Course Practical Assignment - 2nd Deliverable (21 d'abril del 2019)

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Bank client data

Description of input variables:

1. age (numeric)
2. job : type of job (categorical: 'admin', 'blue-collar', 'entrepreneur', 'housemaid', 'management', 'retired', 'self-employed', 'services', 'student', 'technician', 'unemployed', 'unknown')
3. marital : marital status (categorical: 'divorced','married','single','unknown'; note: 'divorced' means divorced or widowed)
4. education (categorical:'basic.4y', 'basic.6y', 'basic.9y', 'high.school', 'illiterate', 'professional.course', 'university.degree', 'unknown')
5. default: has credit in default? (categorical: 'no','yes','unknown')
6. housing: has housing loan? (categorical: 'no','yes','unknown')
7. loan: has personal loan? (categorical: 'no','yes','unknown')# related with the last contact of the current campaign:
8. contact: contact communication type (categorical:'cellular','telephone')
9. month: last contact month of year (categorical: 'jan', 'feb', 'mar',..., 'nov', 'dec')
10. day_of_week: last contact day of the week (categorical:'mon','tue','wed','thu','fri')
11. duration: last contact duration, in seconds (numeric). Important note: this attribute highly affects the output target (e.g., if duration=0 then y='no'). Yet, the duration is not known before a call is performed. Also, after the end of the call y is obviously known. Thus, this input should only be included for benchmark purposes and should be discarded if the intention is to have a realistic predictive model.
12. campaign: number of contacts performed during this campaign and for this client (numeric, includes last contact)
13. pdays: number of days that passed by after the client was last contacted from a previous campaign (numeric; 999 means client was not previously contacted)
14. previous: number of contacts performed before this campaign and for this client (numeric)
15. poutcome: outcome of the previous marketing campaign (categorical: 'failure','nonexistent','success')# social and economic context attributes
16. emp.var.rate: employment variation rate - quarterly indicator (numeric)
17. cons.price.idx: consumer price index - monthly indicator (numeric)
18. cons.conf.idx: consumer confidence index - monthly indicator (numeric)
19. euribor3m: euribor 3 month rate - daily indicator (numeric)
20. nr.employed: number of employees - quarterly indicator (numeric)
21. y - has the client subscribed a term deposit? (binary: 'yes','no')

Loading packages:

Load data from Deliverable 1:

```
#dirwd<-"D:/Users/Usuari/Documents/ADEIpractica"
dirwd<-"D:/Documents/GitHub/ADEI"
setwd(dirwd)

load( paste0(dirwd, "/bank-additional/Bank5000_validated.RData") )
summary(df)
```

```
##       age                       job                    marital
##  Min.   :18.00   job-admin.     :1246   marital-divorced: 554
##  1st Qu.:32.00   job-blue-collar:1171   marital-married :3055
##  Median :38.00   job-technician : 796   marital-single  :1377
##  Mean   :40.07   job-services   : 498
##  3rd Qu.:47.00   job-management : 411
##  Max.   :87.00   job-retired    : 205
##                  (Other)        : 659
##                          education               default
##  education-basic.4y           : 533   default-no     :3954
##  education-basic.6y           : 289   default-unknown:1032
##  education-basic.9y           : 767
##  education-high.school        :1218
##  education-professional.course: 615
##  education-university.degree  :1564
##
##         housing           loan                    contact
##  housing-no :2261   loan-no :4217   contact-cellular :3122
##  housing-yes:2725   loan-yes: 769   contact-telephone:1864
##
##
##
##
##
##        month                day_of_week      duration
##  month-may:1741   day_of_week-1mon:1016   Min.   :   5.0
##  month-jul: 829   day_of_week-2tue:1043   1st Qu.: 101.0
##  month-aug: 697   day_of_week-3wed: 971   Median : 177.0
##  month-jun: 652   day_of_week-4thu:1034   Mean   : 250.6
##  month-nov: 507   day_of_week-5fri: 922   3rd Qu.: 316.0
##  month-apr: 310                           Max.   :1580.0
##  (Other)  : 250
##     campaign          pdays          previous
##  Min.   : 1.000   Min.   : 0.00   Min.   :0.0000
##  1st Qu.: 1.000   1st Qu.:19.00   1st Qu.:0.0000
##  Median : 2.000   Median :19.00   Median :0.0000
##  Mean   : 2.535   Mean   :18.53   Mean   :0.1598
##  3rd Qu.: 3.000   3rd Qu.:19.00   3rd Qu.:0.0000
##  Max.   :25.000   Max.   :19.00   Max.   :4.0000
##
##                  poutcome     emp.var.rate      cons.price.idx
##  poutcome-failure    : 477   Min.   :-3.40000   Min.   :92.20
##  poutcome-nonexistent:4353   1st Qu.:-1.80000   1st Qu.:93.08
##  poutcome-success    : 156   Median : 1.10000   Median :93.75
##                              Mean   : 0.06446   Mean   :93.57
##                              3rd Qu.: 1.40000   3rd Qu.:93.99
##                              Max.   : 1.40000   Max.   :94.77
##
##  cons.conf.idx      euribor3m      nr.employed       y
##  Min.   :-50.80   Min.   :0.635   Min.   :4964   y-no :4429
##  1st Qu.:-42.70   1st Qu.:1.334   1st Qu.:5099   y-yes: 557
##  Median :-41.80   Median :4.857   Median :5191
##  Mean   :-40.43   Mean   :3.614   Mean   :5166
##  3rd Qu.:-36.40   3rd Qu.:4.961   3rd Qu.:5228
```

```
##  Max.   :-26.90   Max.   :5.000   Max.   :5228
##
##   num_missings     num_outliers       num_errors
##  Min.   :0.0000   Min.   :0.00000   Min.   :0
##  1st Qu.:0.0000   1st Qu.:0.00000   1st Qu.:0
##  Median :0.0000   Median :0.00000   Median :0
##  Mean   :0.1111   Mean   :0.00361   Mean   :0
##  3rd Qu.:0.0000   3rd Qu.:0.00000   3rd Qu.:0
##  Max.   :3.0000   Max.   :2.00000   Max.   :0
##
##                 f.season       minutes                   f.age
##  season-spring      :2117   Min.   : 0.08333   f.age-[18,32]:1352
##  season-summer      :2178   1st Qu.: 1.68333   f.age-(32,38]:1205
##  season-autumnwinter: 691   Median : 2.95000   f.age-(38,47]:1220
##                             Mean   : 4.17703   f.age-(47,87]:1209
##                             3rd Qu.: 5.26667
##                             Max.   :26.33333
##
##                      f.duration               f.campaign
##  f.duration-[5,101]       :1252   f.campaign-[0,2] :3392
##  f.duration-(101,177]     :1243   f.campaign-(2,5] :1181
##  f.duration-(177,316]     :1247   f.campaign-(5,25]: 413
##  f.duration-(316,1.58e+03]:1244
##
##
##
##             f.pdays                 f.previous
##  f.pdays-sometime: 177   f.previous-never:4353
##  f.pdays-never   :4809   f.previous-some : 633
##
##
##
##
##
##                  f.emp.var.rate                      f.cons.price.idx
##  f.emp.var.rate-[-Inf,0]:2086   f.cons.price.idx-[92.2,93.1]:1409
##  f.emp.var.rate-(0, Inf]:2900   f.cons.price.idx-(93.1,93.7]:1086
##                                 f.cons.price.idx-(93.7,94]  :1819
##                                 f.cons.price.idx-(94,94.8]  : 672
##
##
##
##                       f.cons.conf.idx                   f.euribor3m
##  f.cons.conf.idx-[-50.8,-42.7]:1856   f.euribor3m-[0.635,1.33]:1254
##  f.cons.conf.idx-(-42.7,-41.8]: 967   f.euribor3m-(1.33,4.86] :1466
##  f.cons.conf.idx-(-41.8,-36.4]:1231   f.euribor3m-(4.86,4.96] :1130
##  f.cons.conf.idx-(-36.4,-26.9]: 932   f.euribor3m-(4.96,5]    :1136
##
##
##
##                            f.nr.employed
##  f.nr.employed-[4.96e+03,5.1e+03] :1639
##  f.nr.employed-(5.1e+03,5.19e+03] :1003
##  f.nr.employed-(5.19e+03,5.23e+03]:2344
```

```
##
##
##
##
```

CORRESPONDENCE ANALYSIS (CA)

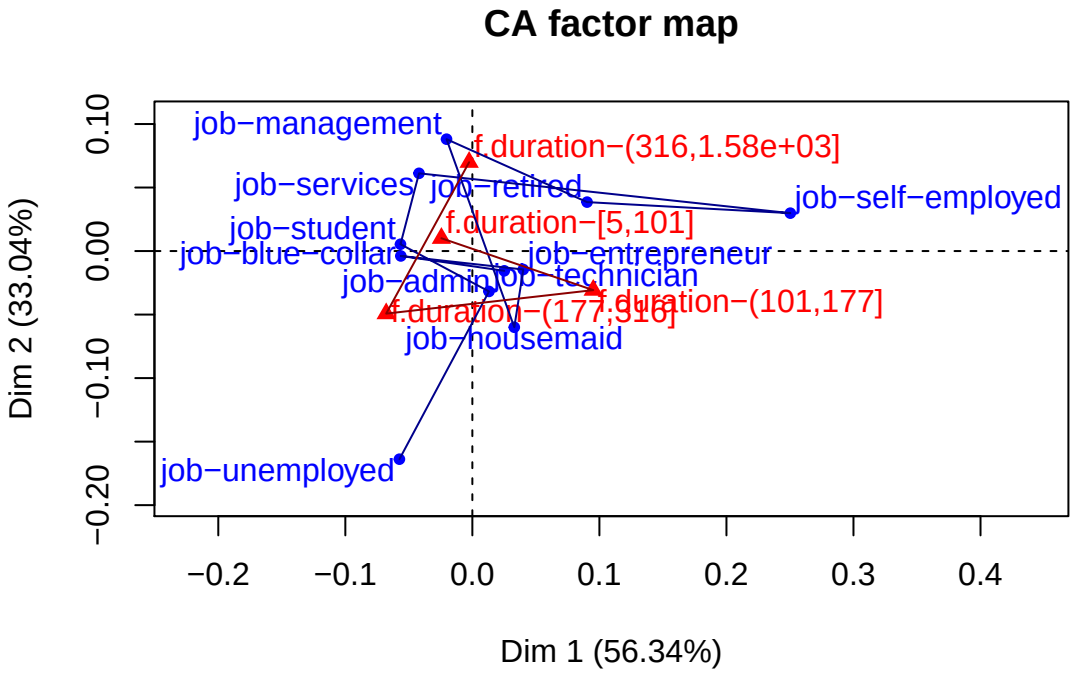
Realitzarem un analisi amb taules de correspondencia i mapes de factors entre la variable numerica target duracio discretitzada en 4 nivells (corregit de l'entrega 1) i diversos factors que hem trobat que tenen una correspondencia significativa.

