Contents

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title: "Entrega-2"
author: "Ivan Cala Mesa - Pau Bosch Ribalta"
date: "April 30, 2023"
output:
pdf_document:
toc: yes
toc_depth: 4
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editor_options:
chunk_output_type: console

R Markdown

Obtenim les dades i les classifiquem:

```
setwd("/home/pau/Escriptori/adei/lab2")
load("./bank-additional-clean.RData")
```

```r
var_dis <- c("age", "job", "marital", "education", "housing", "loan",
             "contact", "month", "day_of_week", "previous", "poutcome",
             "mout")
var_con<- c("age_num", "duration", "campaign", "emp.var.rate", "cons.conf.idx",
            "cons.price.idx", "euribor3m", "nr.employed", "na_count")
var_res<- c("y")
df$default <- NULL
```

Anàlisis MCA

```r
llmout<-which(df$mout=="Yes")
res.mca<-MCA(df[,c(var_res, var_dis[1:11]) ], quali.sup=1, ind.sup=llmout,
             graph = F)
```

1. Eigenvalues and dominant axes. How many axes we have to consider for next Hierarchical Classification stage?

Dimensions a agafar respecte regla de Kaiser agafant el mean.

```r
summary(res.mca, nbelements = 12, nbind = 0)
```

```
##
## Call:
## MCA(X = df[, c(var_res, var_dis[1:11])], ind.sup = llmout, quali.sup = 1,
##      graph = F)
##
##
## Eigenvalues
##                        Dim.1   Dim.2   Dim.3   Dim.4   Dim.5   Dim.6   Dim.7
## Variance               0.216   0.175   0.147   0.142   0.135   0.122   0.115
## % of var.              7.200   5.838   4.900   4.740   4.493   4.076   3.848
## Cumulative % of var.   7.200  13.037  17.938  22.678  27.171  31.248  35.095
##                        Dim.8   Dim.9  Dim.10  Dim.11  Dim.12  Dim.13  Dim.14
## Variance               0.107   0.102   0.099   0.098   0.096   0.095   0.094
## % of var.              3.574   3.416   3.316   3.279   3.197   3.151   3.117
## Cumulative % of var.  38.669  42.085  45.401  48.680  51.877  55.028  58.145
##                       Dim.15  Dim.16  Dim.17  Dim.18  Dim.19  Dim.20  Dim.21
## Variance               0.092   0.091   0.090   0.088   0.087   0.084   0.082
## % of var.              3.077   3.034   2.989   2.934   2.884   2.815   2.724
## Cumulative % of var.  61.222  64.257  67.246  70.180  73.064  75.879  78.603
##                       Dim.22  Dim.23  Dim.24  Dim.25  Dim.26  Dim.27  Dim.28
## Variance               0.081   0.080   0.077   0.076   0.068   0.060   0.055
```

```
## % of var.              2.688   2.677   2.582   2.538   2.266   2.001   1.831
## Cumulative % of var.  81.291  83.968  86.550  89.088  91.354  93.355  95.186
##                      Dim.29  Dim.30  Dim.31  Dim.32  Dim.33
## Variance              0.050   0.043   0.030   0.019   0.002
## % of var.             1.661   1.428   1.009   0.647   0.070
## Cumulative % of var.  96.846  98.274  99.283  99.930 100.000
##
## Categories (the 12 first)
##                     Dim.1     ctr    cos2  v.test     Dim.2     ctr    cos2
## Jove           |    0.877   1.101   0.027  11.565 |  -0.711   0.892   0.018
## Jove-Adult     |    0.038   0.042   0.003   3.964 |  -0.058   0.119   0.007
## Adult          |   -0.239   0.662   0.022 -10.349 |   0.244   0.851   0.023
## Gran           |    1.597   0.652   0.016   8.772 |  -0.551   0.096   0.002
## admin.         |    0.438   1.896   0.059  17.051 |  -0.458   2.554   0.064
## blue-collar    |   -0.667   4.847   0.155 -27.700 |   0.674   6.101   0.159
## management     |    0.132   0.056   0.001   2.664 |  -0.397   0.621   0.013
## self-employed |    0.111   0.036   0.001   2.140 |  -0.222   0.180   0.004
## services       |   -0.192   0.165   0.004  -4.650 |   0.020   0.002   0.000
## technician     |    0.362   0.838   0.023  10.764 |  -0.129   0.131   0.003
## unemployed     |    0.170   0.125   0.003   4.036 |  -0.036   0.007   0.000
## divorced       |    0.010   0.000   0.000   0.235 |  -0.179   0.175   0.004
##                  v.test     Dim.3     ctr    cos2  v.test
## Jove             -9.373 |  -0.520   0.569   0.010  -6.859 |
## Jove-Adult       -5.989 |  -0.220   2.056   0.106 -22.849 |
## Adult            10.565 |   0.517   4.535   0.101  22.345 |
## Gran             -3.024 |   4.408   7.298   0.119  24.216 |
## admin.          -17.818 |  -0.540   4.236   0.090 -21.025 |
## blue-collar      27.984 |   0.623   6.208   0.135  25.862 |
## management       -7.998 |   0.121   0.068   0.001   2.430 |
## self-employed    -4.294 |   0.290   0.366   0.006   5.611 |
## services          0.480 |  -1.350  11.974   0.217 -32.712 |
## technician       -3.835 |  -0.098   0.089   0.002  -2.901 |
## unemployed       -0.861 |   0.919   5.360   0.097  21.841 |
## divorced         -4.321 |  -0.013   0.001   0.000  -0.318 |
##
## Categorical variables (eta2)
##                  Dim.1 Dim.2 Dim.3
## age            | 0.058 0.038 0.234 |
## job            | 0.189 0.185 0.458 |
## marital        | 0.104 0.084 0.090 |
## education      | 0.203 0.215 0.427 |
## housing        | 0.030 0.005 0.025 |
## loan           | 0.002 0.001 0.000 |
## contact        | 0.528 0.049 0.109 |
## month          | 0.488 0.135 0.152 |
## day_of_week    | 0.062 0.014 0.025 |
```

```
## previous      | 0.327 0.594 0.030 |
## poutcome      | 0.384 0.606 0.067 |
##
## Supplementary categories
##                   Dim.1    cos2  v.test     Dim.2    cos2  v.test     Dim.3
## y_no          |  -0.585   0.375 -43.036 |   0.192   0.040  14.131 |  -0.241
## y_yes         |   0.641   0.375  43.036 |  -0.210   0.040 -14.131 |   0.264
##                  cos2  v.test
## y_no            0.064 -17.713 |
## y_yes           0.064  17.713 |
##
## Supplementary categorical variables (eta2)
##                 Dim.1 Dim.2 Dim.3
## y             | 0.375 0.040 0.064 |
```

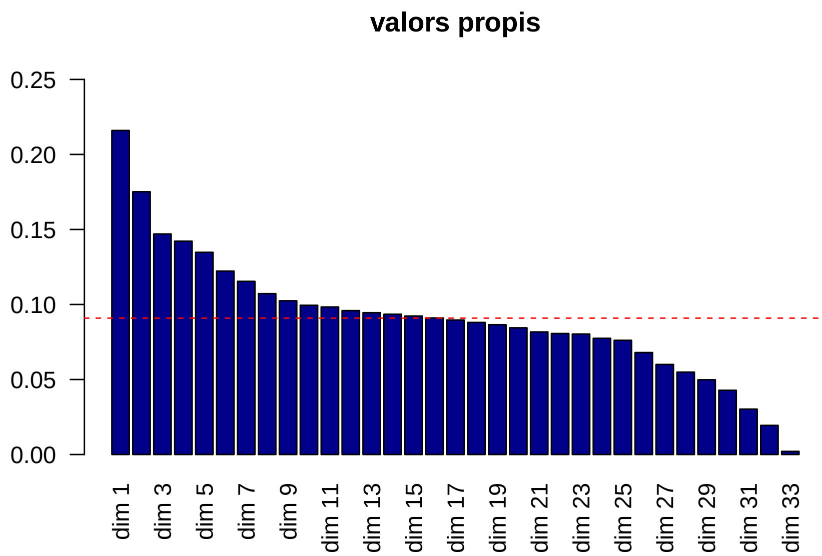
```
mm <- mean(res.mca$eig[,1])
ll<- which(as.data.frame(res.mca$eig[,1])>mm)
length(ll) #Número dimensions
```

```
## [1] 16
```

```
res.mca$eig[length(ll),3]
```

```
## [1] 64.25661
```

```
barplot(res.mca$eig[,1],
        main="valors propis",
        names.arg=paste("dim",1:nrow(res.mca$eig)),
        las = 2,
        ylim = c(0, 0.25),
        col = "blue4")

abline(h = mm,
       col = "red",
       lty = "dashed")
```



Per la regla de Kaiser ens surten 16 dimensions, però el percentatge explicat és 64.2566121%, un percentatge que considerem baix. Per aquest motiu realitzarem l'anàlisis amb la regla del colze:

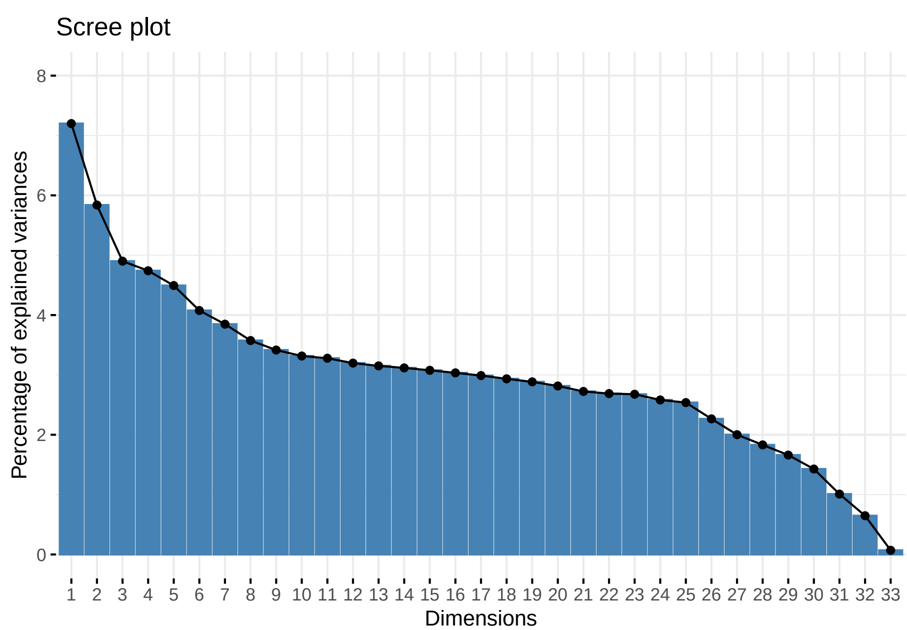
Regla del colze

```
res.mca$eig
```

```
##         eigenvalue percentage of variance cumulative percentage of variance
## dim 1  0.215985532              7.1995177                          7.199518
## dim 2  0.175136654              5.8378885                         13.037406
## dim 3  0.147012791              4.9004264                         17.937833
## dim 4  0.142213865              4.7404622                         22.678295
## dim 5  0.134796116              4.4932039                         27.171499
## dim 6  0.122285019              4.0761673                         31.247666
## dim 7  0.115427448              3.8475816                         35.095247
## dim 8  0.107226255              3.5742085                         38.669456
## dim 9  0.102473603              3.4157868                         42.085243
## dim 10 0.099474533              3.3158178                         45.401061
## dim 11 0.098357758              3.2785919                         48.679652
## dim 12 0.095920509              3.1973503                         51.877003
## dim 13 0.094527756              3.1509252                         55.027928
## dim 14 0.093515471              3.1171824                         58.145110
## dim 15 0.092316196              3.0772065                         61.222317
## dim 16 0.091028857              3.0342952                         64.256612
```

```
## dim 17 0.089676076               2.9892025                  67.245815
## dim 18 0.088030654               2.9343551                  70.180170
## dim 19 0.086521870               2.8840623                  73.064232
## dim 20 0.084453327               2.8151109                  75.879343
## dim 21 0.081712085               2.7237362                  78.603079
## dim 22 0.080640389               2.6880130                  81.291092
## dim 23 0.080312899               2.6770966                  83.968189
## dim 24 0.077456392               2.5818797                  86.550068
## dim 25 0.076140285               2.5380095                  89.088078
## dim 26 0.067968101               2.2656034                  91.353681
## dim 27 0.060034342               2.0011447                  93.354826
## dim 28 0.054925787               1.8308596                  95.185686
## dim 29 0.049820820               1.6606940                  96.846380
## dim 30 0.042831485               1.4277162                  98.274096
## dim 31 0.030266658               1.0088886                  99.282984
## dim 32 0.019421634               0.6473878                  99.930372
## dim 33 0.002088834               0.0696278                 100.000000
```

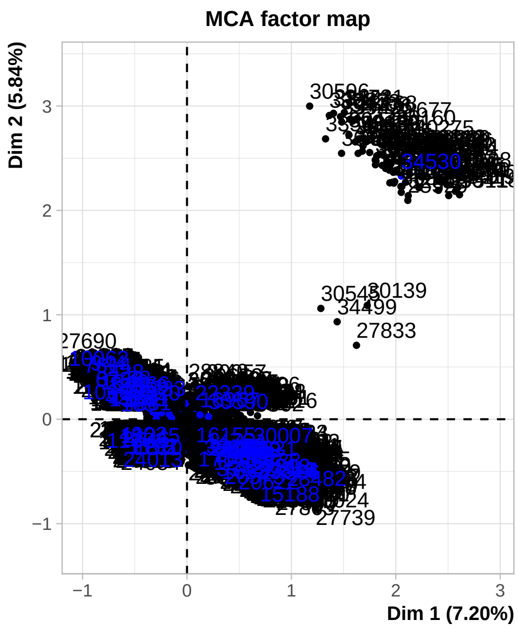
```r
fviz_screeplot(res.mca,
               ylim = c(0, 8),
               ncp = 33)
```



Podem veure que la primera dimensió que té un percentatge acomulat de variança més gran de 85% és la dimensió 24.

2. Individuals point of view

```
plot(res.mca, choix = c("ind"),
     invisible = c("var", "quali.sup"),
     cex = 1)
```



Podem veure dos grups diferenciats d'individuus i un grup petit entre els dos grups. Tal i com veiem a la gràfica, un dels grups té una contribució molt superior als altres tan en la dimensió 1 com en la 2.

```
inds <- res.mca$ind$coord
inds <- as.data.frame(inds)
rang<-inds[order(inds$`Dim 1`, decreasing = TRUE),]
res.mca$ind$coord[row.names(rang)[1:10],1]
```

```
##    30418    30140    30419    30208    30189    29511    30150    30315
## 2.609911 2.595063 2.570233 2.533980 2.522024 2.506387 2.488380 2.463199
##    30185    30244
## 2.454798 2.411644
```

```
df[which(row.names(df) %in% row.names(res.mca$ind$coord
                                      [row.names(rang)[1:10],])),1:20]
```

```
##              age          job marital           education housing loan
## 30189 Jove-Adult        admin.  single         high.school     yes   no
## 30315 Jove-Adult        admin. married   university.degree     yes   no
## 30208 Jove-Adult    technician  single professional.course     yes   no
## 30244 Jove-Adult    technician married professional.course     yes  yes
## 30419 Jove-Adult self-employed  single   university.degree     yes  yes
## 30150      Adult        admin.  single   university.degree      no   no
## 30140 Jove-Adult    technician  single   university.degree     yes   no
## 30185 Jove-Adult        admin.  single         high.school      no   no
## 30418 Jove-Adult        admin.  single   university.degree     yes   no
## 29511 Jove-Adult        admin.  single   university.degree     yes   no
##        contact month day_of_week duration campaign previous poutcome
## 30189 cellular   apr         thu      354        1      Yes  success
## 30315 cellular   apr         thu      483        1      Yes  success
## 30208 cellular   apr         thu      218        1      Yes  success
## 30244 cellular   apr         thu      266        2      Yes  success
## 30419 cellular   apr         thu      509        1      Yes  success
## 30150 cellular   apr         thu      494        1      Yes  success
## 30140 cellular   apr         thu      701        1      Yes  success
## 30185 cellular   apr         thu      252        1      Yes  success
## 30418 cellular   apr         thu      502        1      Yes  success
## 29511 cellular   apr         mon      670        4      Yes  success
##       emp.var.rate cons.price.idx cons.conf.idx euribor3m nr.employed   y
## 30189         -1.8         93.075         -47.1     1.365      5099.1 yes
## 30315         -1.8         93.075         -47.1     1.365      5099.1 yes
## 30208         -1.8         93.075         -47.1     1.365      5099.1 yes
## 30244         -1.8         93.075         -47.1     1.365      5099.1 yes
## 30419         -1.8         93.075         -47.1     1.365      5099.1 yes
## 30150         -1.8         93.075         -47.1     1.365      5099.1 yes
## 30140         -1.8         93.075         -47.1     1.365      5099.1 yes
## 30185         -1.8         93.075         -47.1     1.365      5099.1 yes
## 30418         -1.8         93.075         -47.1     1.365      5099.1 yes
## 29511         -1.8         93.075         -47.1     1.405      5099.1 yes
##       age_num
## 30189      45
## 30315      36
## 30208      36
## 30244      36
## 30419      40
## 30150      53
## 30140      31
## 30185      31
## 30418      30
## 29511      43
```

Los 10 primeros individuos más contributivos en la dimension 1

```r
rang<-inds[order(inds$`Dim 2`, decreasing = TRUE),]
res.mca$ind$coord[row.names(rang)[1:10],2]
```

```
##    30596    34731    32721    33383    30473    28168    34408    34276 
## 2.998819 2.937982 2.930081 2.909436 2.898307 2.882058 2.872351 2.854547 
##    35942    28677 
## 2.846646 2.821221
```

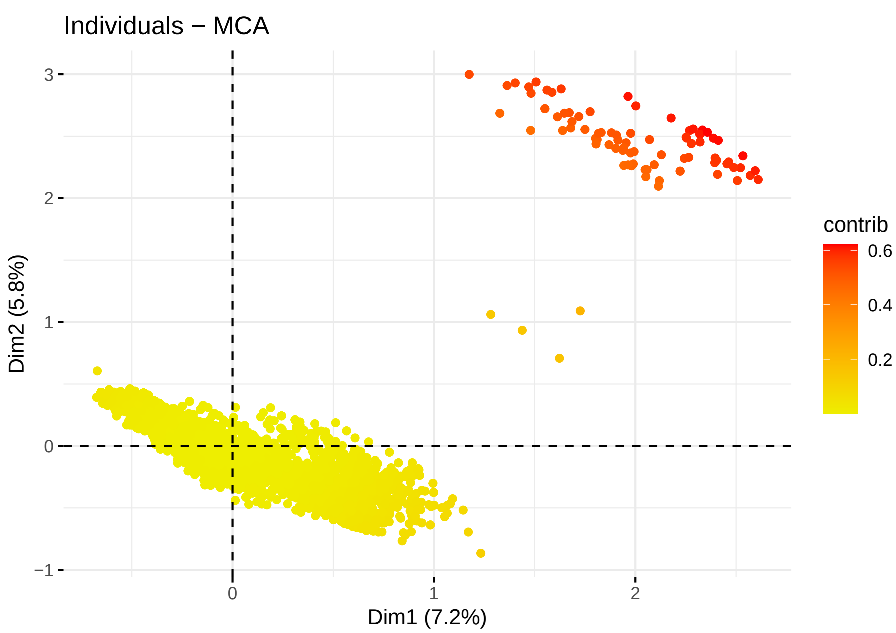
```r
df[which(row.names(df) %in% row.names(res.mca$ind$coord
                                       [row.names(rang)[1:10],])),1:20]
```

```
##               age         job marital education housing loan   contact month
## 28168 Jove-Adult blue-collar married     basic     yes   no telephone   apr
## 28677 Jove-Adult blue-collar married     basic      no   no  cellular   apr
## 32721      Adult blue-collar married     basic      no   no  cellular   may
## 34731      Adult blue-collar married     basic      no   no  cellular   may
## 30596      Adult blue-collar married     basic     yes   no telephone   may
## 35942 Jove-Adult blue-collar married     basic      no  yes  cellular   may
## 30473      Adult blue-collar married     basic     yes   no  cellular   may
## 34408 Jove-Adult blue-collar married     basic      no   no  cellular   may
## 33383      Adult blue-collar married     basic      no   no  cellular   may
## 34276 Jove-Adult blue-collar married     basic      no  yes  cellular   may
##       day_of_week duration campaign previous poutcome emp.var.rate
## 28168         mon     1353        2      Yes  success         -1.8
## 28677         thu      583        1      Yes  success         -1.8
## 32721         mon      474        1      Yes  success         -1.8
## 34731         thu      532        2      Yes  success         -1.8
## 30596         mon      483        4      Yes  success         -1.8
## 35942         mon      487        1      Yes  success         -1.8
## 30473         mon      293        3      Yes  success         -1.8
## 34408         thu      680        1      Yes  success         -1.8
## 33383         tue      309        1      Yes  success         -1.8
## 34276         thu      722        2      Yes  success         -1.8
##       cons.price.idx cons.conf.idx euribor3m nr.employed   y age_num
## 28168         93.075         -47.1     1.466      5099.1 yes      34
## 28677         93.075         -47.1     1.410      5099.1 yes      32
## 32721         92.893         -46.2     1.299      5099.1 yes      50
## 34731         92.893         -46.2     1.266      5099.1 yes      54
## 30596         92.893         -46.2     1.354      5099.1 yes      50
## 35942         92.893         -46.2     1.264      5099.1 yes      43
## 30473         92.893         -46.2     1.354      5099.1 yes      50
## 34408         92.893         -46.2     1.266      5099.1 yes      31
## 33383         92.893         -46.2     1.291      5099.1 yes      48
## 34276         92.893         -46.2     1.266      5099.1 yes      43
```

Els 10 primers individuus més contributius en la dimensió 2

A la següent gràfica podrem veure sobre sobre el pla quins individus son els més contributius (marcats en vermell) i els menys (en groc). Els punts de color blau corresponen a individus suplementaris (individus amb outliers multivariants).

