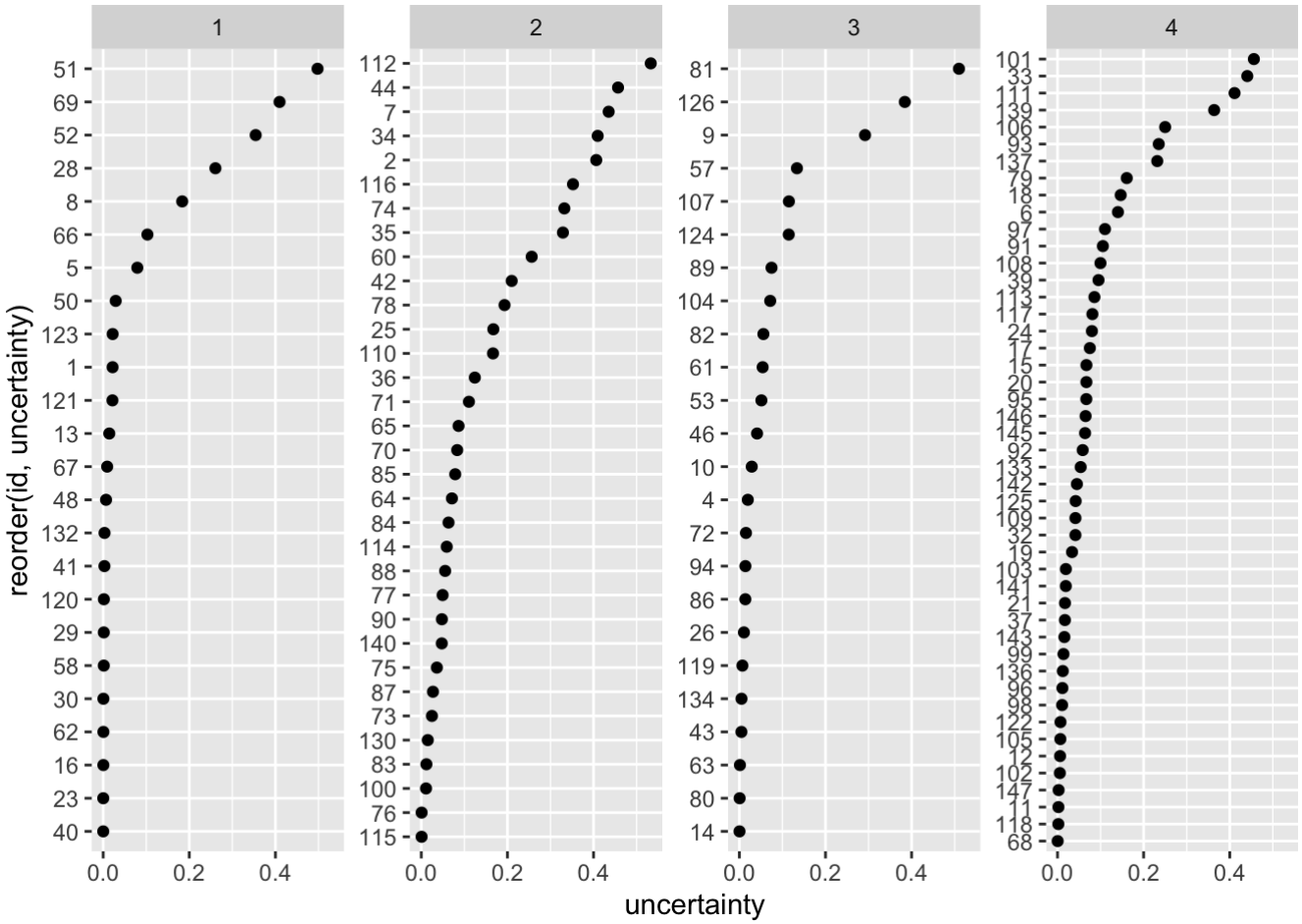



```
probabilities <- df_mc$z

probabilities <- probabilities %>%
  as.data.frame() %>%
  mutate(id = row_number()) %>%
  tidyr::gather(cluster, probability, -id)

ggplot(probabilities, aes(probability)) +
  geom_histogram() +
  facet_wrap(~ cluster, nrow = 2)
```