Primer veiem com la duracio de la trucada no te cap relacio amb el job de l'individu, ja que no podem rebutjar la hipotesi *H0: f.duration no te cap relacio amb la variable job* amb el valor p obtingut en el Chi Square test. Com mes aprop surten al grafic les categories d'ambdues variables analitzades, mes relacionades estan. En aquesta comparacio, com s'acaba de comentar, no es pot extreure res significatiu, mes enlla que potser les categories job-unemployed i job-self-employed van mes per lliure.

```
# H0: f.duration no te cap relacio amb variable job
chisq.test( table( df$job, df$f.duration) )
```

```
##
##  Pearson's Chi-squared test
##
## data:  table(df$job, df$f.duration)
## X-squared = 31.496, df = 30, p-value = 0.3913
```

```
# CA - f.duration vs variable job
res.ca<-CA( table( df$job, df$f.duration ) )
lines(res.ca$row$coord[,1], res.ca$row$coord[,2], col="darkblue")
lines(res.ca$col$coord[,1], res.ca$col$coord[,2], col="darkred")
```



Ara testejarem la mateixa hipotesi i mostrarem el mateix mapa de factors pero amb altres categories factor que si que obtindrem que tenen una relacio significativa. El primer cas es l'epoca de l'any **f.season** en la qual es realitza la trucada (p valor = 2.506e-07). Comparant el profile de la taula de contingencia de proporcions per fila amb el profile marginal de la duracio veiem com hi ha un 28,5% de trucades amb duracions molt curtes a l'estiu respecte un 25% de trucades amb duracions curtes en tot l'any. D'altra banda, hi ha per sobre d'un 27% de trucades amb duracions llargues a la primavera, respecte un 25% de trucades en la mateixa duracio en tot l'any. Si comparem el profile de la taula de contingencia de proporcions per columna amb el profile marginal de la f.season veiem com el 42.5% de trucades es realitzen a la primavera, i en canvi mes d'un 46% de trucades corresponen a la primavera i a duracions llargues. A mes, el 43.7% de trucades es realitzen a l'estiu, i nomes prop d'un 40% de trucades corresponen a l'estiu i a duracions llargues. Aquesta mateixa informacio es pot veure representada en un mapa de factors de dues dimensions. Agafant nomes la primera dimensio ja seria suficient per a representar un 98.9% de la variancia del conjunt de les dades (Kaiser: take as many dimensions as eigenvalue > mean of eigenvalues).

```
chisq.test( table( df$f.season, df$f.duration) )
```

```
##
##  Pearson's Chi-squared test
##
## data:  table(df$f.season, df$f.duration)
## X-squared = 41.318, df = 6, p-value = 2.506e-07
```

```
#Row/Column profile
prop.table( table(df$f.season, df$f.duration), 1 ) #1->per files
```

```
##
##                       f.duration-[5,101] f.duration-(101,177]
##   season-spring               0.2106755            0.2442135
##   season-summer               0.2855831            0.2534435
##   season-autumnwinter         0.2662808            0.2518090
##
##                       f.duration-(177,316] f.duration-(316,1.58e+03]
##   season-spring                  0.2735002                 0.2716108
##   season-summer                  0.2277319                 0.2332415
##   season-autumnwinter            0.2489146                 0.2329957
```

```
#Marginal Row/Column profile
prop.table( table(df$f.duration)) #1->per files
```

```
##
##       f.duration-[5,101]      f.duration-(101,177]
##                0.2511031                 0.2492980
##     f.duration-(177,316] f.duration-(316,1.58e+03]
##                0.2501003                 0.2494986
```

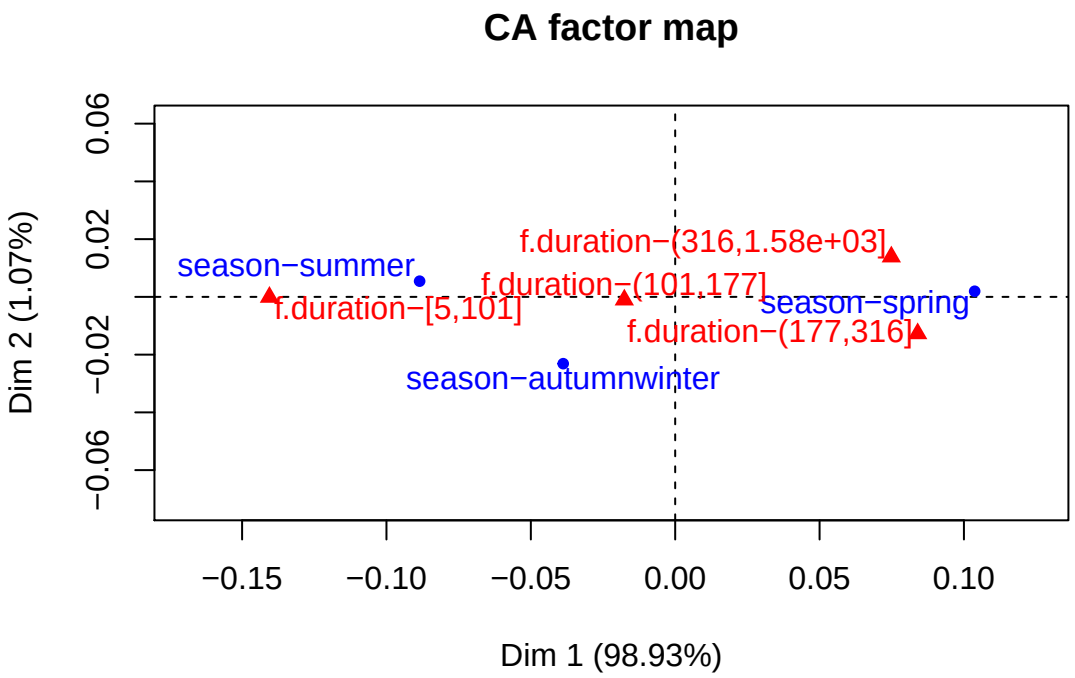
```
prop.table( table(df$f.season, df$f.duration), 2 ) #2->per columnes
```

```
##
##                       f.duration-[5,101] f.duration-(101,177]
##   season-spring               0.3562300            0.4159292
##   season-summer               0.4968051            0.4440869
##   season-autumnwinter         0.1469649            0.1399839
##
##                       f.duration-(177,316] f.duration-(316,1.58e+03]
##   season-spring                  0.4643144                 0.4622186
##   season-summer                  0.3977546                 0.4083601
##   season-autumnwinter            0.1379310                 0.1294212
```

```r
prop.table( table(df$f.season)) #2->per columnes
```

```
##
##       season-spring       season-summer season-autumnwinter
##           0.4245888           0.4368231           0.1385880
```

```r
res.ca<-CA( table( df$f.season, df$f.duration) )
```




```r
attributes(res.ca); res.ca$eig #valors eig no normalitzats!
```

```
## $names
## [1] "eig"  "call" "row"  "col"  "svd"
##
## $class
## [1] "CA"   "list"
```

```
##         eigenvalue percentage of variance
## dim 1 8.198140e-03              98.929073
## dim 2 8.874655e-05               1.070927
##       cumulative percentage of variance
## dim 1                          98.92907
## dim 2                         100.00000
```

```r
mean(res.ca$eig[,1]) #Kaiser: take as many dimensions as eigenvalue > mean of eigenvalues
```

```
## [1] 0.004143443
```

```r
#En una taula de correspondencies simples podem tenir maxim tantes
#dimensions com categories d'una variable menys 1!
#f.season te 3 categories -> -1 -> 2 dimensions!!

#La inercia total ens indica com de relacionades estan les dues variables,
```

```
#com mes proxim el valor a 0, menys relacionades estan!
sum(res.ca$eig[,1])
```

```
## [1] 0.008286887
```

```
#Coordenades:
#res.ca$row #files son la f.season!
#res.ca$col #columnes son la duration!
```

El segon cas en el qual obtenim una relacio significativa (p valor = 1.203e-07) es el valor de l'euribor **f.euribor3m**, el qual es un indicador trimestral. Comparant el profile de la taula de contingencia de proporcions per fila amb el profile marginal de la duracio veiem com hi ha un 30.8% de trucades amb duracions molt curtes quan l'euribor te un valor alt, respecte un 25% de trucades amb duracions sense tenir en compte la fluctuacio de l'indicador. De la mateixa manera, quan el valor de l'euribor es baix, hi ha major % de trucades que acaben amb duracions relativament altes. Si comparem el profile de la taula de contingencia de proporcions per columna amb el profile marginal de f.euribor3m veiem com el 22.8% de trucades es realitzen amb un euribor molt alt, i en canvi un 28.0% de trucades corresponen a un euribor alt i a duracions molt curtes. A mes, mirant el mapa de factors podem veure aquesta mateixa informacio de manera grafica. Si ens centrem en la 1a dimensio del grafic (que representa un 89% de la variancia del conjunt de les dades), podem observar com hi ha una tendencia similar en ambdues variables (tot i que les duracions extremadament llargues trenquen una molt bona correlacio del 1r eix). Tambe veiem com les categories f.euribor3m-(4.96,5] i f.duration-[5,101] estan molt relacionades ja que es troben molt proximes en el mapa de factors; aixi com tambe les categories f.euribor3m-[0.635,1.33] i f.duration-(177,316]. (Kaiser: take as many dimensions as eigenvalue > mean of eigenvalues, el que equival a agafar 1 sola dimensio).

```
chisq.test( table( df$f.euribor3m, df$f.duration) )
```

```
##
##  Pearson's Chi-squared test
##
## data:  table(df$f.euribor3m, df$f.duration)
## X-squared = 49.745, df = 9, p-value = 1.203e-07
```

```
#Row/Column profile
prop.table( table(df$f.euribor3m, df$f.duration), 1 ) #1->per files
```

```
##
##                            f.duration-[5,101] f.duration-(101,177]
##   f.euribor3m-[0.635,1.33]          0.2129187            0.2432217
##   f.euribor3m-(1.33,4.86]           0.2312415            0.2530696
##   f.euribor3m-(4.86,4.96]           0.2619469            0.2345133
##   f.euribor3m-(4.96,5]              0.3080986            0.2658451
##
##                            f.duration-(177,316] f.duration-(316,1.58e+03]
##   f.euribor3m-[0.635,1.33]            0.2775120                 0.2663477
##   f.euribor3m-(1.33,4.86]             0.2694407                 0.2462483
##   f.euribor3m-(4.86,4.96]             0.2353982                 0.2681416
##   f.euribor3m-(4.96,5]                0.2095070                 0.2165493
```

```
#Marginal Row/Column profile
prop.table( table(df$f.duration)) #1->per files
```

```
##
##        f.duration-[5,101]      f.duration-(101,177]
##                 0.2511031                 0.2492980
##      f.duration-(177,316] f.duration-(316,1.58e+03]
##                 0.2501003                 0.2494986
```

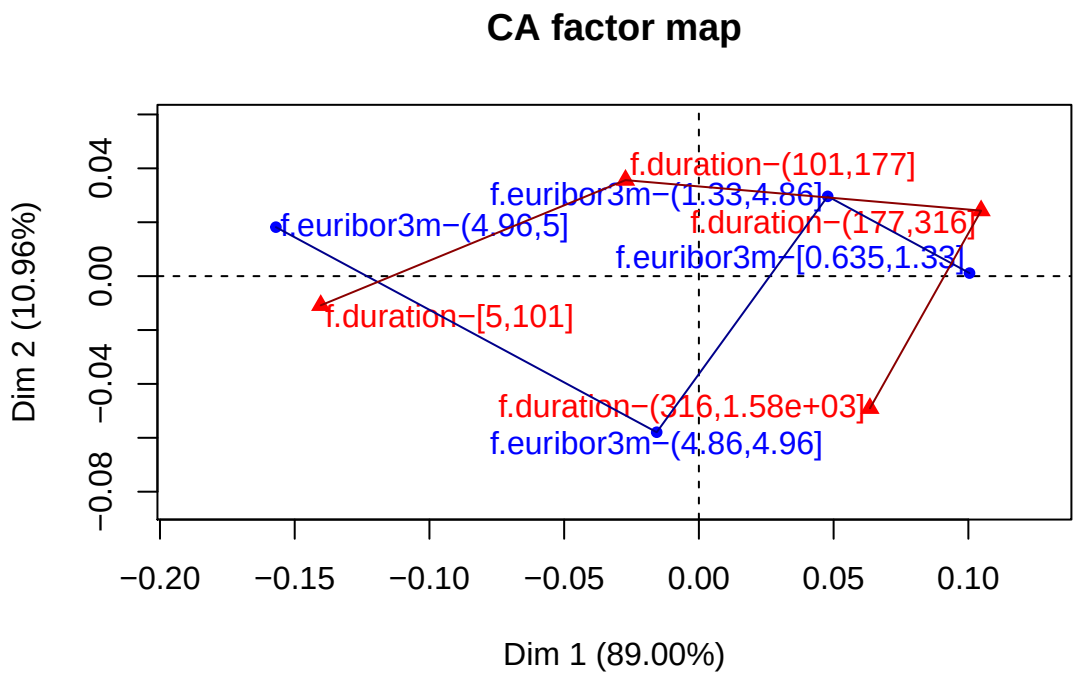
```r
prop.table( table(df$f.euribor3m, df$f.duration), 2 ) #2->per columnes
```

```
##
##                             f.duration-[5,101] f.duration-(101,177]
##   f.euribor3m-[0.635,1.33]          0.2132588            0.2453741
##   f.euribor3m-(1.33,4.86]           0.2707668            0.2984714
##   f.euribor3m-(4.86,4.96]           0.2364217            0.2131939
##   f.euribor3m-(4.96,5]              0.2795527            0.2429606
##
##                             f.duration-(177,316] f.duration-(316,1.58e+03]
##   f.euribor3m-[0.635,1.33]            0.2790698                 0.2684887
##   f.euribor3m-(1.33,4.86]             0.3167602                 0.2901929
##   f.euribor3m-(4.86,4.96]             0.2133119                 0.2435691
##   f.euribor3m-(4.96,5]                0.1908581                 0.1977492
```

```r
prop.table( table(df$f.euribor3m)) #2->per columnes
```

```
##
## f.euribor3m-[0.635,1.33]  f.euribor3m-(1.33,4.86]  f.euribor3m-(4.86,4.96]
##                0.2515042                0.2940233                0.2266346
##     f.euribor3m-(4.96,5]
##                0.2278379
```

```r
res.ca<-CA( table( df$f.euribor3m, df$f.duration) )
lines(res.ca$row$coord[,1], res.ca$row$coord[,2], col="darkblue")
lines(res.ca$col$coord[,1], res.ca$col$coord[,2], col="darkred")
```




```r
attributes(res.ca); res.ca$eig #valors eig no normalitzats!
```

```
## $names
## [1] "eig"  "call" "row"  "col"  "svd"
```

```
##
## $class
## [1] "CA"   "list"
```

```
##         eigenvalue percentage of variance
## dim 1 8.879478e-03            88.99940237
## dim 2 1.093876e-03            10.96396899
## dim 3 3.654443e-06             0.03662864
##       cumulative percentage of variance
## dim 1                          88.99940
## dim 2                          99.96337
## dim 3                         100.00000
```

```
mean(res.ca$eig[,1]) #Kaiser: take as many dimensions as eigenvalue > mean of eigenvalues
```

```
## [1] 0.00332567
```

```
#En una taula de correspondencies simples podem tenir maxim tantes
#dimensions com categories d'una variable menys 1!
#f.euribor3m te 4 categories -> -1 -> 3 dimensions!!

#La inercia total ens indica com de relacionades estan les dues variables,
#com mes proxim el valor a 0, menys relacionades estan!
sum(res.ca$eig[,1])
```

```
## [1] 0.009977009
```

```
#A vegades va be eliminar algunes categories amb pocs individus d'una variable
#per a poder veure millor les possibles relacions!
```