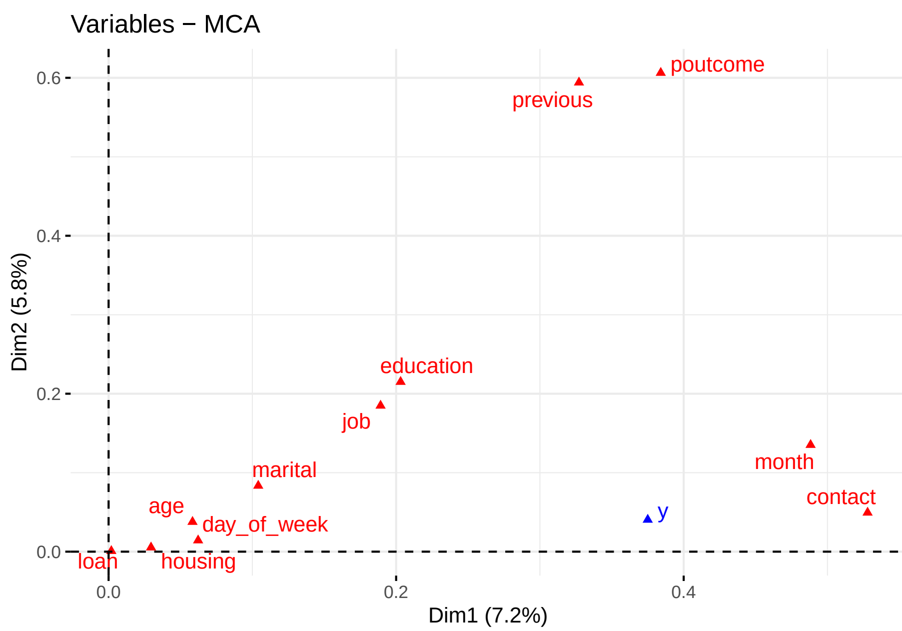
```
# A l'hora de fer les gràfiques per individus i categories,
# posarem com a invisible els individus suplementaris per no tenir-los en
# compte (individus amb outliers multivariants)

fviz_mca_ind(
  res.mca,
  geom=c("point"),
  col.ind="contrib",
  invisible=c("ind.sup"),
  gradient.cols=c("yellow2", "red")
)
```



Com podrem veure en el següent punt, les categories més representatives en les dues dimensions són succes i yes en gran mesura. Això ho podem veure en els individus més representatius, que comparteixen valors.

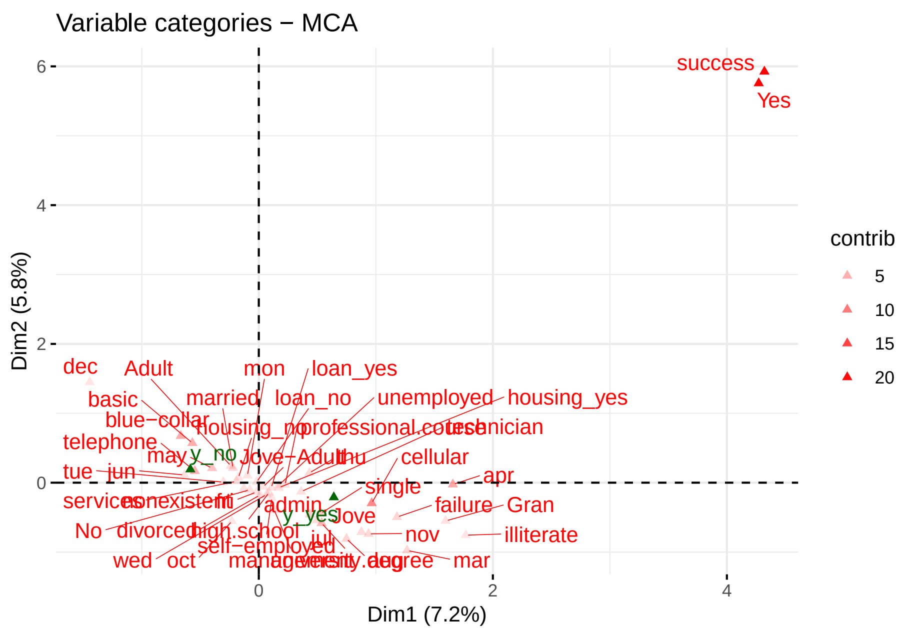
3. Interpreting map of categories

```
fviz_mca_var(res.mca,
             choice="mca.cor",
             repel = T)
```



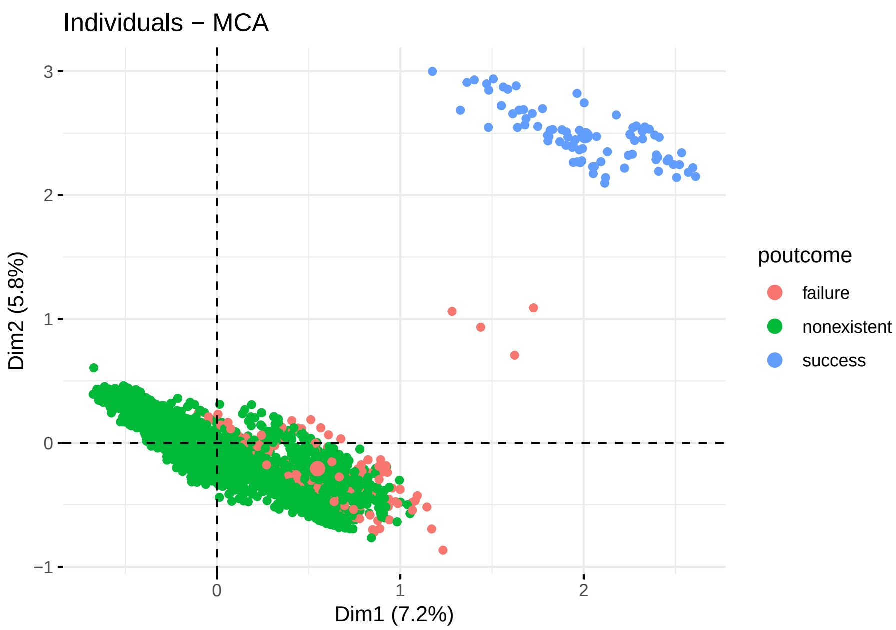
Podem veure que contribueixen en gran mesura les variables “previous” i “poutcome” per ambdues dimensions, mentres que per la dimensió 1 també contribuieixen “month”, “contact” i “y”, aquesta última en menor mesura.

```
fviz_mca_var(res.mca,
             alpha.var="contrib",
             repel = T)
```

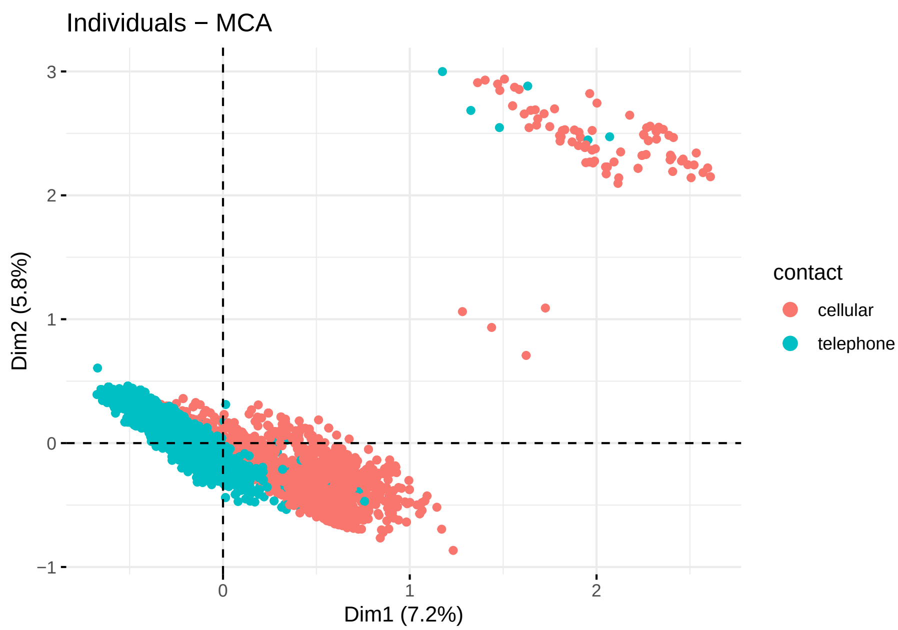


Les categories més contributives en ambdos dimensions és “success” (categoria de “poutcome”, variable que hem vist que contribuia en les dues dimensions) i “yes” (categoria de previous), la resta de categories no són tan determinants.