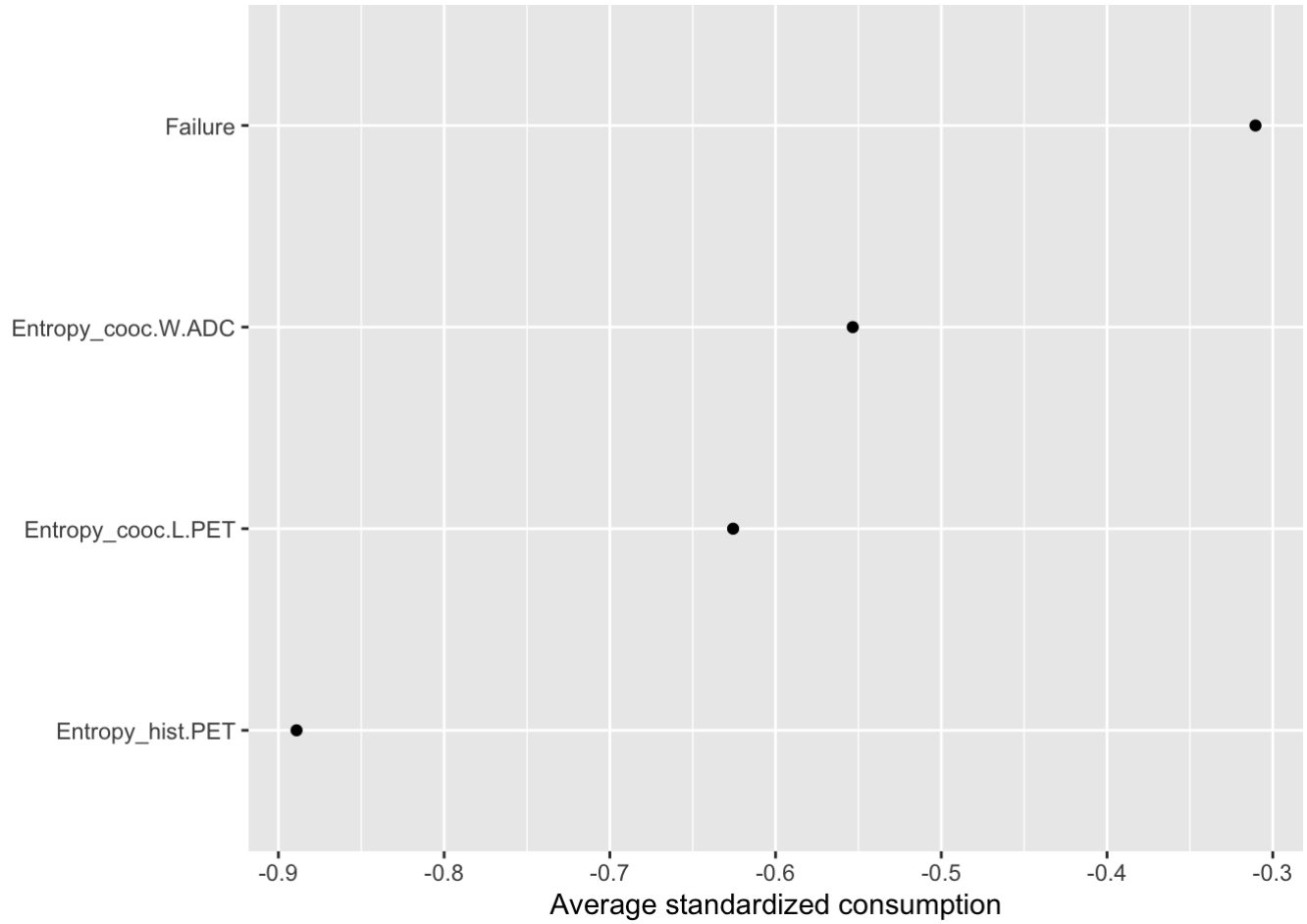
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```
uncertainty <- data.frame(
  id = 1:nrow(df_failure),
  cluster = df_mc$classification,
  uncertainty = df_mc$uncertainty
)

uncertainty %>%
  group_by(cluster) %>%
  filter(uncertainty > 0.0001) %>%
  ggplot(aes(uncertainty, reorder(id, uncertainty))) +
  geom_point() +
  facet_wrap(~ cluster, scales = 'free_y', nrow = 1)
```