PRINCIPAL COMPONENT ANALYSIS (PCA)

Primerament realitzem un PCA sobre les variables continues de la nostra mostra de dades, on la variables "duration" ha de ser suplementaria, ja que es tracta de la variable target!

Eigenvalues and dominant axes

El summary ens permet veure els 9 diferents eigenvalues obtinguts amb aquest PCA, amb les seves dades corresponents de percentatges de variancia del conjunt de les dades que respresenten. Segons el criteri de Kaiser, que diu que s'han de descartar les dimensions amb valors eig normalitzats per sota d'1, hauriem d'agafar les 3 primeres dimensions per a una bona representacio del conjunt de dades. Essent flexibles amb el criteri de Kaiser, podriem agafar tambe la quarta dimensio, la qual te una variancia del 0.9656, amb un valor molt proxim a 1. La incorporacio d'aquesta nova dimensio ens donaria una variancia acumulada del 81%, obtenint d'aquesta manera una variancia acumulada per sobre el 80%. Per ultim, si ens basem en la regla del colze (llegurament subjectiva), i l'apliquem sobre el grafic dels eigenvalues i %variancies obtingut amb les llibreries *ggplot*, hauriem d'agafar les 3 primeres dimensions.

```
vars_con<-names(df)[c(1, 11:14, 16:20)]; vars_con #variables continues
```

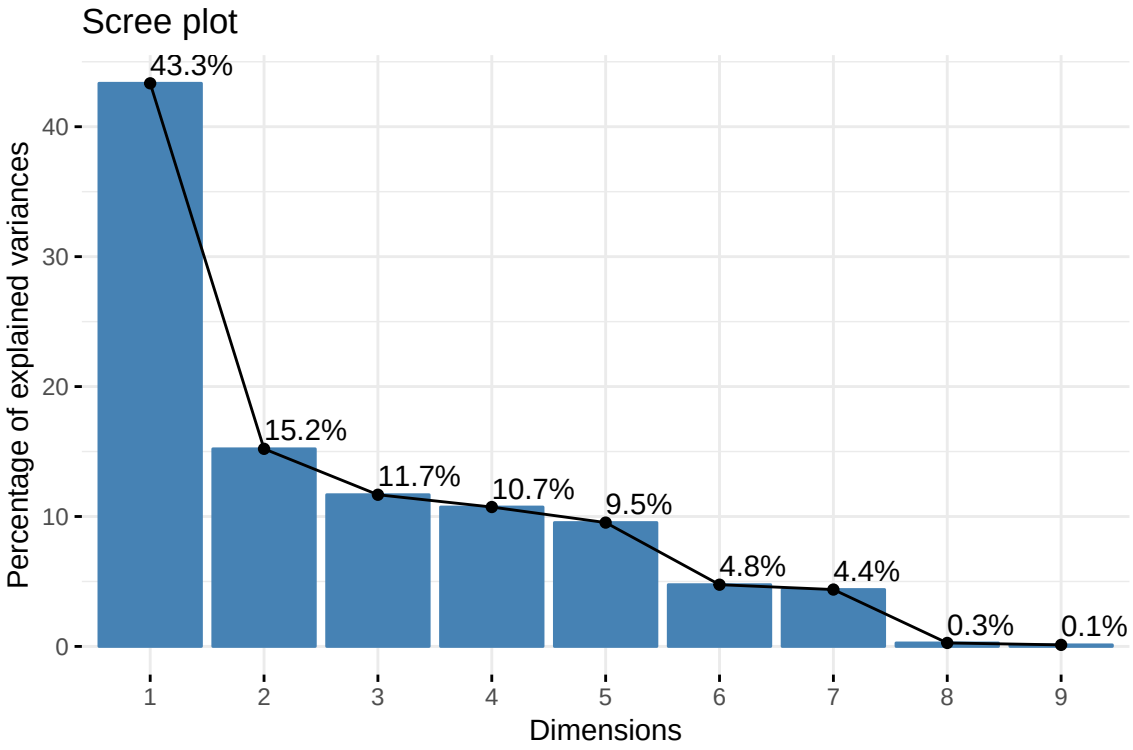
```
##  [1] "age"            "duration"       "campaign"       "pdays"
##  [5] "previous"       "emp.var.rate"   "cons.price.idx" "cons.conf.idx"
##  [9] "euribor3m"      "nr.employed"
```

```
vars_dis<-names(df)[c(2:10, 15, 21, 25, 27:36)] #variables discretes

# PCA:
res.pca<-PCA( df[, vars_con], quanti.sup=2, graph=FALSE) #"duration" com a suplementaria
```

```r
#nb.dec: number of decimal printed
#ncp: number of dimensions printed
summary(res.pca, nb.dec=2, ncp=5, nbind=0)
```

```
##
## Call:
## PCA(X = df[, vars_con], quanti.sup = 2, graph = FALSE)
##
##
## Eigenvalues
##                        Dim.1  Dim.2  Dim.3  Dim.4  Dim.5  Dim.6  Dim.7
## Variance               3.90   1.37   1.05   0.97   0.86   0.43   0.39
## % of var.             43.34  15.21  11.67  10.73   9.53   4.75   4.38
## Cumulative % of var.  43.34  58.55  70.22  80.95  90.48  95.24  99.61
##                        Dim.8  Dim.9
## Variance               0.02   0.01
## % of var.              0.27   0.12
## Cumulative % of var.  99.88 100.00
##
## Variables
##                   Dim.1   ctr  cos2   Dim.2   ctr  cos2   Dim.3   ctr  cos2
## age             | -0.02  0.01  0.00 |  0.35  8.73  0.12 |  0.67 42.16  0.44
## campaign        |  0.20  1.03  0.04 |  0.01  0.01  0.00 | -0.35 11.85  0.12
## pdays           |  0.43  4.84  0.19 | -0.71 37.11  0.51 |  0.32  9.77  0.10
## previous        | -0.59  9.05  0.35 |  0.55 21.75  0.30 | -0.32  9.71  0.10
## emp.var.rate    |  0.97 23.96  0.93 |  0.17  2.19  0.03 | -0.09  0.75  0.01
## cons.price.idx  |  0.75 14.49  0.57 |  0.25  4.49  0.06 | -0.25  5.88  0.06
## cons.conf.idx   |  0.16  0.68  0.03 |  0.56 23.16  0.32 |  0.46 19.73  0.21
## euribor3m       |  0.97 23.91  0.93 |  0.19  2.54  0.03 | -0.01  0.01  0.00
## nr.employed     |  0.93 22.02  0.86 |  0.01  0.02  0.00 | -0.04  0.14  0.00
##                   Dim.4   ctr  cos2   Dim.5   ctr  cos2
## age             |  0.39 15.54  0.15 |  0.53 33.33  0.29 |
## campaign        |  0.89 81.66  0.79 | -0.22  5.44  0.05 |
## pdays           |  0.08  0.68  0.01 | -0.05  0.31  0.00 |
## previous        | -0.05  0.29  0.00 |  0.14  2.42  0.02 |
## emp.var.rate    | -0.06  0.43  0.00 |  0.07  0.54  0.00 |
## cons.price.idx  | -0.07  0.52  0.00 |  0.26  7.62  0.07 |
## cons.conf.idx   | -0.03  0.09  0.00 | -0.66 50.14  0.43 |
## euribor3m       | -0.07  0.54  0.01 | -0.02  0.05  0.00 |
## nr.employed     | -0.05  0.25  0.00 |  0.04  0.15  0.00 |
##
## Supplementary continuous variable
##                   Dim.1  cos2   Dim.2  cos2   Dim.3  cos2   Dim.4  cos2
## duration        | -0.03  0.00 |  0.00  0.00 |  0.00  0.00 | -0.07  0.00 |
##                 Dim.5  cos2
## duration         0.04  0.00 |
```

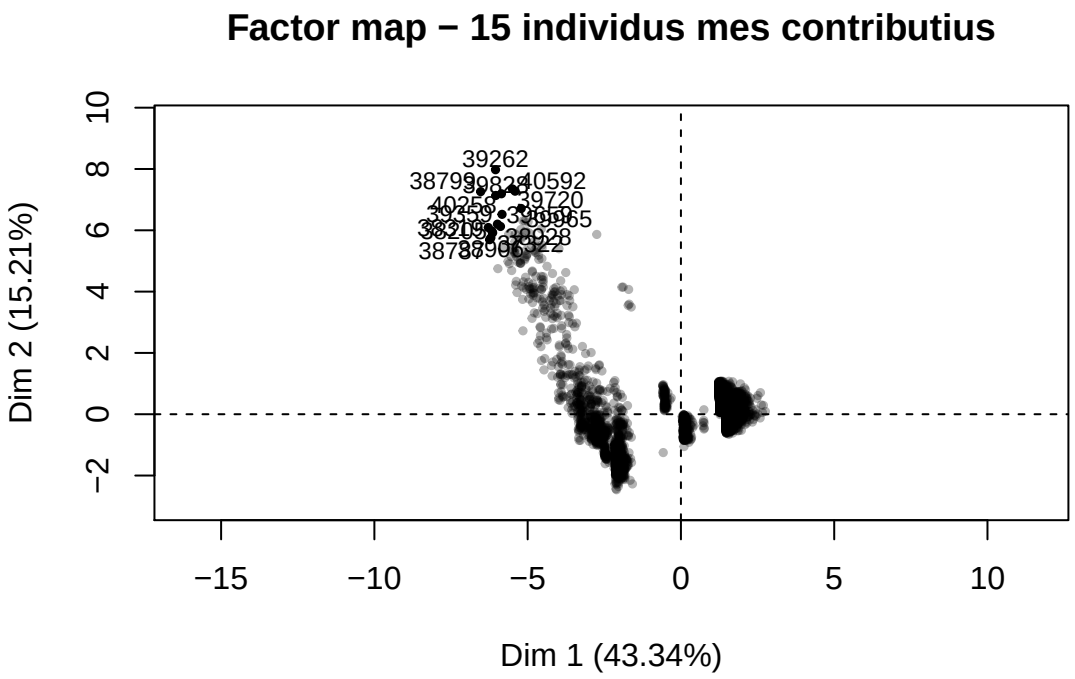
```r
#GGPLOT: Use modern ggplot facilities per la regla de l'ultim colze:
#at some point the marginal gain will drop, giving an angle in the graph
fviz_eig(res.pca, addlabels=TRUE)
```