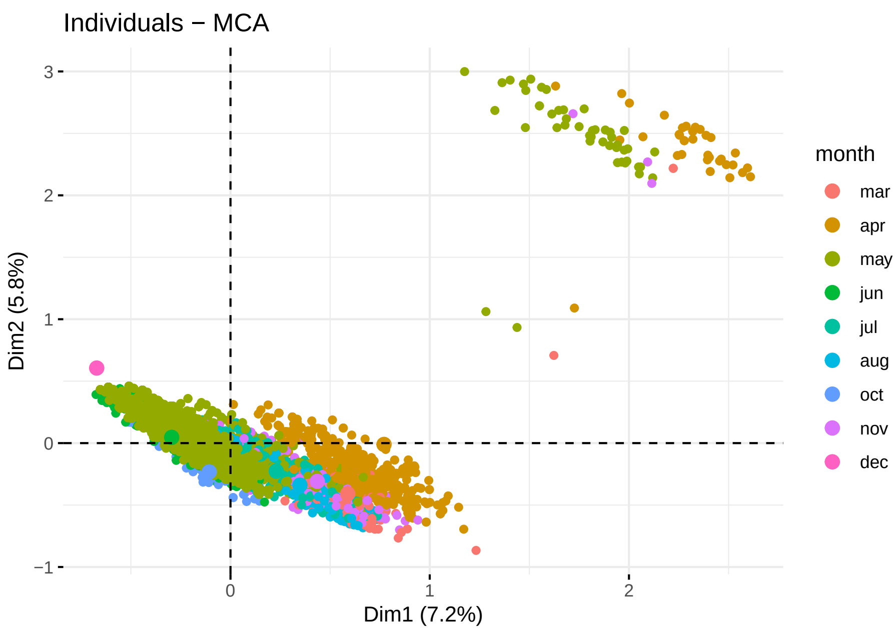
```r
# A l'hora de fer les gràfiques per individus i categories, posarem
# com a invisible els individus suplementaris per no tenir-los en compte
# (individus amb outliers multivariants)
fviz_mca_ind(res.mca,
             label="none",
             invisible=c("ind.sup"),
             geom = c("point"),
             habillage="poutcome")
```




```
fviz_mca_ind(res.mca,
             label="none",
             invisible=c("ind.sup"),
             geom = c("point"),
             habillage="contact")
```




```r
fviz_mca_ind(res.mca,
             label="none",
             invisible=c("ind.sup"),
             geom = c("point"),
             habillage="month")
```



En els tres gràfics, podem veure com les categories formen grups diferenciats, sobretot en les dues primeres. A la última gràfica les categories no estan tan marcades, tot i que es veu una tendència igual entre categories.

4. Interpreting the axes association to factor map

```
res.des <- dimdesc(res.mca)
```

```
res.des$`Dim 1`$quali
```

```
##                      R2       p.value
## y           0.374987432  0.000000e+00
## contact     0.527902185  0.000000e+00
## month       0.488263590  0.000000e+00
## previous    0.327162493  0.000000e+00
## poutcome    0.384056740  0.000000e+00
## education   0.203105403 2.555766e-241
## job         0.189176924 2.541743e-220
## marital     0.104098708 1.426304e-118
## day_of_week 0.062267605  1.968206e-67
## age         0.058376451  4.596511e-64
## housing     0.029524225  4.813177e-34
## loan        0.001906531  2.143411e-03
```

Les variables que més ens representan la primera dimensió són les variables següents:

- contact (0.528)
- month (0.488)
- poutcome (0.384)

Aquestes tres variables són les que hem vist que estaven més relacionades anteriorment de forma gràfica.

```
res.des$`Dim 1`$category
```

```
##                                   Estimate       p.value
## poutcome=success                1.17531597  0.000000e+00
## previous=Yes                    1.01047661  0.000000e+00
## month=apr                       0.64675641  0.000000e+00
## contact=cellular                0.35132508  0.000000e+00
## y=y_yes                         0.28488898  0.000000e+00
## education=university.degree     0.05900022 2.383815e-128
## marital=single                  0.19670535 2.666734e-114
## job=admin.                      0.18013247  4.137677e-67
## day_of_week=thu                 0.19339224  6.660628e-53
## month=mar                       0.46472456  6.802393e-45
## month=nov                       0.31200496  1.079628e-39
## month=aug                       0.22458575  4.665454e-37
## housing=housing_yes             0.07985867  4.813177e-34
## age=Jove                        0.14354196  2.506712e-31
## job=technician                  0.14485506  2.581261e-27
## month=jul                       0.10589318  1.029731e-24
## age=Gran                        0.47806017  1.307906e-18
## job=unemployed                  0.05540381  5.365573e-05
## loan=loan_yes                   0.02895621  2.143411e-03
## job=management                  0.03794035  7.710261e-03
## education=illiterate            0.63136693  1.235638e-02
## day_of_week=wed                 0.02407510  2.879632e-02
## job=self-employed               0.02795219  3.237426e-02
## loan=loan_no                   -0.02895621  2.143411e-03
## education=high.school          -0.14980519  4.746968e-04
## day_of_week=mon                -0.05256369  3.291634e-04
## age=Jove-Adult                 -0.24629074  7.288918e-05
## job=services                   -0.11268984  3.254931e-06
## education=professional.course -0.08612124  1.676784e-09
## month=jun                      -0.41903271  1.194469e-18
```

```
## age=Adult                        -0.37531139  2.372548e-25
## day_of_week=tue                  -0.14817144  8.073767e-34
## housing=housing_no               -0.07985867  4.813177e-34
## poutcome=failure                 -0.28388793  1.169020e-65
## marital=married                  -0.15185866  6.566766e-96
## job=blue-collar                  -0.33359402 2.665337e-183
## education=basic                  -0.45444072 1.483351e-208
## poutcome=nonexistent             -0.89142804  0.000000e+00
## previous=No                      -1.01047661  0.000000e+00
## month=may                        -0.30916544  0.000000e+00
## contact=telephone                -0.35132508  0.000000e+00
## y=y_no                           -0.28488898  0.000000e+00
```

Les categories que més representen la primera dimensió són les següents:

- success de poutcome (1.175)
- Yes de previous (1.01)
- apr de month (0.647)

Tot i que hi hagi contribucions negatives amb valors més destacats, no els tenim en compte ja que són categories contràries a les que tenim en positiu.

Aquestes tres categories són les que hem vist que estaven més relacionades anteriorment de forma gràfica.

```
res.des$`Dim 2`$quali
```

```
##                       R2       p.value
## previous    0.5940564621  0.000000e+00
## poutcome    0.6062924147  0.000000e+00
## education   0.2149866672 2.160555e-257
## job         0.1848775504 1.122408e-214
## month       0.1351545003 2.072247e-149
## marital     0.0835207347  3.160431e-94
## contact     0.0494419477  2.166185e-56
## y           0.0404296938  3.143042e-46
## age         0.0377013815  7.044337e-41
## day_of_week 0.0142988220  1.337097e-14
## housing     0.0053479661  2.667713e-07
## loan        0.0008247522  4.355077e-02
```

Les variables que més ens representan la segona dimensió són les variables següents:

- poutcome (0.6062)
- previous (0.5940)
- education (0.215)

Aquestes tres variables són les que hem vist que estaven més relacionades anteriorment de forma gràfica.

```
res.des$`Dim 2`$category
```

```
##                              Estimate       p.value
## poutcome=success           1.73394719  0.000000e+00
## previous=Yes               1.22612449  0.000000e+00
## education=basic            0.31810208 9.138533e-212
## job=blue-collar            0.31488937 2.189283e-187
## month=may                  0.17499654 1.506661e-102
## marital=married            0.14623996  1.751311e-89
## contact=telephone          0.09681807  2.166185e-56
## y=y_no                     0.08423522  3.143042e-46
## age=Adult                  0.21471233  2.315031e-26
## age=Jove-Adult             0.08827440  1.987533e-09
## education=high.school      0.01860896  9.527271e-09
## housing=housing_no         0.03060577  2.667713e-07
## day_of_week=thu            0.06294006  9.326999e-07
## day_of_week=mon            0.04771803  1.318104e-04
## loan=loan_no               0.01714975  4.355077e-02
## loan=loan_yes             -0.01714975  4.355077e-02
## age=Gran                  -0.11796644  2.483794e-03
## month=oct                 -0.14489659  3.614771e-04
## job=technician            -0.02121630  1.242614e-04
## day_of_week=fri           -0.05220759  1.885359e-05
## job=self-employed         -0.06021933  1.728930e-05
## marital=divorced          -0.01775560  1.526968e-05
## housing=housing_yes       -0.03060577  2.667713e-07
## day_of_week=wed           -0.06639553  4.421294e-08
## poutcome=failure          -0.95300863  1.250230e-12
## job=management            -0.13337023  1.030364e-15
## age=Jove                  -0.18502029  4.814380e-21
## month=nov                 -0.22143499  4.994564e-25
## month=mar                 -0.32129786  3.766175e-27
## month=jul                 -0.13918909  2.462041e-29
## month=aug                 -0.25156750  4.941531e-43
## y=y_yes                   -0.08423522  3.143042e-46
## contact=cellular          -0.09681807  2.166185e-56
## job=admin.                -0.15882870  2.586561e-73
```

```
## marital=single               -0.12848436  1.929238e-79
## poutcome=nonexistent         -0.78093856 6.075965e-139
## education=university.degree -0.16532509 8.613027e-153
## previous=No                  -1.22612449  0.000000e+00
```

Les categories que més representen la segona dimensió són les següents:

- success de poutcome (1.734)
- Yes de previous (1.226)
- basic de education (0.318)

Aquestes tres categories són les que hem vist que estaven més relacionades anteriorment de forma gràfica.

```
res.des$`Dim 3`$quali
```

```
##                     R2       p.value
## job         0.45767503  0.000000e+00
## education   0.42707963  0.000000e+00
## age         0.23380846 9.505926e-285
## month       0.15175628 5.160481e-170
## contact     0.10850285 2.414833e-125
## marital     0.09033880 3.122212e-102
## poutcome    0.06740715  1.530758e-75
## y           0.06352746  1.877783e-72
## previous    0.03006950  1.190896e-34
## housing     0.02525844  2.622655e-29
## day_of_week 0.02524322  2.528430e-26
```

Les variables que més ens representan la segona dimensió són les variables següents:

- job (0.458)
- education (0.427)
- age (0.234)

```
res.des$`Dim 3`$category
```

```
##                                   Estimate       p.value
## education=basic                0.03036553  0.000000e+00
## job=blue-collar                0.24075041 2.869731e-158
## age=Gran                       1.28909975 9.665342e-138
## contact=cellular               0.13140691 2.414833e-125
## job=unemployed                 0.35425607 4.453087e-111
## marital=married                0.11728914  2.174045e-83
## y=y_yes                        0.09674160  1.877783e-72
## month=apr                      0.18403860  6.229941e-69
## poutcome=failure               0.41986805  1.832819e-43
## previous=No                    0.25273932  1.190896e-34
## housing=housing_yes            0.06093985  2.622655e-29
## month=aug                      0.11799097  2.284992e-25
## month=nov                      0.09532077  7.725177e-15
## month=jul                      0.01548543  5.942950e-13
## day_of_week=wed                0.07781044  2.614175e-11
## day_of_week=thu                0.07066121  4.948072e-11
## job=self-employed              0.11327939  1.918956e-08
## month=mar                      0.06475565  1.590061e-07
## education=illiterate           1.06838259  1.358657e-06
## poutcome=nonexistent           0.04610141  3.030347e-06
## job=management                 0.04816927  1.506661e-02
## education=university.degree -0.25750295  4.547814e-02
## day_of_week=tue               -0.02438976  1.598485e-02
## job=technician                -0.03553068  3.713086e-03
## month=jun                     -0.20722310  1.264593e-03
## day_of_week=mon               -0.04162443  9.623346e-05
## day_of_week=fri               -0.08245746  1.849777e-11
## age=Jove                      -0.60057120  6.233578e-12
## month=oct                     -0.64919397  3.733186e-19
## housing=housing_no            -0.06093985  2.622655e-29
## previous=Yes                  -0.25273932  1.190896e-34
## poutcome=success              -0.46596946  6.149424e-36
## y=y_no                        -0.09674160  1.877783e-72
## marital=single                -0.15058853  1.507932e-98
## job=admin.                    -0.20528163 1.083739e-102
## month=may                     -0.20002879 4.193292e-107
## age=Adult                     -0.20294259 1.890559e-116
## age=Jove-Adult                -0.48558596 5.626479e-122
## contact=telephone             -0.13140691 2.414833e-125
## job=services                  -0.51564283 3.571756e-264
## education=high.school         -0.62594578  0.000000e+00
```