```
cluster2 <- df_failure %>%
  scale() %>%
  as.data.frame() %>%
  mutate(cluster = df_mc$classification) %>%
  filter(cluster == 2) %>%
  select(-cluster)

cluster2 %>%
  tidyr::gather(product, std_count) %>%
  group_by(product) %>%
  summarize(avg = mean(std_count)) %>%
  ggplot(aes(avg, reorder(product, avg))) +
  geom_point() +
  labs(x = "Average standardized consumption", y = NULL)
```



However, if I do the model-based clustering for the entire data set, it would not be able to plot the graphs since every time it will return the `figure margin is too large` error. Therefore, without plotting the `density`, `uncetainty`, and `classification` graphs, one should be able to reach the results as followed:

```
# Apply GMM model with 3 components
arrest_final_mc <- Mclust(final_m3, G = 3)

# Plot results
# par(mar=c(1,1,1,1))
# plot(arrest_mc, what = "density")
# plot(arrest_mc, what = "uncertainty")

# Observations with high uncertainty
sort(arrest_final_mc$uncertainty, decreasing = TRUE) %>% head()
```

```
##          100           93           48            4            1            2
## 3.485515e-07 5.757084e-11 5.693224e-13 8.881784e-16 0.000000e+00 0.000000e+00
```

```
summary(arrest_mc)
```

```
## ----------------------------------------------------
## Gaussian finite mixture model fitted by EM algorithm
## ----------------------------------------------------
##
## Mclust VVI (diagonal, varying volume and shape) model with 3 components:
##
##  log-likelihood   n df       BIC       ICL
##       -627.5309 197 26 -1392.425 -1407.834
##
## Clustering table:
##  1  2  3
## 89 58 50
```

```
arrest_optimal_final <- Mclust(final_m3)