Individuals point of view

Pintem primer el mapa de factors dels individus de les dues primeres dimensions (70% de la variancia del conjunt de dades) i etiquetem amb el numero d'individu els 15 mes contributius. A continuacio mostrem per a cadascun dels dos primers eixos, les coordenades i el registre complet d'aquests 3 individus mes contributius. Es fa exactament el mateix amb els individus mes ben representats (cos2) en les dues primeres dimensions.

```
#nomes pinta les etiquetes dels 15 individus mes contributius!
plot(res.pca, choix="ind", cex=0.75, col.ind="black", select="contrib 15", title="Factor map - 15 indivi
```




```
#2 individus mes contributius al 1r eix:
contrib<-sort(res.pca$ind$contrib[,1], decreasing=TRUE)[1:2]; contrib
```

```
##     38799     38319
## 0.2194923 0.2029850
```

```
df[c(names(contrib)), ]
```

```
##       age             job         marital                   education
## 38799  62   job-housemaid marital-married education-university.degree
## 38319  37 job-blue-collar marital-married          education-basic.6y
##          default     housing    loan          contact     month
## 38799 default-no housing-yes loan-no contact-cellular month-nov
## 38319 default-no  housing-no loan-no contact-cellular month-oct
##            day_of_week duration campaign pdays previous         poutcome
## 38799 day_of_week-4thu      237        1     3        3 poutcome-success
## 38319 day_of_week-4thu      128        2     6        3 poutcome-failure
##       emp.var.rate cons.price.idx cons.conf.idx euribor3m nr.employed
## 38799         -3.4         92.649         -30.1     0.714      5017.5
## 38319         -3.4         92.431         -26.9     0.740      5017.5
##           y num_missings num_outliers num_errors            f.season
## 38799  y-no            0            0          0 season-autumnwinter
## 38319 y-yes            0            0          0 season-autumnwinter
##        minutes         f.age           f.duration       f.campaign
## 38799 3.950000 f.age-(47,87] f.duration-(177,316] f.campaign-[0,2]
## 38319 2.133333 f.age-(32,38] f.duration-(101,177] f.campaign-[0,2]
##                f.pdays      f.previous          f.emp.var.rate
## 38799 f.pdays-sometime f.previous-some f.emp.var.rate-[-Inf,0]
## 38319 f.pdays-sometime f.previous-some f.emp.var.rate-[-Inf,0]
##                   f.cons.price.idx               f.cons.conf.idx
```

```
## 38799 f.cons.price.idx-[92.2,93.1] f.cons.conf.idx-(-36.4,-26.9]
## 38319 f.cons.price.idx-[92.2,93.1] f.cons.conf.idx-(-36.4,-26.9]
##                    f.euribor3m                    f.nr.employed
## 38799 f.euribor3m-[0.635,1.33] f.nr.employed-[4.96e+03,5.1e+03]
## 38319 f.euribor3m-[0.635,1.33] f.nr.employed-[4.96e+03,5.1e+03]
```

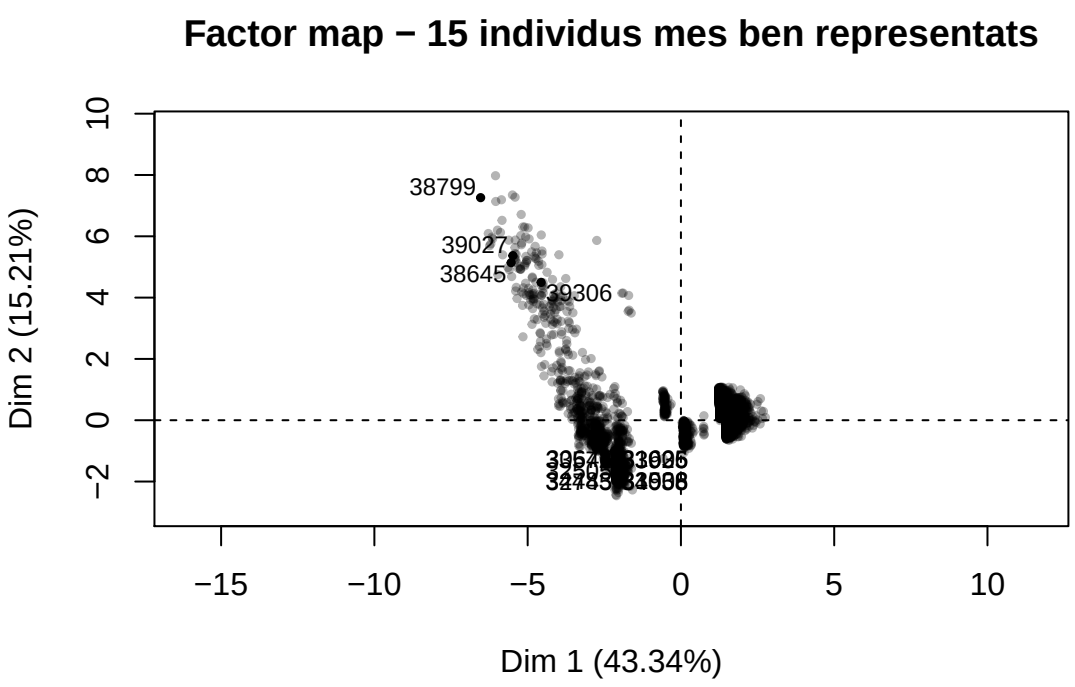
```
#2 individus mes contributius al 2n eix:
contrib<-sort(res.pca$ind$contrib[,2], decreasing=TRUE)[1:2]; contrib
```

```
##     39262     39720
## 0.9322541 0.7912329
```

```
df[c(names(contrib)), ]
```

```
##       age         job         marital          education    default
## 39262  80 job-retired marital-married education-basic.4y default-no
## 39720  80 job-retired marital-married education-basic.4y default-no
##         housing    loan          contact     month      day_of_week
## 39262 housing-no loan-no contact-cellular month-mar day_of_week-5fri
## 39720 housing-no loan-no contact-cellular month-may day_of_week-1mon
##       duration campaign pdays previous         poutcome emp.var.rate
## 39262      213        3     6        4 poutcome-success         -1.8
## 39720      382        1     3        3 poutcome-success         -1.8
##       cons.price.idx cons.conf.idx euribor3m nr.employed     y
## 39262         93.369         -34.8     0.649      5008.7 y-yes
## 39720         93.876         -40.0     0.697      5008.7 y-yes
##       num_missings num_outliers num_errors      f.season  minutes
## 39262            0            0          0 season-spring 3.550000
## 39720            0            0          0 season-spring 6.366667
##                f.age                f.duration       f.campaign
## 39262 f.age-(47,87]      f.duration-(177,316] f.campaign-(2,5]
## 39720 f.age-(47,87] f.duration-(316,1.58e+03] f.campaign-[0,2]
##                 f.pdays      f.previous          f.emp.var.rate
## 39262 f.pdays-sometime f.previous-some f.emp.var.rate-[-Inf,0]
## 39720 f.pdays-sometime f.previous-some f.emp.var.rate-[-Inf,0]
##                   f.cons.price.idx               f.cons.conf.idx
## 39262 f.cons.price.idx-(93.1,93.7] f.cons.conf.idx-(-36.4,-26.9]
## 39720   f.cons.price.idx-(93.7,94] f.cons.conf.idx-(-41.8,-36.4]
##                    f.euribor3m                    f.nr.employed
## 39262 f.euribor3m-[0.635,1.33] f.nr.employed-[4.96e+03,5.1e+03]
## 39720 f.euribor3m-[0.635,1.33] f.nr.employed-[4.96e+03,5.1e+03]
```

```
#nomes pinta les etiquetes dels 15 individus mes ben representats!
plot(res.pca, choix="ind", cex=0.75, col.ind="black", select="cos2 15", title="Factor map - 15 individus
```




```
#2 individus mes ben representats al 1r eix:
repr<-sort(res.pca$ind$cos2[,1], decreasing=TRUE)[1:2]; repr
```

```
##     18385     13817
## 0.8444095 0.8442091
```

```
#df[c(names(repr)), ]
#2 individus mes ben representats al 2n eix:
repr<-sort(res.pca$ind$cos2[,2], decreasing=TRUE)[1:2]; repr
```

```
##     39431     39350
## 0.5706147 0.5679583
```