Les categories que més representen la segona dimensió són les següents:

- Gran de age (1.289)

- illiterate de education (1.068)
- oct de month (-0.649)

5. Perform a MCA taking into account also supplementary variables

Realitzarem el nou anàlisis MCA amb les variables continues com a suplementàries. Per a realitzar el nou model obviarem la variable "age_num", ja que la tenim en compte a la variable "age" i ens alteraria els resultats tenir-la en compte dues vegades.

```
res.mca_sup<-MCA(df[,c(var_res, var_con[2:8], var_dis[1:11]) ], quali.sup=1,
                 quanti.sup = c(2:8), ind.sup=llmout, graph = F)
```

```
res.des_sup <- dimdesc(res.mca_sup)
```

```
res.des_sup
```

```
## $`Dim 1`
##
## Link between the variable and the continuous variables (R-square)
## =================================================================================
##                 correlation       p.value
## duration          0.2522384  1.453834e-72
## nr.employed      -0.4591929 2.942456e-256
## emp.var.rate     -0.5906105  0.000000e+00
## euribor3m        -0.5952353  0.000000e+00
## cons.conf.idx    -0.6546221  0.000000e+00
## cons.price.idx   -0.6697710  0.000000e+00
##
## Link between the variable and the categorical variable (1-way anova)
## =============================================
##                      R2       p.value
## y           0.374987432  0.000000e+00
## contact     0.527902185  0.000000e+00
## month       0.488263590  0.000000e+00
## previous    0.327162493  0.000000e+00
## poutcome    0.384056740  0.000000e+00
## education   0.203105403 2.555766e-241
## job         0.189176924 2.541743e-220
## marital     0.104098708 1.426304e-118
## day_of_week 0.062267605  1.968206e-67
## age         0.058376451  4.596511e-64
## housing     0.029524225  4.813177e-34
```

```
## loan        0.001906531  2.143411e-03
##
## Link between variable abd the categories of the categorical variables
## ================================================================
##                                  Estimate       p.value
## poutcome=success               1.17531597  0.000000e+00
## previous=Yes                   1.01047661  0.000000e+00
## month=apr                      0.64675641  0.000000e+00
## contact=cellular               0.35132508  0.000000e+00
## y=y_yes                        0.28488898  0.000000e+00
## education=university.degree    0.05900022 2.383815e-128
## marital=single                 0.19670535 2.666734e-114
## job=admin.                     0.18013247  4.137677e-67
## day_of_week=thu                0.19339224  6.660628e-53
## month=mar                      0.46472456  6.802393e-45
## month=nov                      0.31200496  1.079628e-39
## month=aug                      0.22458575  4.665454e-37
## housing=housing_yes            0.07985867  4.813177e-34
## age=Jove                       0.14354196  2.506712e-31
## job=technician                 0.14485506  2.581261e-27
## month=jul                      0.10589318  1.029731e-24
## age=Gran                       0.47806017  1.307906e-18
## job=unemployed                 0.05540381  5.365573e-05
## loan=loan_yes                  0.02895621  2.143411e-03
## job=management                 0.03794035  7.710261e-03
## education=illiterate           0.63136693  1.235638e-02
## day_of_week=wed                0.02407510  2.879632e-02
## job=self-employed              0.02795219  3.237426e-02
## loan=loan_no                  -0.02895621  2.143411e-03
## education=high.school         -0.14980519  4.746968e-04
## day_of_week=mon               -0.05256369  3.291634e-04
## age=Jove-Adult                -0.24629074  7.288918e-05
## job=services                  -0.11268984  3.254931e-06
## education=professional.course -0.08612124  1.676784e-09
## month=jun                     -0.41903271  1.194469e-18
## age=Adult                     -0.37531139  2.372548e-25
## day_of_week=tue               -0.14817144  8.073767e-34
## housing=housing_no            -0.07985867  4.813177e-34
## poutcome=failure              -0.28388793  1.169020e-65
## marital=married               -0.15185866  6.566766e-96
## job=blue-collar               -0.33359402 2.665337e-183
## education=basic               -0.45444072 1.483351e-208
## poutcome=nonexistent          -0.89142804  0.000000e+00
## previous=No                   -1.01047661  0.000000e+00
## month=may                     -0.30916544  0.000000e+00
## contact=telephone             -0.35132508  0.000000e+00
```

```
## y=y_no                        -0.28488898  0.000000e+00
##
## $`Dim 2`
##
## Link between the variable and the continuous variables (R-square)
## =================================================================================
##                 correlation      p.value
## cons.price.idx  0.09636262 1.145336e-11
## cons.conf.idx   0.09399734 3.601633e-11
## campaign       -0.04611342 1.186972e-03
## nr.employed    -0.09247914 7.404675e-11
## duration       -0.13111935 2.174986e-20
##
## Link between the variable and the categorical variable (1-way anova)
## =============================================
##                       R2       p.value
## previous    0.5940564621  0.000000e+00
## poutcome    0.6062924147  0.000000e+00
## education   0.2149866672 2.160555e-257
## job         0.1848775504 1.122408e-214
## month       0.1351545003 2.072247e-149
## marital     0.0835207347  3.160431e-94
## contact     0.0494419477  2.166185e-56
## y           0.0404296938  3.143042e-46
## age         0.0377013815  7.044337e-41
## day_of_week 0.0142988220  1.337097e-14
## housing     0.0053479661  2.667713e-07
## loan        0.0008247522  4.355077e-02
##
## Link between variable abd the categories of the categorical variables
## ================================================================
##                                Estimate       p.value
## poutcome=success             1.73394719  0.000000e+00
## previous=Yes                 1.22612449  0.000000e+00
## education=basic              0.31810208 9.138533e-212
## job=blue-collar              0.31488937 2.189283e-187
## month=may                    0.17499654 1.506661e-102
## marital=married              0.14623996  1.751311e-89
## contact=telephone            0.09681807  2.166185e-56
## y=y_no                       0.08423522  3.143042e-46
## age=Adult                    0.21471233  2.315031e-26
## age=Jove-Adult               0.08827440  1.987533e-09
## education=high.school        0.01860896  9.527271e-09
## housing=housing_no           0.03060577  2.667713e-07
## day_of_week=thu              0.06294006  9.326999e-07
## day_of_week=mon              0.04771803  1.318104e-04
```

```
## loan=loan_no                 0.01714975  4.355077e-02
## loan=loan_yes               -0.01714975  4.355077e-02
## age=Gran                    -0.11796644  2.483794e-03
## month=oct                   -0.14489659  3.614771e-04
## job=technician              -0.02121630  1.242614e-04
## day_of_week=fri             -0.05220759  1.885359e-05
## job=self-employed           -0.06021933  1.728930e-05
## marital=divorced            -0.01775560  1.526968e-05
## housing=housing_yes         -0.03060577  2.667713e-07
## day_of_week=wed             -0.06639553  4.421294e-08
## poutcome=failure            -0.95300863  1.250230e-12
## job=management              -0.13337023  1.030364e-15
## age=Jove                    -0.18502029  4.814380e-21
## month=nov                   -0.22143499  4.994564e-25
## month=mar                   -0.32129786  3.766175e-27
## month=jul                   -0.13918909  2.462041e-29
## month=aug                   -0.25156750  4.941531e-43
## y=y_yes                     -0.08423522  3.143042e-46
## contact=cellular            -0.09681807  2.166185e-56
## job=admin.                  -0.15882870  2.586561e-73
## marital=single              -0.12848436  1.929238e-79
## poutcome=nonexistent        -0.78093856 6.075965e-139
## education=university.degree -0.16532509 8.613027e-153
## previous=No                 -1.22612449  0.000000e+00
##
## $`Dim 3`
##
## Link between the variable and the continuous variables (R-square)
## =================================================================================
##                correlation      p.value
## duration         0.1400398 4.646852e-23
## nr.employed     -0.1218646 8.315456e-18
## emp.var.rate    -0.1844349 4.757303e-39
## euribor3m       -0.1954924 9.525318e-44
## cons.conf.idx   -0.2419309 9.945248e-67
## cons.price.idx  -0.2519419 2.158776e-72
##
## Link between the variable and the categorical variable (1-way anova)
## =============================================
##                     R2       p.value
## job         0.45767503  0.000000e+00
## education   0.42707963  0.000000e+00
## age         0.23380846 9.505926e-285
## month       0.15175628 5.160481e-170
## contact     0.10850285 2.414833e-125
## marital     0.09033880 3.122212e-102
```

```
## poutcome    0.06740715  1.530758e-75
## y           0.06352746  1.877783e-72
## previous    0.03006950  1.190896e-34
## housing     0.02525844  2.622655e-29
## day_of_week 0.02524322  2.528430e-26
##
## Link between variable abd the categories of the categorical variables
## ================================================================
##                                Estimate       p.value
## education=basic              0.03036553  0.000000e+00
## job=blue-collar              0.24075041 2.869731e-158
## age=Gran                     1.28909975 9.665342e-138
## contact=cellular             0.13140691 2.414833e-125
## job=unemployed               0.35425607 4.453087e-111
## marital=married              0.11728914  2.174045e-83
## y=y_yes                      0.09674160  1.877783e-72
## month=apr                    0.18403860  6.229941e-69
## poutcome=failure             0.41986805  1.832819e-43
## previous=No                  0.25273932  1.190896e-34
## housing=housing_yes          0.06093985  2.622655e-29
## month=aug                    0.11799097  2.284992e-25
## month=nov                    0.09532077  7.725177e-15
## month=jul                    0.01548543  5.942950e-13
## day_of_week=wed              0.07781044  2.614175e-11
## day_of_week=thu              0.07066121  4.948072e-11
## job=self-employed            0.11327939  1.918956e-08
## month=mar                    0.06475565  1.590061e-07
## education=illiterate         1.06838259  1.358657e-06
## poutcome=nonexistent         0.04610141  3.030347e-06
## job=management               0.04816927  1.506661e-02
## education=university.degree -0.25750295  4.547814e-02
## day_of_week=tue             -0.02438976  1.598485e-02
## job=technician              -0.03553068  3.713086e-03
## month=jun                   -0.20722310  1.264593e-03
## day_of_week=mon             -0.04162443  9.623346e-05
## day_of_week=fri             -0.08245746  1.849777e-11
## age=Jove                    -0.60057120  6.233578e-12
## month=oct                   -0.64919397  3.733186e-19
## housing=housing_no          -0.06093985  2.622655e-29
## previous=Yes                -0.25273932  1.190896e-34
## poutcome=success            -0.46596946  6.149424e-36
## y=y_no                      -0.09674160  1.877783e-72
## marital=single              -0.15058853  1.507932e-98
## job=admin.                  -0.20528163 1.083739e-102
## month=may                   -0.20002879 4.193292e-107
## age=Adult                   -0.20294259 1.890559e-116
```

```
## age=Jove-Adult                  -0.48558596 5.626479e-122
## contact=telephone               -0.13140691 2.414833e-125
## job=services                    -0.51564283 3.571756e-264
## education=high.school           -0.62594578  0.000000e+00
```

Per cada dimensió podem veure les correlacions que hi ha, la majoria d'aquestes són pels índex econòmics i de forma negativa.