summary(arrest_optimal_final)
```

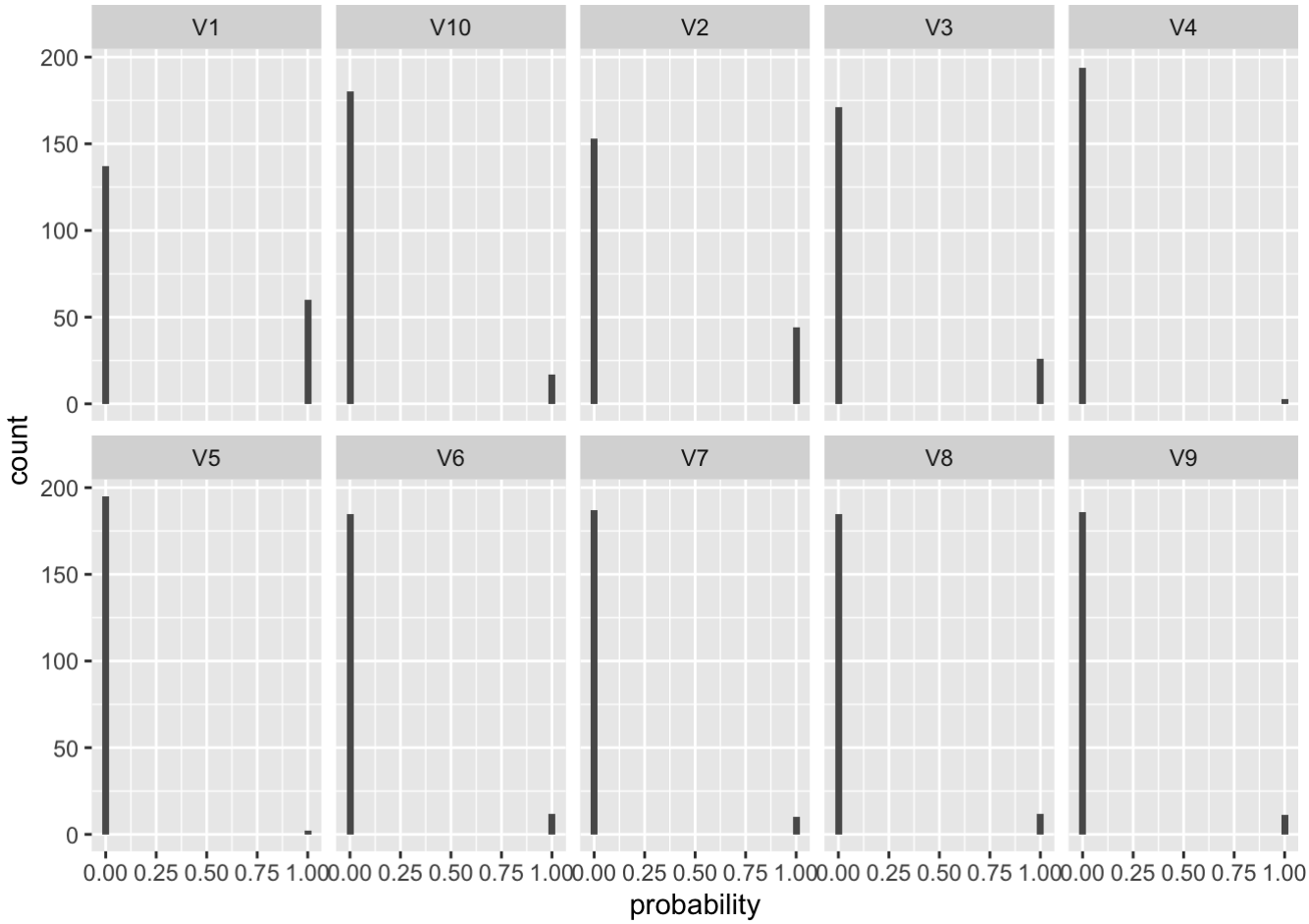
```
## ----------------------------------------------------
## Gaussian finite mixture model fitted by EM algorithm
## ----------------------------------------------------
##
## Mclust VVI (diagonal, varying volume and shape) model with 7 components:
##
##  log-likelihood   n   df      BIC      ICL
##       -33791.44 197 6012 -99345.5 -99345.5
##
## Clustering table:
##  1  2  3  4  5  6  7
## 94 38  3 12  9 34  7
```

```
legend_args <- list(x = "bottomright", ncol = 5)
#plot(arrest_optimal_final, what = 'BIC', legendArgs = legend_args)
#plot(arrest_optimal_final, what = 'classification')
#plot(arrest_optimal_final, what = 'uncertainty')

df_finalmc <- Mclust(final_m3, 1:20)