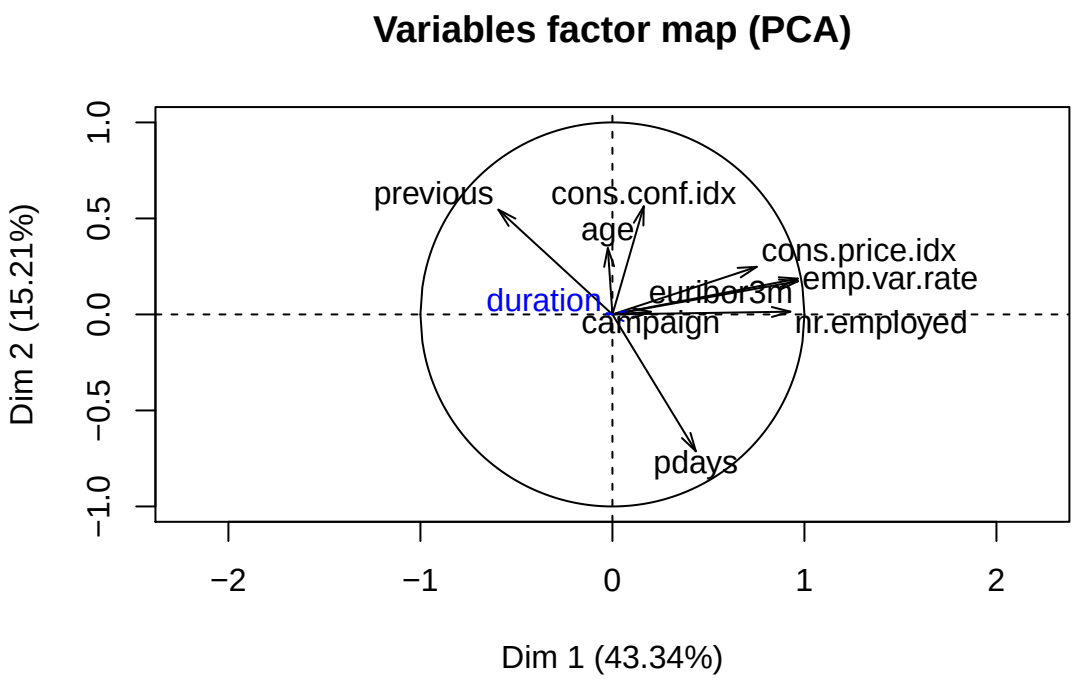
```
#df[c(names(repr)), ]
```

Interpretation of the PCA

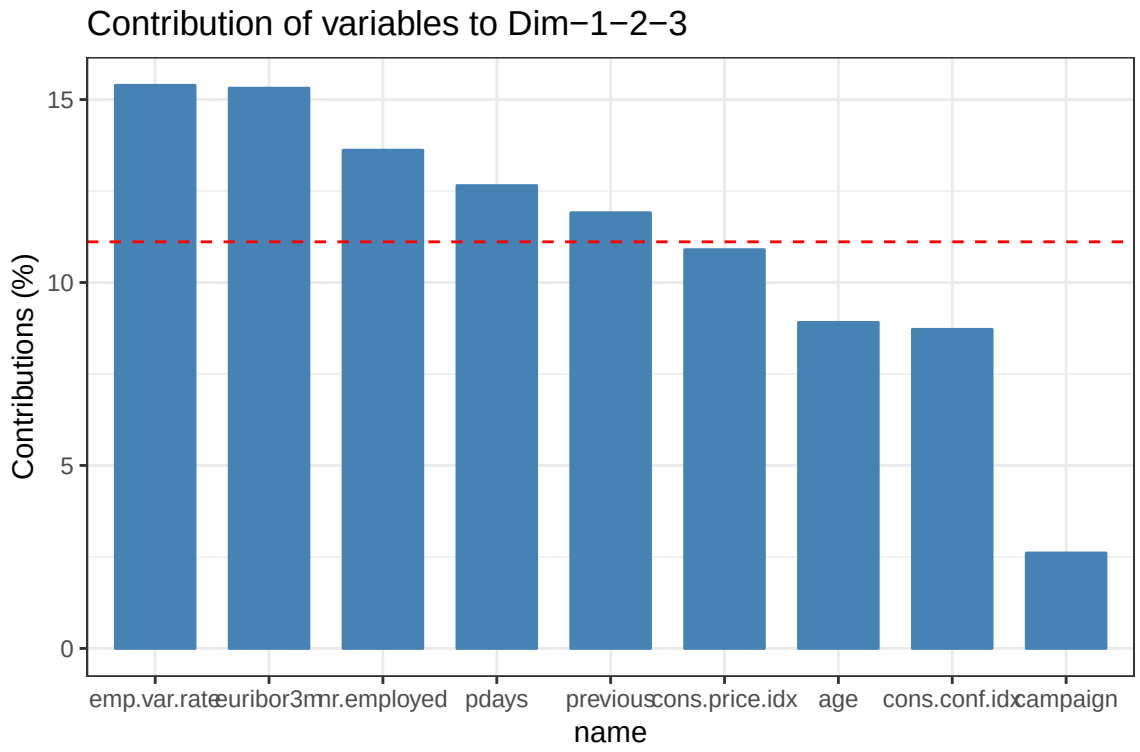
En el mapa de factors de les variables (2D, primeres dues dimensions) es pot observar en blau la variable "duration" com a suplementaria, la qual surt quasi centrada, el que vol dir que les variables vars_con utilitzades en el PCA no ens ajuden a dir res o predir el valors de la variable target. La variable previous (numero de contactes en campanyes antigues) esta relacionada inversament amb pdays (dies que feia que no es trucava el client per altres campanyes), ja que que com es pot veure en el grafic, ambdues fletxes apunten oposadament. Sembla ser tambe que tots els indicadors socioeconomics (a excepcio una mica de cons.conf.idx) apunten en la mateixa direccio, el que vol dir que estan relacionats entre ells i contribueixen d'una manera similar als eixos. Es pot veure el % de contribucio de les variables a les tres primeres dimensions mitjancant una eina de la llibreria *ggplot*, on es veu com basicament els indicadors socioeconomics i les variables "previous", "campaign" i "age" son les variables numeriques que mes han contribuit. El summary ens permet veure tambe de forma numerica la contribucio (ctr) de cadascuna de les variables en els 4 primers eixos, aixi com la qualitat de la representacio (cos2) de les mateixes en cadascun dels eixos. Si be s'acaben de descriure les variables mes contributives, les que estan millor representades (cos2 mes proxim a 1) en el primer eix son euribor3m, emp.var.rate i nr.employed; i en el segon eix son pdays, previous i cons.conf.idx. Un l'ultim mapa

de factors de variables observem els eixos de les dimensions 3 i 4, les quals representen aproximadament un 11% de la variancia de les dades cadascuna.

```
# PCA:
plot.PCA(res.pca, choix = c("var") ) #variables factor map
```




```
#GGPLOT contribution of variables
#fviz_pca_var(res.pca)
fviz_contrib(res.pca, choice="var", axes=1:3)+theme_bw()
```

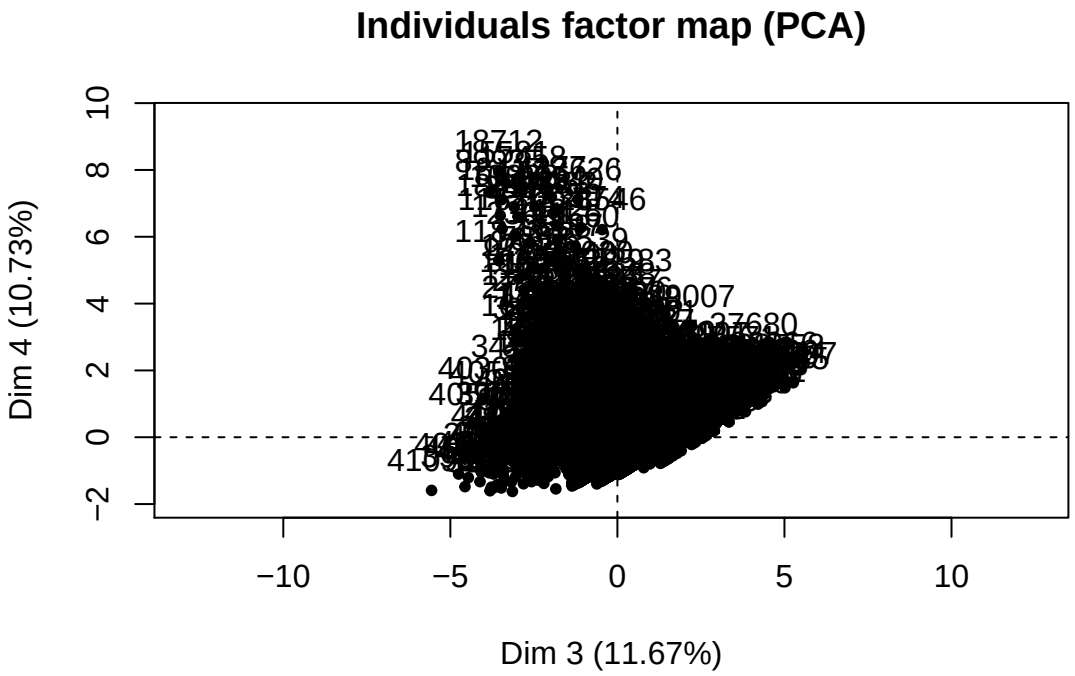


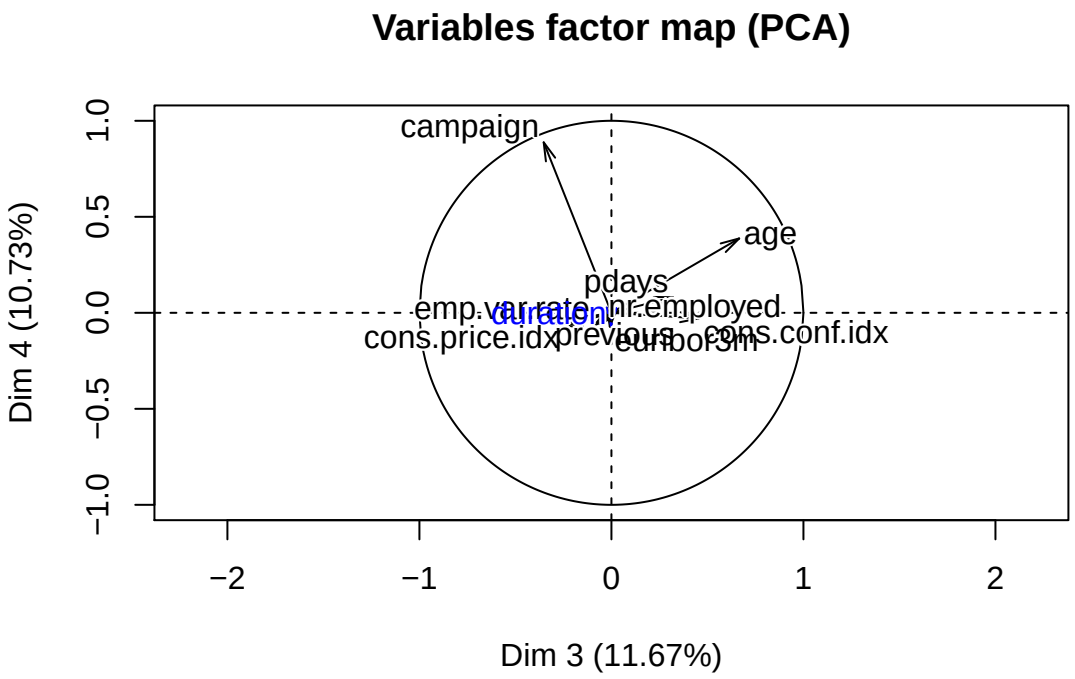

```
summary(res.pca, nb.dec=2, ncp=2, nbind=0)
```

```
##
## Call:
## PCA(X = df[, vars_con], quanti.sup = 2, graph = FALSE)
##
##
## Eigenvalues
##                        Dim.1  Dim.2  Dim.3  Dim.4  Dim.5  Dim.6  Dim.7
## Variance                3.90   1.37   1.05   0.97   0.86   0.43   0.39
## % of var.              43.34  15.21  11.67  10.73   9.53   4.75   4.38
## Cumulative % of var.   43.34  58.55  70.22  80.95  90.48  95.24  99.61
##                        Dim.8  Dim.9
## Variance                0.02   0.01
## % of var.               0.27   0.12
## Cumulative % of var.   99.88 100.00
##
## Variables
##                   Dim.1   ctr  cos2   Dim.2   ctr  cos2
## age             | -0.02  0.01  0.00 |  0.35  8.73  0.12 |
## campaign        |  0.20  1.03  0.04 |  0.01  0.01  0.00 |
## pdays           |  0.43  4.84  0.19 | -0.71 37.11  0.51 |
## previous        | -0.59  9.05  0.35 |  0.55 21.75  0.30 |
## emp.var.rate    |  0.97 23.96  0.93 |  0.17  2.19  0.03 |
## cons.price.idx  |  0.75 14.49  0.57 |  0.25  4.49  0.06 |
## cons.conf.idx   |  0.16  0.68  0.03 |  0.56 23.16  0.32 |
## euribor3m       |  0.97 23.91  0.93 |  0.19  2.54  0.03 |
## nr.employed     |  0.93 22.02  0.86 |  0.01  0.02  0.00 |
##
```

```
## Supplementary continuous variable
##                   Dim.1  cos2   Dim.2  cos2
## duration        | -0.03  0.00 |  0.00  0.00 |
```

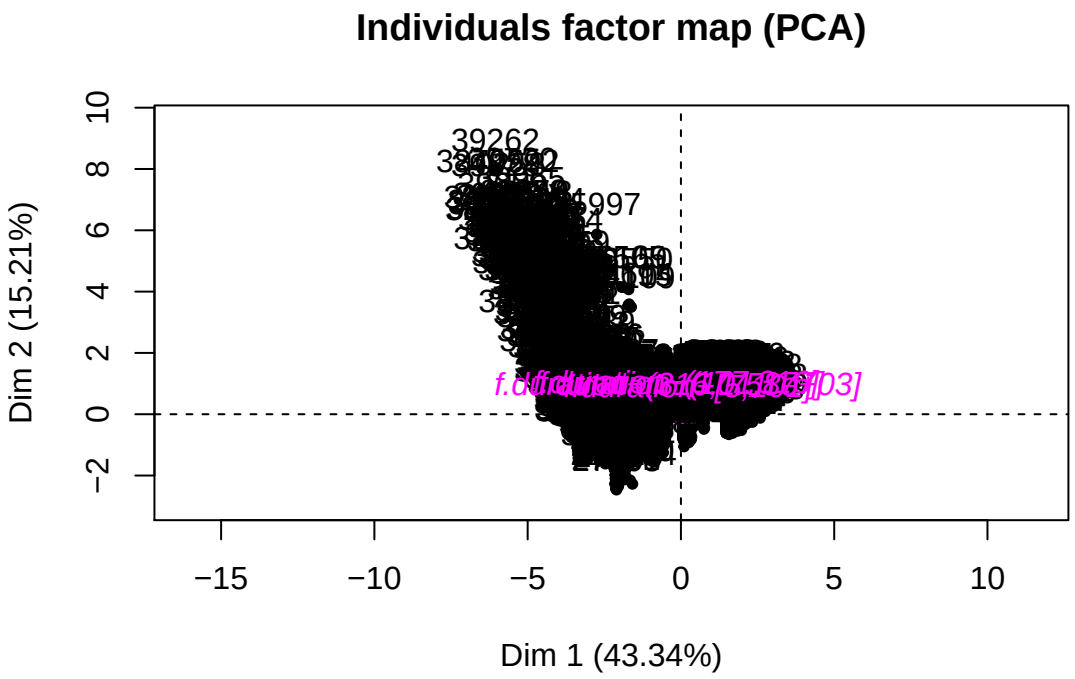
```
#veure eixos 3 i 4:
res.pca<-PCA(df[, vars_con], quanti.sup=2, axes=3:4)
```