Tant per variables com per categories, el fet d'incloure les variables continues com a suplementàries no ha variat el seu resultat ni contribució.

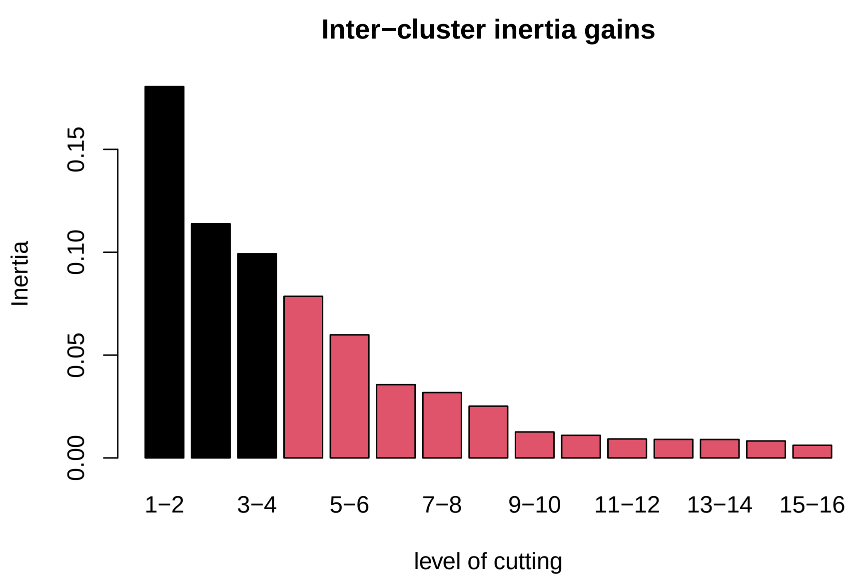
Clustering MCA

Description of clusters

```r
# Posem nb.clust = -1 perquè utilitzi el numero de clusters que ens recomana
res.hcmc_mca<-HCPC(res.mca, nb.clust = -1, order=TRUE, graph = F)
```

Agafem 4 clusters, ja que són els que ens indica el propi HCPC que hem d'incloure degut a la inèrcia acumulada d'aquests.

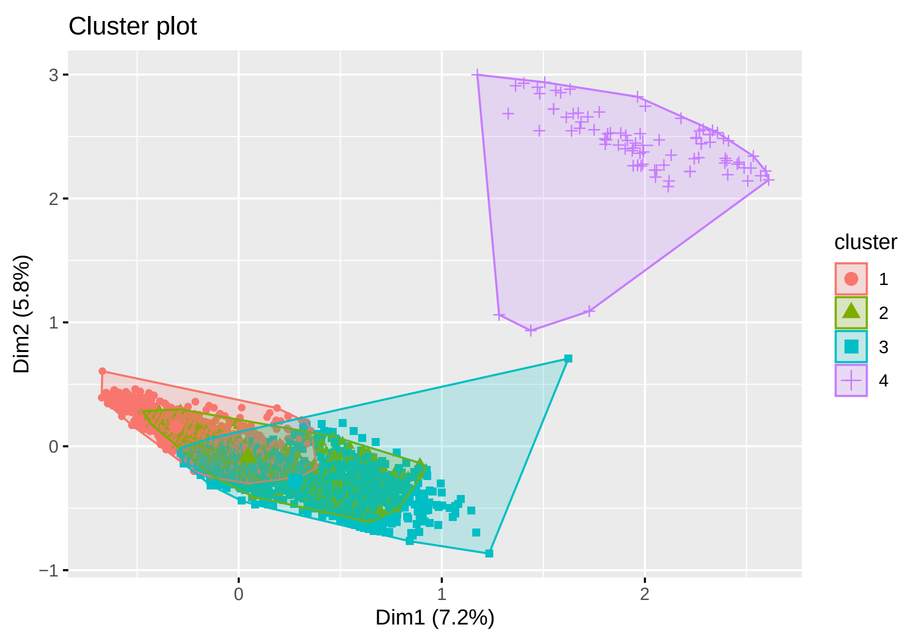
```r
#fviz_dend(res.hcmc_mca, show_labels = FALSE)
plot(res.hcmc_mca, choice = "bar")
```



A la primera gràfica podem veure la inèrcia de cada grup de clusters i la distància entre cadascun d'ells. Observem que a mida que anem augmentant el número de cluster, la inèrcia es va igualant més amb la del següent cluster.

A la gràfica de barres següent es pot veure les inèrcies exactes per cada parella de clusters. Veiem que les més significatives són de la 1 a la 4 (les que ens recomanava agafar el HCPC).

```
fviz_cluster(res.hcmc_mca, geom = "point")
```



A la gràfica factor map (la última), podem veure com el cluster 1, 3 i 4 estan completament difgerenciats, però el cluster 2 està dispers amb el primer i tercer cluster. També observem com els clusters 3 i 4 tenen punts molt desviats que provoquen que abarquin molta superfície sense punts significatius.

```
res.hcmc_mca$desc.var$test.chi2
```

```
##                   p.value df
## job          0.000000e+00 18
## education    0.000000e+00 12
## previous     0.000000e+00  3
## poutcome     0.000000e+00  6
## month       2.749774e-235 24
## contact     9.965243e-211  3
## y           4.828120e-166  3
```

```
## marital      2.045561e-64  6
## age          6.296158e-21  9
## day_of_week  5.642845e-12 12
## housing      6.548853e-12  3
```

Les següents variables són les que ens aporten més informació per representar els clusters. Són totes variables discretes ja que es tracta d'un anàlisis MCA:

- job
- education
- previous
- poutcome

```
res.hcmc_mca$desc.var$category
```

```
## $`1`
##                                 Cla/Mod      Mod/Cla     Global       p.value
## education=basic               86.133487  66.56291685 35.1821862  0.000000e+00
## job=blue-collar               90.532081  51.44508671 25.8704453  0.000000e+00
## contact=telephone             60.247462  84.43752779 63.8056680 9.477077e-177
## month=may                     57.993351  85.32681192 66.9838057 3.520823e-146
## y=y_no                        62.098335  71.32058693 52.2874494 1.785644e-135
## marital=married               53.888000  74.87772343 63.2591093  4.968708e-55
## job=services                  76.571429  17.87461094 10.6275304  6.875358e-53
## poutcome=nonexistent          47.500536  98.44375278 94.3522267  7.002413e-34
## education=high.school         59.367194  31.70297910 24.3117409  1.989472e-28
## previous=No                   46.342469 100.00000000 98.2388664  5.871416e-24
## housing=housing_no            50.695012  55.13561583 49.5141700  4.920995e-13
## age=Adult                     50.221239  30.28012450 27.4493927  4.717230e-05
## month=jun                     58.152174   4.75767008  3.7246964  4.860564e-04
## day_of_week=tue               49.832776  26.50066696 24.2105263  6.050054e-04
## loan=loan_no                  46.290170  87.10538017 85.6680162  8.287388e-03
## month=oct                     29.268293   0.53357048  0.8299595  3.542951e-02
## day_of_week=wed               42.227378  16.18497110 17.4493927  3.217246e-02
## loan=loan_yes                 40.960452  12.89461983 14.3319838  8.287388e-03
## marital=divorced              39.196941   9.11516229 10.5870445  2.047602e-03
## age=Jove                      32.738095   2.44553135  3.4008097  6.343174e-04
## day_of_week=thu               40.081384  17.51889729 19.8987854  1.232443e-04
## month=jul                     33.587786   5.86927523  7.9554656  5.715705e-07
## age=Gran                       3.333333   0.04446421  0.6072874  3.092767e-07
## job=self-employed             29.106628   4.49088484  7.0242915  9.457441e-11
## housing=housing_yes           40.457097  44.86438417 50.4858300  4.920995e-13
## poutcome=failure              17.857143   1.55624722  3.9676113  1.144982e-16
## poutcome=success               0.000000   0.00000000  1.6801619  7.070463e-23
```

```
## previous=Yes                       0.000000  0.00000000  1.7611336  5.871416e-24
## month=mar                          2.542373  0.13339262  2.3886640  4.227342e-27
## month=nov                          8.556150  0.71142730  3.7854251  2.406330e-29
## month=aug                         11.567164  1.37839040  5.4251012  1.103349e-34
## job=management                    15.466667  2.57892397  7.5910931  1.622807e-37
## marital=single                    27.863777 16.00711427 26.1538462  2.705281e-51
## job=admin.                        23.123382 11.91640729 23.4615385  5.726114e-72
## month=apr                          6.378132  1.24499778  8.8866397  3.025751e-80
## y=y_yes                           27.365295 28.67941307 47.7125506 1.785644e-135
## education=professional.course      1.437700  0.40017786 12.6720648 2.460003e-162
## contact=cellular                  19.574944 15.56247221 36.1943320 9.477077e-177
## job=technician                     2.002670  0.66696309 15.1619433 1.377363e-190
## education=university.degree        2.184996  1.33392619 27.7935223  0.000000e+00
##                                      v.test
## education=basic                         Inf
## job=blue-collar                         Inf
## contact=telephone                 28.345623
## month=may                         25.746578
## y=y_no                            24.772245
## marital=married                   15.624362
## job=services                      15.306910
## poutcome=nonexistent              12.133687
## education=high.school             11.058706
## previous=No                       10.094021
## housing=housing_no                 7.227463
## age=Adult                          4.069213
## month=jun                          3.488325
## day_of_week=tue                    3.429360
## loan=loan_no                       2.640131
## month=oct                         -2.103415
## day_of_week=wed                   -2.142261
## loan=loan_yes                     -2.640131
## marital=divorced                  -3.083240
## age=Jove                          -3.416500
## day_of_week=thu                   -3.839581
## month=jul                         -5.000584
## age=Gran                          -5.117704
## job=self-employed                 -6.475379
## housing=housing_yes               -7.227463
## poutcome=failure                  -8.288695
## poutcome=success                  -9.846880
## previous=Yes                     -10.094021
## month=mar                        -10.781114
## month=nov                        -11.246622
## month=aug                        -12.284049
## job=management                   -12.800795
```

```
## marital=single                -15.066123
## job=admin.                    -17.940188
## month=apr                     -18.969884
## y=y_yes                       -24.772245
## education=professional.course -27.151061
## contact=cellular              -28.345623
## job=technician                -29.446951
## education=university.degree         -Inf
##
## $`2`
##                                 Cla/Mod     Mod/Cla     Global      p.value
## education=professional.course 92.971246  67.6744186 12.6720648 0.000000e+00
## job=technician                88.651535  77.2093023 15.1619433 0.000000e+00
## month=aug                     34.328358  10.6976744  5.4251012 6.104470e-12
## previous=No                   17.720997 100.0000000 98.2388664 5.046124e-08
## age=Jove-Adult                18.989959  74.7674419 68.5425101 1.140506e-05
## poutcome=nonexistent          17.850247  96.7441860 94.3522267 4.129123e-04
## day_of_week=tue               19.565217  27.2093023 24.2105263 2.520745e-02
## age=Gran                       3.333333   0.1162791  0.6072874 2.645836e-02
## age=Adult                     15.339233  24.1860465 27.4493927 1.741316e-02
## job=self-employed              9.221902   3.7209302  7.0242915 8.581173e-06
## age=Jove                       4.761905   0.9302326  3.4008097 6.527235e-07
## month=apr                      8.883827   4.5348837  8.8866397 1.253005e-07
## poutcome=success               0.000000   0.0000000  1.6801619 1.100549e-07
## previous=Yes                   0.000000   0.0000000  1.7611336 5.046124e-08
## job=unemployed                 7.495069   4.4186047 10.2631579 1.343328e-11
## job=services                   5.714286   3.4883721 10.6275304 7.876437e-17
## job=management                 3.466667   1.5116279  7.5910931 7.748804e-18
## education=university.degree    9.541151  15.2325581 27.7935223 2.408001e-21
## education=high.school          6.827644   9.5348837 24.3117409 2.928148e-33
## job=blue-collar                4.147105   6.1627907 25.8704453 3.846798e-59
## job=admin.                     2.588438   3.4883721 23.4615385 6.370328e-69
## education=basic                3.739931   7.5581395 35.1821862 6.391386e-94
##                                  v.test
## education=professional.course       Inf
## job=technician                      Inf
## month=aug                      6.877190
## previous=No                    5.449678
## age=Jove-Adult                 4.388661
## poutcome=nonexistent           3.531691
## day_of_week=tue                2.238209
## age=Gran                      -2.219417
## age=Adult                     -2.377866
## job=self-employed             -4.450147
## age=Jove                      -4.974927
## month=apr                     -5.285590
```

```
## poutcome=success                -5.309287
## previous=Yes                    -5.449678
## job=unemployed                  -6.763892
## job=services                    -8.333082
## job=management                  -8.603253
## education=university.degree     -9.485683
## education=high.school          -12.015997
## job=blue-collar                -16.216639
## job=admin.                     -17.546104
## education=basic                -20.559018
##
## $`3`
##                                 Cla/Mod     Mod/Cla     Global       p.value
## education=university.degree   86.598689 68.13753582 27.7935223  0.000000e+00
## job=admin.                    72.131148 47.90830946 23.4615385 7.295011e-192
## contact=cellular              58.836689 60.28653295 36.1943320 2.586108e-148
## y=y_yes                       51.803140 69.97134670 47.7125506 9.515429e-121
## month=apr                     76.765376 19.31232092  8.8866397  2.709105e-77
## job=management                79.733333 17.13467049  7.5910931  3.553602e-75
## marital=single                52.089783 38.56733524 26.1538462  2.184403e-47
## month=nov                     76.470588  8.19484241  3.7854251  1.407523e-31
## job=self-employed             60.518732 12.03438395  7.0242915  4.199892e-23
## poutcome=failure              66.326531  7.44985673  3.9676113  2.600404e-19
## month=mar                     73.728814  4.98567335  2.3886640  1.020654e-17
## previous=No                   35.936534 99.94269341 98.2388664  1.144210e-15
## age=Jove                      61.309524  5.90257880  3.4008097  3.635738e-12
## age=Gran                      93.333333  1.60458453  0.6072874  3.811565e-11
## month=aug                     54.104478  8.30945559  5.4251012  1.159896e-10
## month=jul                     50.127226 11.28939828  7.9554656  3.779458e-10
## housing=housing_yes           39.414595 56.33237822 50.4858300  1.221197e-09
## day_of_week=thu               40.488301 22.80802292 19.8987854  1.721074e-04
## marital=divorced              42.447419 12.72206304 10.5870445  3.672714e-04
## job=unemployed                42.406312 12.32091691 10.2631579  4.992983e-04
## day_of_week=wed               39.443155 19.48424069 17.4493927  5.647987e-03
## month=oct                     51.219512  1.20343840  0.8299595  3.806523e-02
## age=Adult                     32.669617 25.38681948 27.4493927  1.608590e-02
## month=jun                     25.543478  2.69340974  3.7246964  3.955253e-03
## education=high.school         31.806828 21.89111748 24.3117409  3.241826e-03
## poutcome=nonexistent          34.649217 92.55014327 94.3522267  6.875285e-05
## day_of_week=tue               29.933110 20.51575931 24.2105263  6.301578e-06
## housing=housing_no            31.152903 43.66762178 49.5141700  1.221197e-09
## previous=Yes                   1.149425  0.05730659  1.7611336  1.144210e-15
## poutcome=success               0.000000  0.00000000  1.6801619  1.336576e-16
## job=services                  16.190476  4.87106017 10.6275304  1.268130e-24
## marital=married               27.200000 48.71060172 63.2591093  1.050906e-54
## job=technician                 6.542056  2.80802292 15.1619433  3.344219e-88
```

```
## education=professional.course  3.194888  1.14613181 12.6720648  9.838051e-96
## y=y_no                        20.286489 30.02865330 52.2874494 9.515429e-121
## month=may                     23.209429 44.01146132 66.9838057 8.495490e-140
## contact=telephone             21.986041 39.71346705 63.8056680 2.586108e-148
## job=blue-collar                3.990610  2.92263610 25.8704453 3.266085e-204
## education=basic                8.745685  8.71060172 35.1821862 1.448069e-207
##                                   v.test
## education=university.degree          Inf
## job=admin.                     29.546446
## contact=cellular               25.936442
## y=y_yes                        23.365829
## month=apr                      18.609144
## job=management                 18.345995
## marital=single                 14.459480
## month=nov                      11.691575
## job=self-employed               9.899112
## poutcome=failure                8.984446
## month=mar                       8.571591
## previous=No                     8.010309
## age=Jove                        6.950663
## age=Gran                        6.611223
## month=aug                       6.444490
## month=jul                       6.262874
## housing=housing_yes             6.077436
## day_of_week=thu                 3.756789
## marital=divorced                3.562549
## job=unemployed                  3.481133
## day_of_week=wed                 2.767547
## month=oct                       2.074152
## age=Adult                      -2.406961
## month=jun                      -2.881709
## education=high.school          -2.943826
## poutcome=nonexistent           -3.980561
## day_of_week=tue                -4.516010
## housing=housing_no             -6.077436
## previous=Yes                   -8.010309
## poutcome=success               -8.270269
## job=services                  -10.243317
## marital=married               -15.576540
## job=technician                -19.909834
## education=professional.course -20.760576
## y=y_no                        -23.365829
## month=may                     -25.170195
## contact=telephone             -25.936442
## job=blue-collar               -30.492603
## education=basic               -30.744506
```

```
##
## $`4`
##                          Cla/Mod    Mod/Cla    Global       p.value     v.test
## previous=Yes          98.8505747 100.000000  1.761134 9.693892e-186  29.065884
## poutcome=success     100.0000000  96.511628  1.680162 2.126492e-177  28.398230
## contact=cellular       4.4742729  93.023256 36.194332  5.878562e-29  11.167541
## y=y_yes                3.6487060 100.000000 47.712551  1.008897e-28  11.119452
## month=apr              7.9726651  40.697674  8.886640  1.072676e-15   8.018244
## day_of_week=thu        3.7639878  43.023256 19.898785  9.257787e-07   4.906793
## job=technician         2.8037383  24.418605 15.161943  2.337339e-02   2.267276
## month=jun              0.0000000   0.000000  3.724696  3.712800e-02  -2.084354
## month=may              1.3901481  53.488372 66.983806  9.052054e-03  -2.610082
## month=aug              0.0000000   0.000000  5.425101  7.908101e-03  -2.655968
## month=jul              0.0000000   0.000000  7.955466  7.511337e-04  -3.370201
## day_of_week=tue        0.6688963   9.302326 24.210526  4.297599e-04  -3.521100
## y=y_no                 0.0000000   0.000000 52.287449  1.008897e-28 -11.119452
## contact=telephone      0.1903553   6.976744 63.805668  5.878562e-29 -11.167541
## poutcome=nonexistent   0.0000000   0.000000 94.352227 4.020961e-114 -22.704752
## previous=No            0.0000000   0.000000 98.238866 9.693892e-186 -29.065884
```

- Cluster 1

Per aquest primer cluster tenim que les categories de education basic i high.school són les més representatives. Els resultats ens mostren que el 66,56% de education que trobem al claster són de la categoria basic i el 31,7% són de high.school, la resta de categories apareixen amb un percentatge més baix.

Pel que fa a la variable job, les categories blue.collar (51,45%), services (17,87%) i admin (11.92%), són les categories de job amb més presència dins el cluster.

Com a informació addicional, comentar que cap dels individus dins del cluster ha estat contactat previament (previous=no), això provoca que hi hagi un 0% de poutcome=success.

- Cluster 2

Pel segon cluster, tenim que les categories de education professional.course i university.degree són les més representatives, tot i que aquesta segona de forma negativa. Això ens mostra que dins d'aquest cluster, la majoria de persones tenen estudis superiors, professional.course (67.67%) i university.degree (15.23%).