summary(df_finalmc)
```

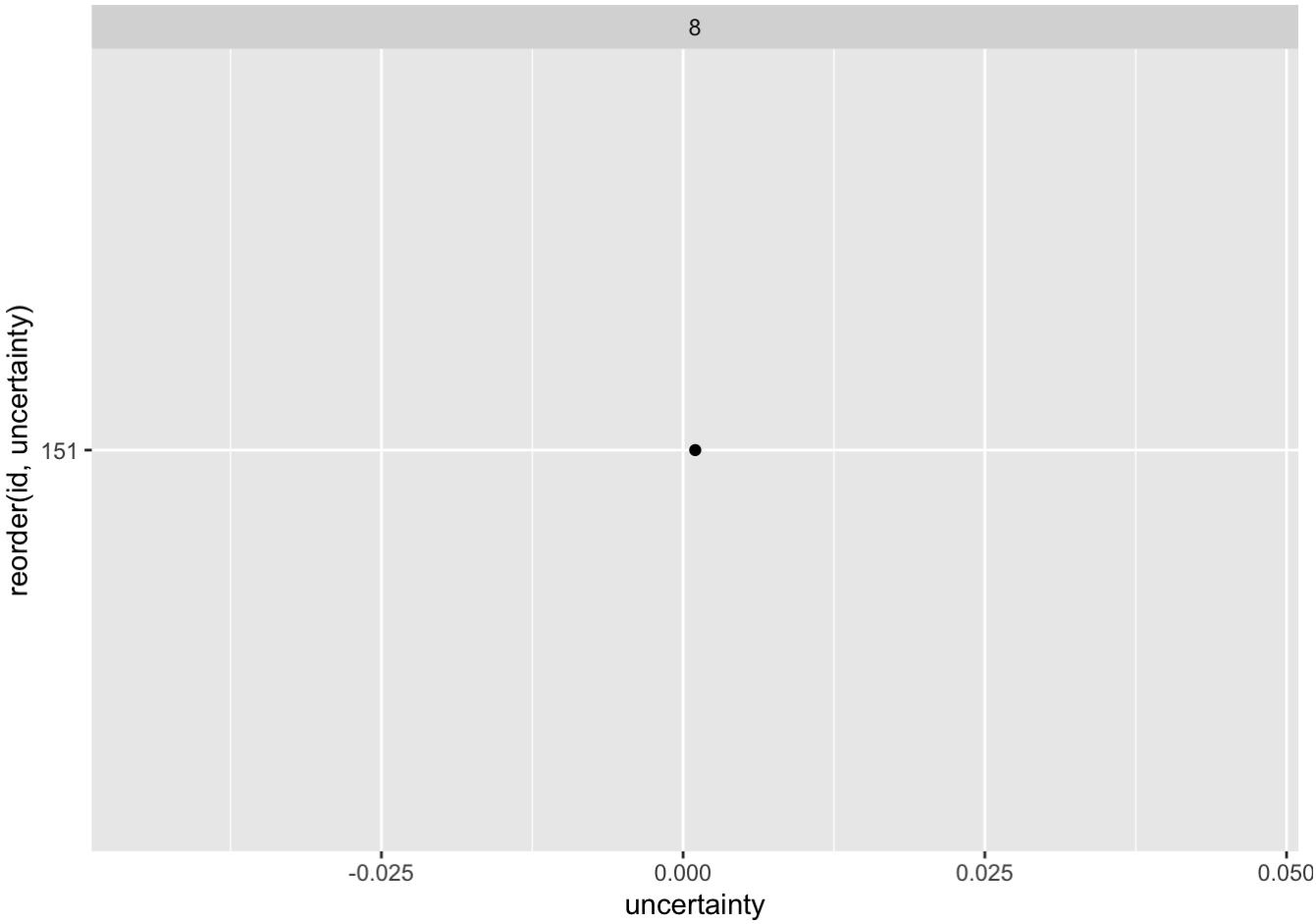
```
## ----------------------------------------------------
## Gaussian finite mixture model fitted by EM algorithm
## ----------------------------------------------------
##
## Mclust VEI (diagonal, equal shape) model with 10 components:
##
##  log-likelihood   n   df       BIC       ICL
##       -36831.86 197 4737 -98690.26 -98690.27
##
## Clustering table:
##  1  2  3  4  5  6  7  8  9 10
## 60 44 26  3  2 12 10 12 11 17
```

```
# plot(df_finalmc, what = 'BIC',
#     legendArgs = list(x = "bottomright", ncol = 5))

probabilities <- df_finalmc$z

probabilities <- probabilities %>%
  as.data.frame() %>%
  mutate(id = row_number()) %>%
  tidyr::gather(cluster, probability, -id)