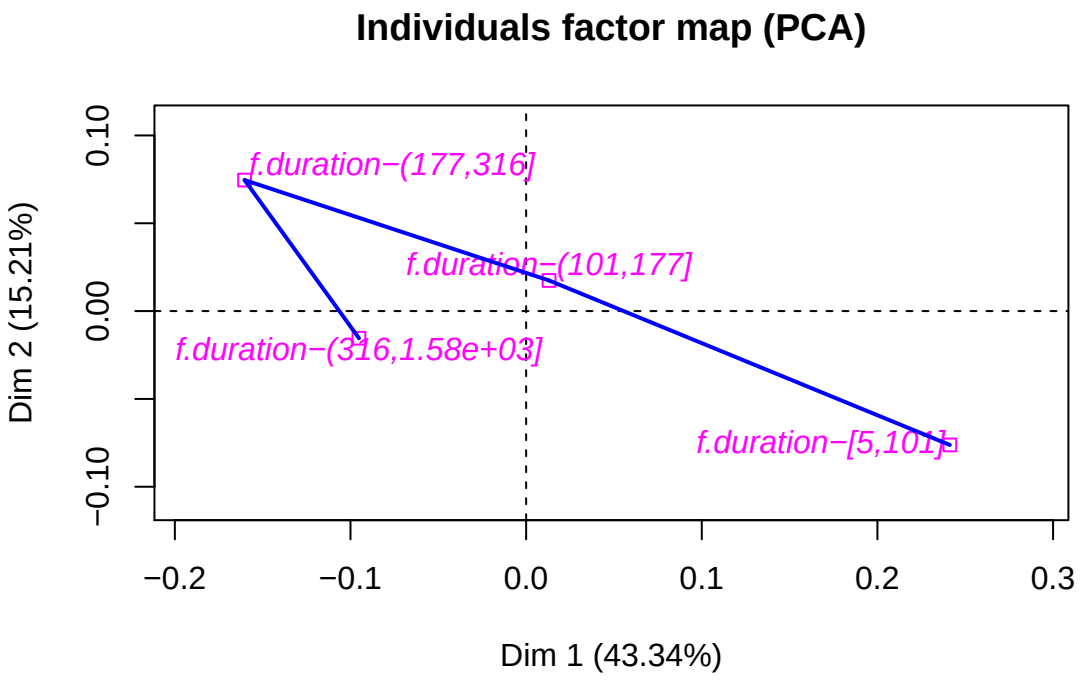


Com que es dificil extreure conclusions a partir nomes de les variables numeriques, en el grafics seguents es pot observar el posicionament de les dues variables suplementaries “f.duration” i “f.euribor3m” en el mapa de factors dels individus. En el cas de f.duration, si es mira al mapa de factors ampliat on nomes es representa aquesta variable, sembla ser que te una tendencia a creixer cap al 2n i 3r quadrant composat per les dues primeres dimensions. En el cas de f.euribor3m, de la mateixa manera, tambe es pot trobar un progressio de les dades al llarg del primer eix, ja que el valor de l’euribor3m augmenta amb el valor de la primera dimensio de les dades.

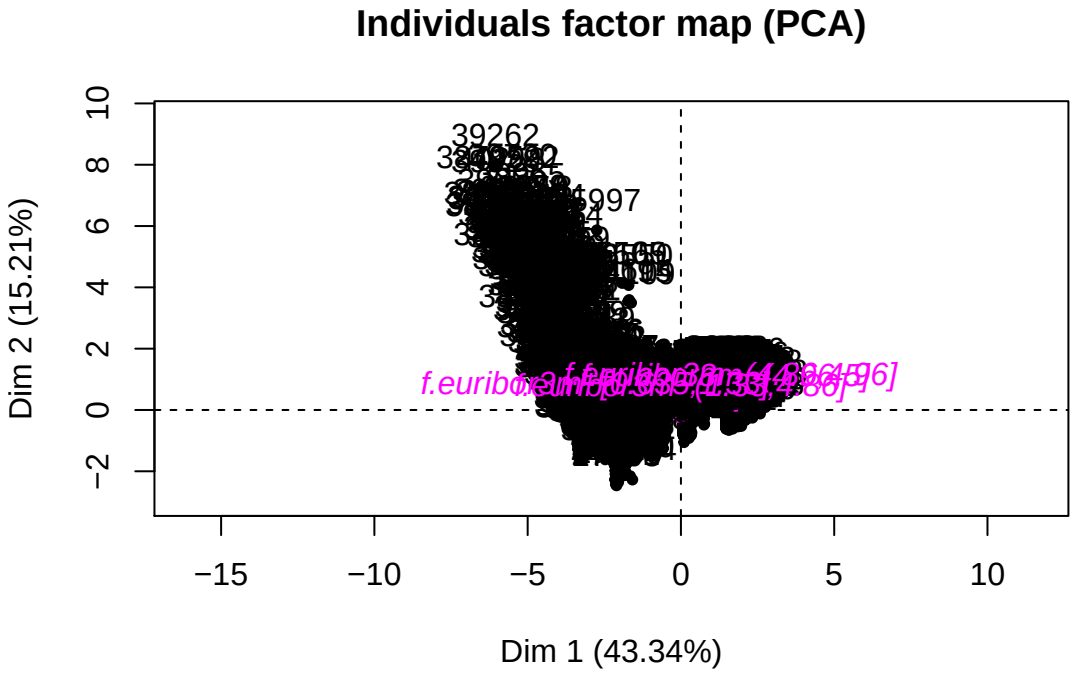
```
par(mfrow=c(1,1))

#ara afegim dues variables suplementaries!
res.pca<-PCA( df[, c("f.duration", vars_con) ], quanti.sup=3, quali.sup=1, graph = FALSE )
plot.PCA(res.pca, choix = c("ind") )
```




```
#Unir punts de variables suplementaries en el factor map per a una bona representacio:
plot.PCA(res.pca, choix="ind", invisible="ind")
lines(res.pca$quali.sup$coord[1:2, 1:2], col="blue", lwd="2")
lines(res.pca$quali.sup$coord[2:3, 1:2], col="blue", lwd="2")
lines(res.pca$quali.sup$coord[3:4, 1:2], col="blue", lwd="2")
```

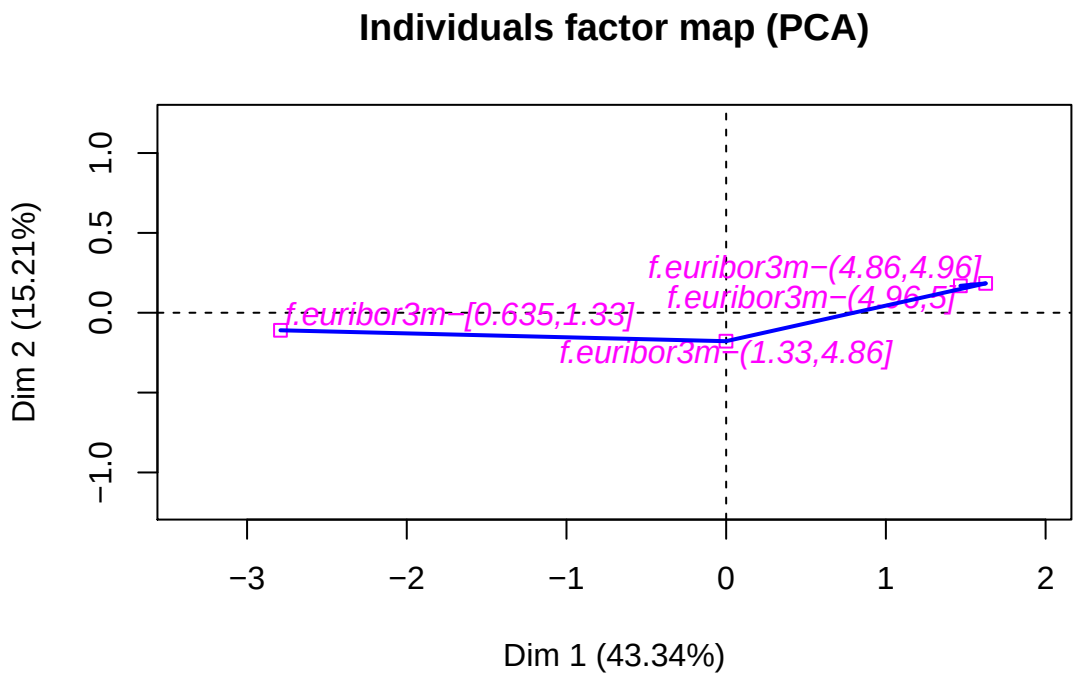



```
res.pca<-PCA( df[, c("f.euribor3m", vars_con) ], quanti.sup=3, quali.sup=1, graph = FALSE )
plot.PCA(res.pca, choix = c("ind") )
```




```
plot.PCA(res.pca, choix="ind", invisible="ind")
lines(res.pca$quali.sup$coord[1:2, 1:2], col="blue", lwd="2")
```

```r
lines(res.pca$quali.sup$coord[2:3, 1:2], col="blue", lwd="2")
lines(res.pca$quali.sup$coord[3:4, 1:2], col="blue", lwd="2")
```



K-Means Classification (Partitioning - Supervised learning)

K-means es un algoritme de clustering que te com a objectiu agrupar les observacions en un determinat nombre de grups o clusters els quals comparteixin caracteristiques similars. Dit d'altra manera, agrupa els individus de manera que els que estan dins un mateix cluster tinguin unes distancies euclidianes entre ells mes petties que respecte els individus d'altres clusters. Cal tenir en compte que com que el parametre passat a la crida *kmeans* es el numero de clusters que s'han d'obtenir (i no el conjunt inicial de centres), es seleccionen aleatoriament un conjunt inicial de k centres de cluster. Aixo vol dir que aquesta seleccio aleatoria pot tenir gran influencia en el resultat final, el qual sera diferent en cada execucio de l'alogritme. Per tal de reduir soroll de les dades innecessari, treballarem nomes amb les 4 primeres dimensions obtingudes del PCA.