Pel que fa a job, la categoria amb més força dins del cluster és technician (77.21%), la resta tenen menys importància.

- Cluster 3

En el tercer cluster, tenim que les categories més representatives per education són university.degree (68.14%) i high.school (21.89%).

Pel que fa a la variable job, les categories més significatives són admin (47,91%), management (17,13) i self-employed (12,03%). Aquestes tres categories estan bastant relacionades amb el tipus de feina que són, ja que feines administratives, de control i d'autònom són similars.

- Cluster 4

En aquest últim cluster, com que tenen un gran pes previous i poutcome, les variables job i education no són representatives. En el cas de previous, la categoria més significant és yes (100%) i de poutcome és success (96,51%). Destacar també que tots els poutcome=success es troben en aquest cluster.

- Cut quality

La qualitat de la partició amb 4 clusters és del 48.2918107.

Parangons and class-specific individuals

```
res.hcmc_mca$desc.ind$para
```

```
## Cluster: 1
##        218       2140        162         70        217
## 0.07651285 0.07651285 0.07651285 0.07651285 0.08021202
## ------------------------------------------------------------
## Cluster: 2
##     21748     19754      2385      2006     35970
## 0.2762256 0.2964458 0.2977149 0.3060090 0.3098983
## ------------------------------------------------------------
## Cluster: 3
##     12566     17809     25995     14696     15936
## 0.1232529 0.1243103 0.1244148 0.1356608 0.1464823
## ------------------------------------------------------------
## Cluster: 4
##     25854     30502     33387     30464     34649
## 0.3519480 0.3537620 0.3607975 0.4241063 0.4299914
```

En les taules anteriors podem veure els 5 parangons més cercans als centroides per cadascún dels clusters.

```
res.hcmc_mca$desc.ind$dist
```

```
## Cluster: 1
##    30005     1760     1730     1764     1725
## 1.941382 1.577068 1.570114 1.522564 1.522564
## ------------------------------------------------------------
## Cluster: 2
##    27724    30302    27767    30141    19249
## 1.999976 1.534193 1.516153 1.510455 1.502705
## ------------------------------------------------------------
## Cluster: 3
##    28615    28541    29982    30001    30384
## 2.643395 2.627127 2.507550 2.507550 2.368233
## ------------------------------------------------------------
## Cluster: 4
##    30154    28677    30236    30239    30208
## 3.528231 3.510440 3.508366 3.506306 3.506113
```

En les taules anteriors podem veure els 5 parangons més allunyats als centroides per cadascún dels clusters.

```
res.hcmc_mca$data.clust[which(rownames(res.hcmc_mca$data.clust)%in%names
                              (res.hcmc_mca$desc.ind$para[[1]])),]
```

```
##         y        age         job marital education     housing     loan
## 217  y_no Jove-Adult blue-collar  single     basic housing_yes  loan_no
## 218  y_no Jove-Adult blue-collar  single     basic housing_yes loan_yes
## 2140 y_no Jove-Adult blue-collar  single     basic housing_yes loan_yes
## 162  y_no Jove-Adult blue-collar  single     basic housing_yes loan_yes
## 70   y_no Jove-Adult blue-collar  single     basic housing_yes loan_yes
##        contact month day_of_week previous    poutcome clust
## 217  telephone   may         mon       No nonexistent     1
## 218  telephone   may         mon       No nonexistent     1
## 2140 telephone   may         mon       No nonexistent     1
## 162  telephone   may         mon       No nonexistent     1
## 70   telephone   may         mon       No nonexistent     1
```

```
res.hcmc_mca$data.clust[which(rownames(res.hcmc_mca$data.clust)%in%names
                              (res.hcmc_mca$desc.ind$dist[[1]])),]
```

```
##           y  age        job marital   education     housing     loan   contact
## 30005 y_yes Gran unemployed married       basic housing_yes  loan_no telephone
## 1764  y_yes Jove   services  single high.school housing_yes  loan_no telephone
```

```
## 1725   y_no Jove   services  single high.school housing_yes  loan_no telephone
## 1730   y_no Jove   services  single high.school  housing_no  loan_no telephone
## 1760   y_no Jove   services  single high.school  housing_no loan_yes telephone
##       month day_of_week previous    poutcome clust
## 30005   apr         tue       No nonexistent     1
## 1764    may         fri       No nonexistent     1
## 1725    may         fri       No nonexistent     1
## 1730    may         fri       No nonexistent     1
## 1760    may         fri       No nonexistent     1
```

```
res.hcmc_mca$data.clust[which(rownames(res.hcmc_mca$data.clust)%in%names
                              (res.hcmc_mca$desc.ind$para[[2]])),]
```

```
##           y        age           job marital           education     housing
## 19754 y_yes Jove-Adult    technician married         high.school  housing_no
## 21748 y_yes Jove-Adult      services married professional.course  housing_no
## 35970 y_yes Jove-Adult    technician married professional.course  housing_no
## 2006   y_no      Adult    technician  single professional.course housing_yes
## 2385   y_no Jove-Adult self-employed  single professional.course housing_yes
##           loan   contact month day_of_week previous    poutcome clust
## 19754  loan_no telephone   aug         fri       No nonexistent     2
## 21748  loan_no  cellular   aug         tue       No nonexistent     2
## 35970  loan_no  cellular   may         mon       No nonexistent     2
## 2006   loan_no telephone   may         mon       No nonexistent     2
## 2385  loan_yes telephone   may         tue       No nonexistent     2
```

```
res.hcmc_mca$data.clust[which(rownames(res.hcmc_mca$data.clust)%in%names
                              (res.hcmc_mca$desc.ind$dist[[2]])),]
```

```
##           y        age        job marital           education     housing
## 27767 y_yes Jove-Adult technician  single professional.course housing_yes
## 19249 y_yes Jove-Adult technician  single professional.course housing_yes
## 30141 y_yes Jove-Adult technician married professional.course housing_yes
## 30302 y_yes      Adult technician married professional.course housing_yes
## 27724 y_yes       Gran technician married professional.course housing_yes
##           loan  contact month day_of_week previous    poutcome clust
## 27767 loan_yes cellular   mar         fri       No nonexistent     2
## 19249 loan_yes cellular   aug         wed       No nonexistent     2
## 30141  loan_no cellular   apr         thu       No     failure     2
## 30302 loan_yes cellular   apr         thu       No     failure     2
## 27724  loan_no cellular   mar         tue       No nonexistent     2
```

```r
res.hcmc_mca$data.clust[which(rownames(res.hcmc_mca$data.clust)%in%names
                              (res.hcmc_mca$desc.ind$para[[3]])),]
```

```
##           y        age        job marital         education     housing    loan
## 17809 y_yes Jove-Adult     admin. married university.degree  housing_no loan_no
## 15936 y_yes Jove-Adult     admin. married university.degree  housing_no loan_no
## 12566 y_yes Jove-Adult management married       high.school housing_yes loan_no
## 25995 y_yes      Adult     admin. married       high.school  housing_no loan_no
## 14696 y_yes Jove-Adult management married       high.school housing_yes loan_no
##        contact month day_of_week previous    poutcome clust
## 17809 cellular   jul         tue       No nonexistent     3
## 15936 cellular   jul         mon       No nonexistent     3
## 12566 cellular   jul         mon       No nonexistent     3
## 25995 cellular   nov         wed       No nonexistent     3
## 14696 cellular   jul         tue       No nonexistent     3
```

```r
res.hcmc_mca$data.clust[which(rownames(res.hcmc_mca$data.clust)%in%names
                              (res.hcmc_mca$desc.ind$dist[[3]])),]
```

```
##           y  age        job marital education     housing     loan  contact
## 30384 y_yes Gran unemployed  single     basic housing_yes  loan_no cellular
## 28541 y_yes Gran unemployed married     basic  housing_no  loan_no cellular
## 29982 y_yes Gran unemployed married     basic  housing_no  loan_no cellular
## 30001 y_yes Gran unemployed married     basic  housing_no  loan_no cellular
## 28615 y_yes Gran unemployed married     basic  housing_no loan_yes cellular
##       month day_of_week previous    poutcome clust
## 30384   apr         thu       No nonexistent     3
## 28541   apr         wed       No     failure     3
## 29982   apr         tue       No     failure     3
## 30001   apr         tue       No     failure     3
## 28615   apr         wed       No     failure     3
```

```r
res.hcmc_mca$data.clust[which(rownames(res.hcmc_mca$data.clust)%in%names
                              (res.hcmc_mca$desc.ind$para[[4]])),]
```

```
##           y        age         job marital   education     housing     loan
## 34649 y_yes Jove-Adult  technician  single       basic housing_yes  loan_no
## 25854 y_yes Jove-Adult blue-collar  single high.school housing_yes  loan_no
## 30464 y_yes Jove-Adult  unemployed married high.school  housing_no  loan_no
## 30502 y_yes Jove-Adult  unemployed married high.school housing_yes  loan_no
## 33387 y_yes Jove-Adult      admin.  single       basic  housing_no loan_yes
##        contact month day_of_week previous poutcome clust
## 34649 cellular   may         thu      Yes  success     4
```

```
## 25854 cellular   nov         wed      Yes  success     4
## 30464 cellular   may         mon      Yes  success     4
## 30502 cellular   may         mon      Yes  success     4
## 33387 cellular   may         tue      Yes  success     4
```

```
res.hcmc_mca$data.clust[which(rownames(res.hcmc_mca$data.clust)%in%names
                              (res.hcmc_mca$desc.ind$dist[[4]])),]
```

```
##           y        age         job marital           education     housing
## 30239 y_yes      Adult  technician married professional.course housing_yes
## 28677 y_yes Jove-Adult blue-collar married               basic  housing_no
## 30208 y_yes Jove-Adult  technician  single professional.course housing_yes
## 30154 y_yes Jove-Adult    services married         high.school housing_yes
## 30236 y_yes      Adult  technician married professional.course housing_yes
##           loan  contact month day_of_week previous poutcome clust
## 30239  loan_no cellular   apr         thu      Yes  success     4
## 28677  loan_no cellular   apr         thu      Yes  success     4
## 30208  loan_no cellular   apr         thu      Yes  success     4
## 30154  loan_no cellular   apr         thu      Yes  success     4
## 30236 loan_yes cellular   apr         thu      Yes  success     4
```

En les taules anteriors hem pogut veure els valors de les variables que tenen els individus més propers i llunyans de cada cluster. D'això podem treure unes quantes conclusions:

- Els individus més propers, tenen valors de les variables corresponents amb les categories vistes a la descripció de clusters, per tant, té sentit que siguin els individus més propers al centroide.
- Els individus més llunyans, tenen valors de les variables contraris amb les categories vistes a la descripció de clusters, per tant, té sentit que siguin els individus més llunyans al centroide.