ggplot(probabilities, aes(probability)) +
  geom_histogram() +
  facet_wrap(~ cluster, nrow = 2)
```

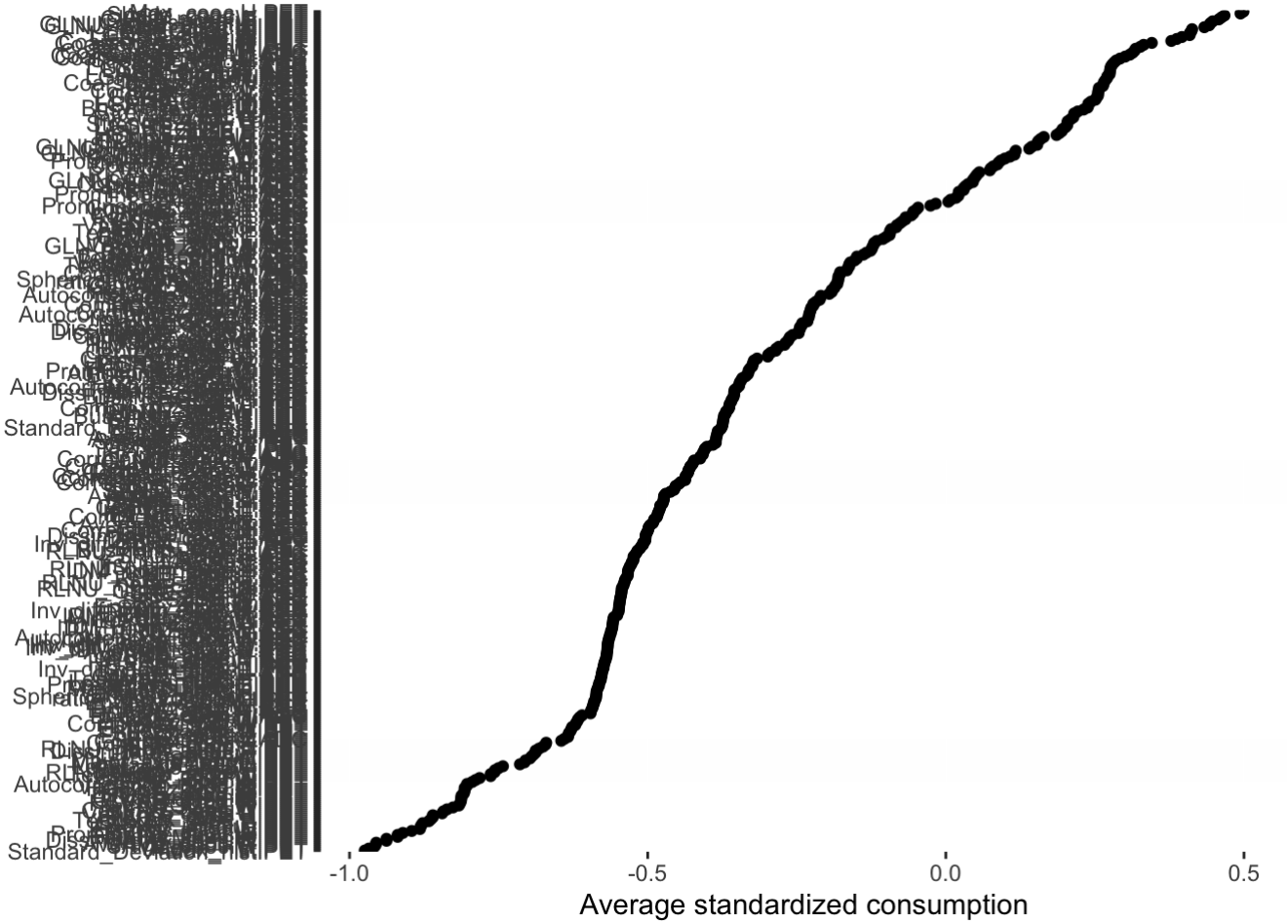
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```
uncertainty <- data.frame(
  id = 1:nrow(final_m3),
  cluster = df_finalmc$classification,
  uncertainty = df_finalmc$uncertainty
)

uncertainty %>%
  group_by(cluster) %>%
  filter(uncertainty > 0.0001) %>%
  ggplot(aes(uncertainty, reorder(id, uncertainty))) +
  geom_point() +
  facet_wrap(~ cluster, scales = 'free_y', nrow = 1)
```




```
cluster2 <- final_m3 %>%
  scale() %>%
  as.data.frame() %>%
  mutate(cluster = df_finalmc$classification) %>%
  filter(cluster == 2) %>%
  select(-cluster)

cluster2 %>%
  tidyr::gather(product, std_count) %>%
  group_by(product) %>%
  summarize(avg = mean(std_count)) %>%
  ggplot(aes(avg, reorder(product, avg))) +
  geom_point() +
  labs(x = "Average standardized consumption", y = NULL)
```


-1.0
-0.5
0.0
0.5
Average standardized consumption