L'objecte retornat per la crida *kmeans* ens permet consultar diferents atributs. L'atribut withinss correspon a la suma del quadrat de les distancies inter-cluster, es a dir, hi ha un valor per a cada cluster. L'atribut betweenss es un sol valor mig que correspon a la suma del quadrat de les distancies inter-cluster. A partir d'aquest valor mig i el total de les distancies totss podem obtenir el nivell de representacio que obtenim nomes amb els centres de gravetat dels clusters sobre el conjunt de les dades.

```r
#only 4 significant axes in order to avoid unnecessary noise
dclu<-res.pca$ind$coord[,1:4]

#fixed number of clusters (a random set of rows are chosen as the initial centers)
kcla<-kmeans(dclu, 7)
summary(kcla)
```

```
##              Length Class  Mode
## cluster      4986   -none- numeric
```

```
## centers        28   -none- numeric
## totss           1   -none- numeric
## withinss        7   -none- numeric
## tot.withinss    1   -none- numeric
## betweenss       1   -none- numeric
## size            7   -none- numeric
## iter            1   -none- numeric
## ifault          1   -none- numeric
```

```
table(kcla$cluster)
```

```
##
##    1    2    3    4    5    6    7
##  343 1657  883  281 1403  248  171
```

```
attributes(kcla)
```

```
## $names
## [1] "cluster"      "centers"      "totss"        "withinss"
## [5] "tot.withinss" "betweenss"    "size"         "iter"
## [9] "ifault"
##
## $class
## [1] "kmeans"
```

```
#INTRA-CLUSTER DISTANCES
kcla$withinss
```

```
## [1]  483.3356 1482.1199  939.7402 1047.3004 1181.9092  680.7826  845.8692
```

```
#$withinss: is the within cluster sum of squares.
#So it results in a vector with a number for each cluster.

#INTER-CLUSTER DISTANCES
kcla$betweenss
```

```
## [1] 29665.91
```

```
#$betweenss: is the between clusters sum of squares.
#In fact it is the mean of distances between cluster centers.

# Some equalities may help to understand:
#     $tot.withinss = sum($withinss)
#     $totss = $tot.withinss + $betweenss
kcla$tot.withinss
```

```
## [1] 6661.057
```

```
kcla$totss
```

```
## [1] 36326.97
```

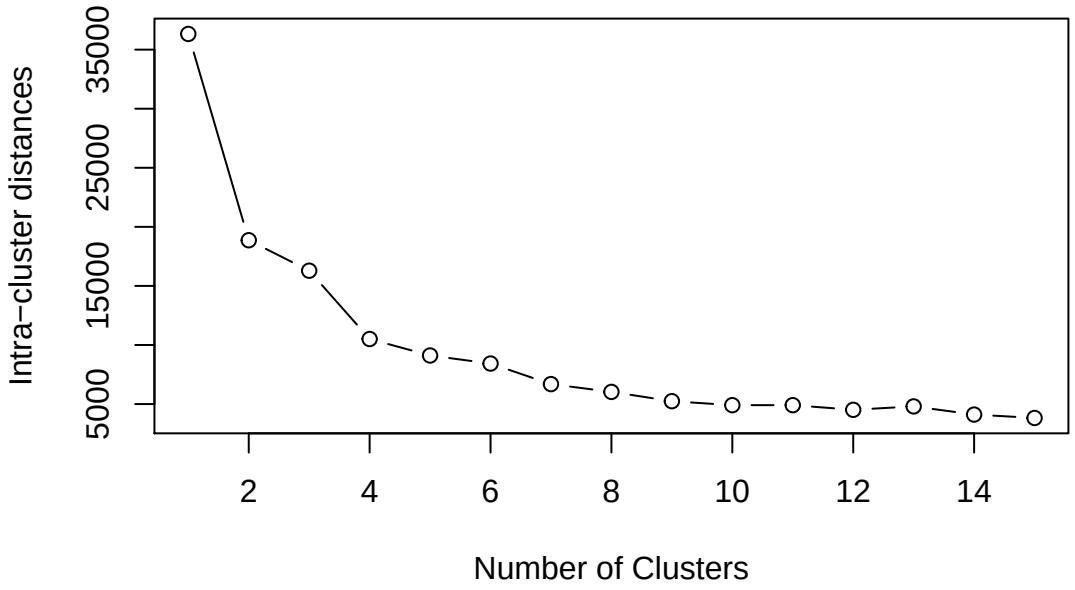
```
kcla$betweenss/kcla$totss
```

```
## [1] 0.816636
```

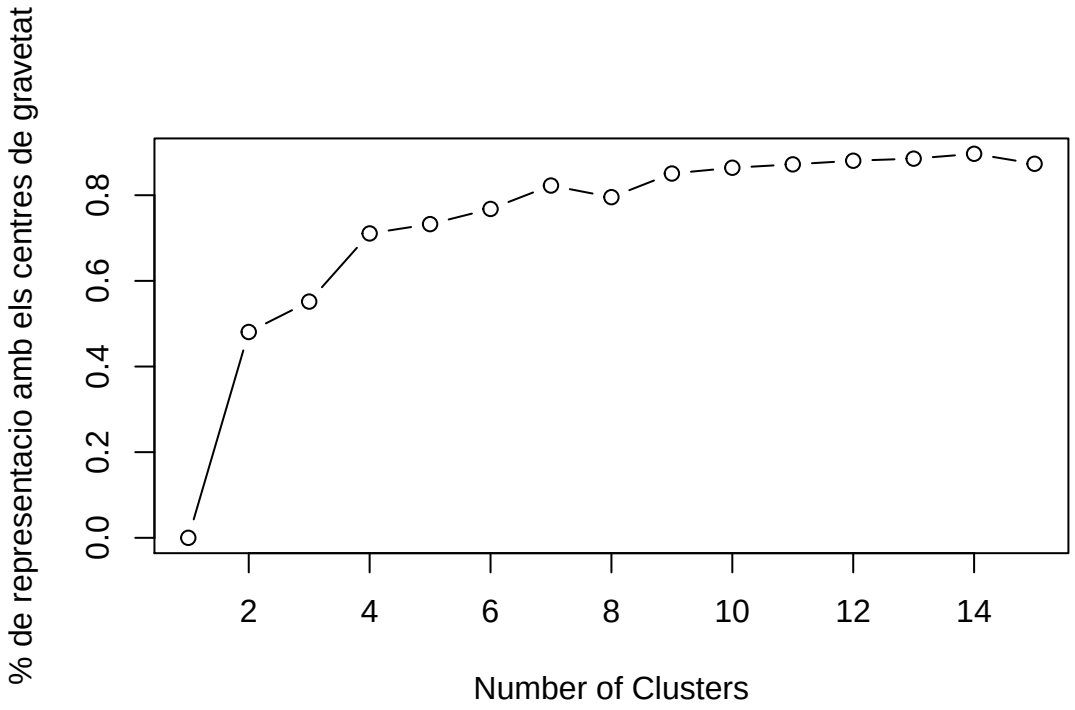
```
#nomes amb els centres de gravetat estariem obtenint una representacio de les dades del X%
```

Si executem k-means per a diferents valors k podem observar com evolucionen les distancies intra-clusters o el % de representacio obtingut en cada cas. L'execucio d'unes quantes vegades del seguent chunk de codi ens ha ajudat en la seleccio del nombre de clusters k=7.

```r
wss <- sum(kmeans(dclu,1)$withinss) #k=1
for (i in 2:15) wss[i] <- sum(kmeans(dclu,i)$withinss) #k=2to15

plot(1:15, wss, type="b", xlab="Number of Clusters", ylab="Intra-cluster distances")
```




```r
km<-kmeans(dclu,1)
repr <- km$betweenss/km$totss #k=1
for (i in 2:15){
  km<-kmeans(dclu,i)
  repr[i] <- km$betweenss/km$totss
}

plot(1:15, repr, type="b", xlab="Number of Clusters", ylab="% de representacio amb els centres de grave
```



Hierarchical Clustering (Unsupervised learning)

Aquest punt compren la realitzacio d'una clusteritzacio aglomerativa jerarquitzada dels individus. HCPC de la llibreria FactoMineR utilitza les distancies de entre clusters diferents, per tal de minimitzar la inercia inter-cluster.

La primera de les comandes HCPC esta comentada ja que requereix l'interacio de l'usuari per a triar per on tallar l'arbre de clusters que es mostra a l'usuari. Despres d'estar interactuant amb diferents opcions de numero de clusters, s'ha decidit finalment agafar nb.clust = 7, tal i com es pot veure a continuacio. Es mostren els grafics corresponents a l'arbre el qual s'ha tallat a l'altura de 7 clusters, aixi com el mapa de factors de les dues primeres dimensions del PCA.

```
#PCA calculat amb 4 significant axes:
vars_con<-names(df)[c(1, 12:14, 16:20)]; vars_con
```

```
## [1] "age"            "campaign"       "pdays"          "previous"
## [5] "emp.var.rate"   "cons.price.idx" "cons.conf.idx"  "euribor3m"
## [9] "nr.employed"
```

```
res.pca<-PCA( df[, c("duration", "y", "loan", "month", "job", "poutcome", "education", "housing", vars_

#res.hcpc<-HCPC(res.pca, order=TRUE)

res.hcpc<-HCPC(res.pca, nb.clust=7, order=TRUE, graph=FALSE); res.hcpc
```

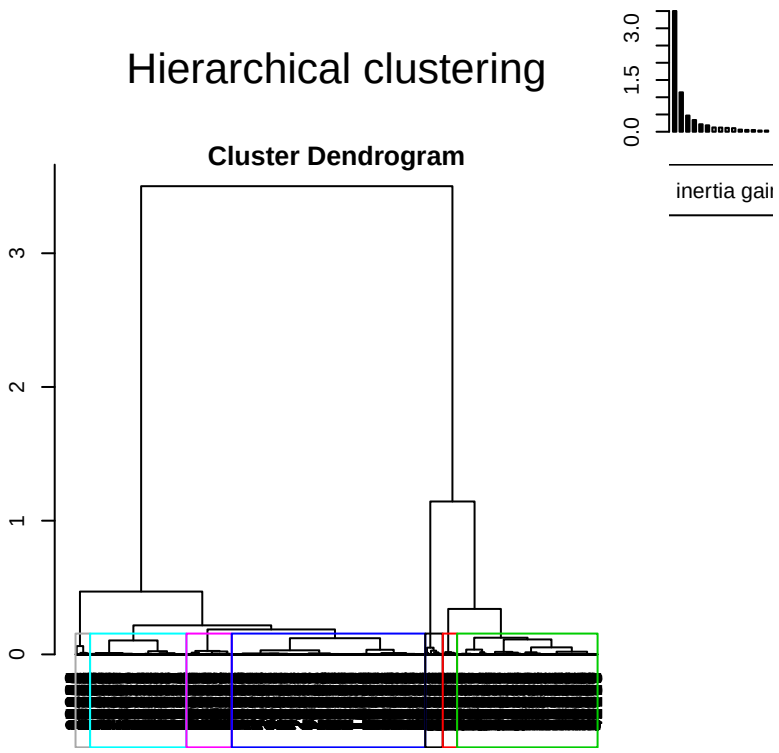
```
## **Results for the Hierarchical Clustering on Principal Components**
##    name
## 1  "$data.clust"
## 2  "$desc.var"
## 3  "$desc.var$quanti.var"
```

```
## 4  "$desc.var$quanti"
## 5  "$desc.var$test.chi2"
## 6  "$desc.axes$category"
## 7  "$desc.axes"
## 8  "$desc.axes$quanti.var"
## 9  "$desc.axes$quanti"
## 10 "$desc.ind"
## 11 "$desc.ind$para"
## 12 "$desc.ind$dist"
## 13 "$call"
## 14 "$call$t"
##    description
## 1  "dataset with the cluster of the individuals"
## 2  "description of the clusters by the variables"
## 3  "description of the cluster var. by the continuous var."
## 4  "description of the clusters by the continuous var."
## 5  "description of the cluster var. by the categorical var."
## 6  "description of the clusters by the categories."
## 7  "description of the clusters by the dimensions"
## 8  "description of the cluster var. by the axes"
## 9  "description of the clusters by the axes"
## 10 "description of the clusters by the individuals"
## 11 "parangons of each clusters"
## 12 "specific individuals"
## 13 "summary statistics"
## 14 "description of the tree"
```

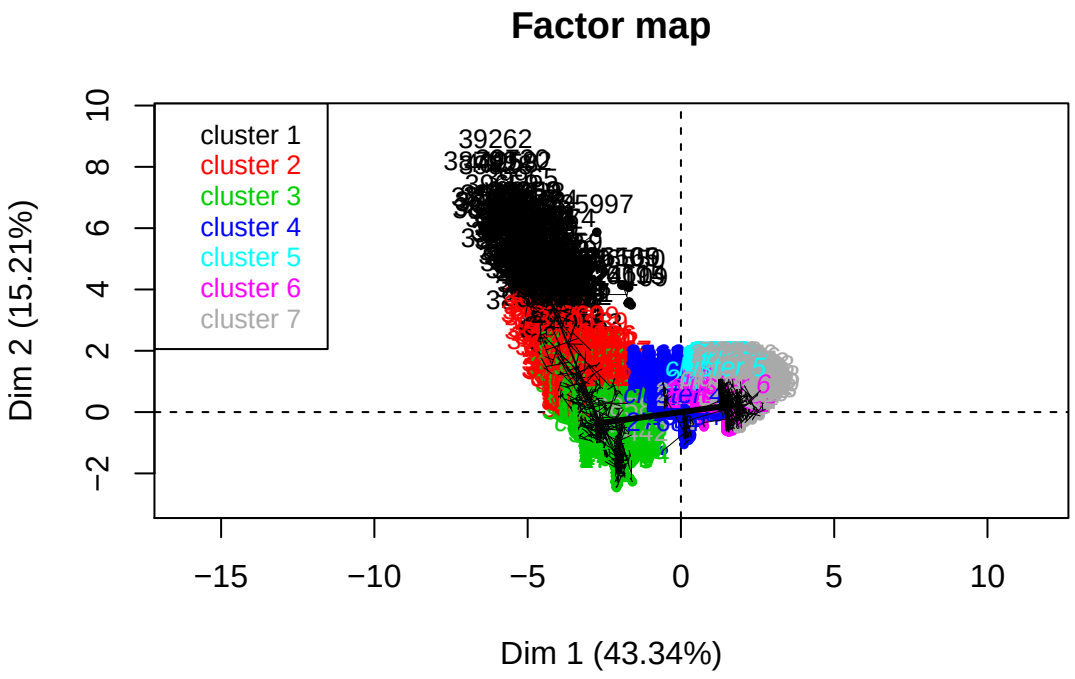
```
attributes(res.hcpc)
```

```
## $names
## [1] "data.clust" "desc.var"   "desc.axes"  "call"       "desc.ind"
##
## $class
## [1] "HCPC"
```

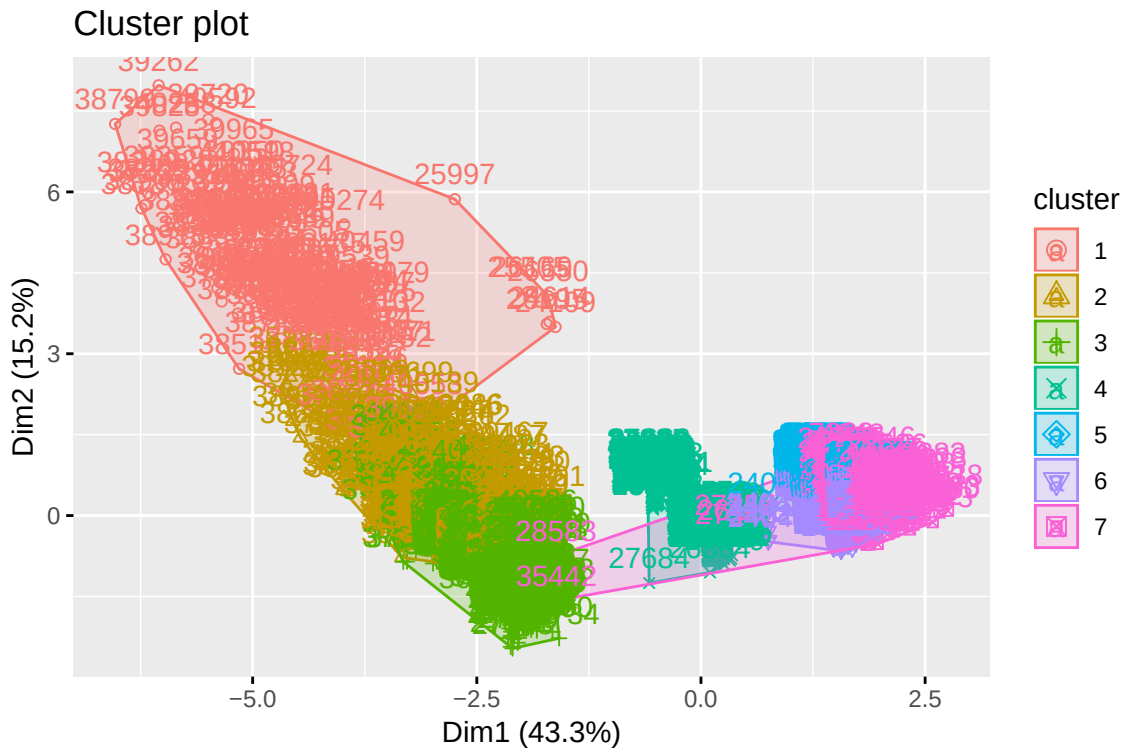
```
plot.HCPC(res.hcpc, choice="tree")
```




```
plot.HCPC(res.hcpc, choice="map")
```

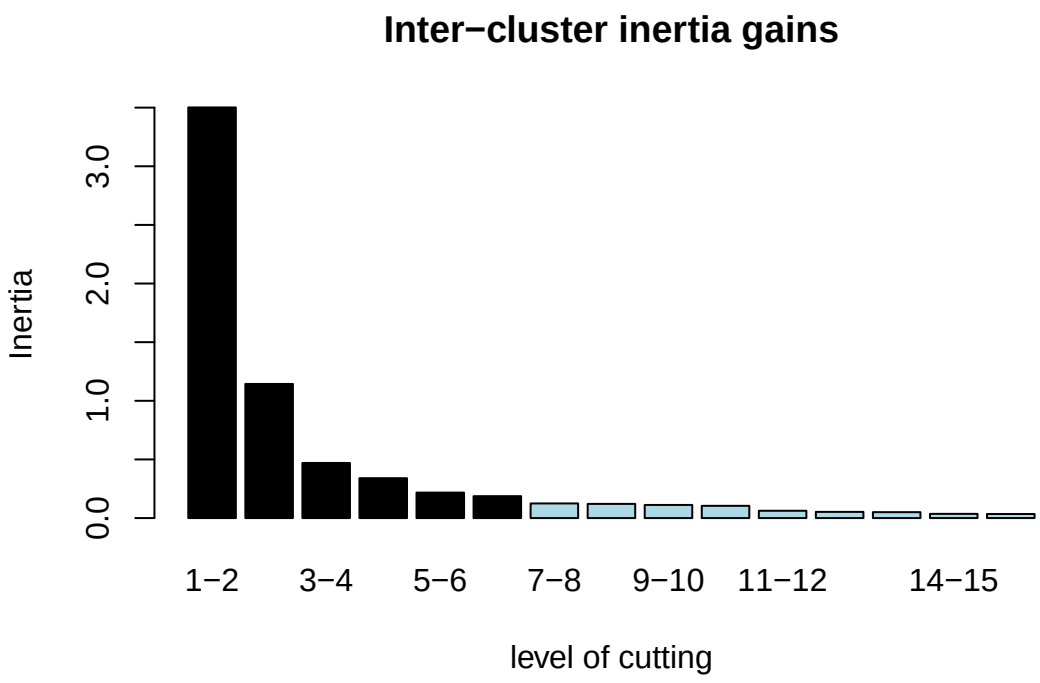



```
fviz_cluster(res.hcpc)
```



El guanys (d'1 a 2 clusters, de 2 a 3, de 3 a 4, etc.) d'inercia es poden observar en negre a la figura inferior, on tambe es pot veure la relacio entre altres nivells de tall i els seus guanys. Els valors *within* ens mostren la inercia dins de cada cluster, que si fos un sol cluster (1) seria la total del conjunt de dades, la qual equival a la suma de tots els guanys d'inercies *inert.gain*. Amb la seleccio de 6 clusters que hem agafat estariem obtenint una representacio de les dades del 80.4%, la qual es molt bona! Finalment, tambe podem veure la distribucio en nombre d'individus en els diferents clusters.

```
plot.HCPC(res.hcpc, choice="bar")
```




```
res.hcpc$call$t$inert.gain[1:6]
```

```
## [1] 3.5016630 1.1436272 0.4699006 0.3400760 0.2171351 0.1867086
```

```
sum(res.hcpc$call$t$inert.gain)
```

```
## [1] 7.285793
```

```
res.hcpc$call$t$within[1:7]
```

```
## [1] 7.285793 3.784130 2.640503 2.170602 1.830526 1.613391 1.426683
```

```
#X clusters corresponen al %? d'inercia
sum(res.hcpc$call$t$inert.gain[1:6]) / sum(res.hcpc$call$t$inert.gain) * 100
```

```
## [1] 80.41829
```

```
table(res.hcpc$data.clust$clust) #nombre d'individus en cada cluster
```

```
##
##    1    2    3    4    5    6    7
##  176  313 1155  430 1268 1441  203
```

Sobre les variables categoriques que han estat incloses com a suplementaries

Aqui analitzarem la representacio i relacio de les variables categoriques que s'han inclos com a suplementaries en el PCA destinat a la clusteritzacio jerarquica. Aquestes variables han estat les seguents: "y", "loan", "month", "job", "poutcome", "education" i "housing".

En un primer output basat en el *test chi2* veiem rapidament quines d'aquestes variables discretes suplementaries estan significativament (p-value < 0.05) relacionades globalment amb la particio de clusters establerta. Les variables "month" i "poutcome" tenen un p-valor tan baix que R no el pot representar i ens el marca com a

0; de la mateixa manera, les variables "y(target)", "job", "education" i "housing" estan tambe relacionades amb el particionament seleccionat.

En un segon output desglosat per numero de cluster veiem la sobrerepresentacio i infrarepresentacio de diferents categories en els diferents clusters, ajudant aixi a caracteritzar els diferents grups formats. La presentacio de les dades es la mateixa que la mostrada en el catdes pero amb el numero de cluster com a variable fixada, per tant seran interpretades de la mateixa manera descrita en el primer deliverable. En una primera **descripcio general**, podem veure com els clusters 1 i 2, i en menor mesura el 3, tenen una sobrerepresentacio d'acceptacio de producte financer. Pel que fa a la resta de clusters, tenen una infrarepresentacio del mateix. El 71% d'acceptacions del producte financer es troben als 3 primers clusters, mentres que el 29% restant es troben als altres 4. Cada cluster a mes, te un lleuger esbiaix en certes catergoreis professionals i d'educacio. El **primer cluster** es troba caracteritzat per una immensa sobrerepresentacio dels clients amb acceptacio d'una campanya anterior (poutcome-success es un 86% dins el cluster 1 respecte un 3% global); aixo es tradueix tambe en que el 97% d'individus que havien acceptat anteriorment un producte estan situats en aquest cluster. El **segon cluster** es troba sobrerepresentat pels individus retirats (27% respecte un 4% global), el 41% dels quals pertanyen a aquest cluster. També trobem que mes de la meitat de trucades realitzades als mesos d'octubre, setembre i desembre son classificades dins del cluster numero 2. A mes a mes, el segon i en especial el **tercer cluster** (59% dels poutcome-failure pertanyen a aquest) es troben forca sobrerepresentats per individus que anteriorment no van acceptar una campanya (pero aquesta si). Tambe inclouen una sobrerepresentacio d'individus housing-yes. Aquest tercer cluster compren a mes una sobrerepresentacio dels mesos d'abril, maig i marc. El 99.7% d'individus del **quart cluster** van ser contactats el mes de novembre, el que es tradueix en una immensa sobrerepresentacio en aquest grup, que a mes no va acceptar el producte financer (97.0%). El **cinque cluster**, **sise cluster** i **sete cluster** estan formats integrament per individus dels quals no es te informacio d'exit o fracas en contactes de campanyes anteriors. El cinque cluster te una sobrerepresentacio dels mesos agost i maig; mentres que el sise i sete clusters la tenen dels mesos juliol i juny. Aquests dos ultims clusters tenen a mes una sobrerepresentacio housing-no (i infra de housing-yes), essent el sete cluster lleugerament diferent del sise pel fet de contenir tambe una sobrereprentacio de l'agost i una major infrarepresentacio d'acceptacio del producte financer.

```
# Factors globally related to clustering partition:
res.hcpc$desc.var$test.chi2
```

```
##                 p.value df
## month      0.000000e+00 54
## poutcome   0.000000e+00 12
## y         4.530266e-154  6
## job       1.045918e-146 60
## education  2.331835e-28 30
## housing    2.178875e-07  6
```

```
# Categories over/under represented in each cluster:
res.hcpc$desc.var$category
```

```
## $`1`
##                                       Cla/Mod   Mod/Cla     Global
## poutcome=poutcome-success            96.794872 85.795455  3.1287605
## y=y-yes                              18.850987 59.659091 11.1712796
## month=month-oct                      19.587629 10.795455  1.9454473
## month=month-mar                      22.727273  8.522727  1.3237064
## month=month-sep                      18.032787  6.250000  1.2234256
## month=month-dec                      26.923077  3.977273  0.5214601
## job=job-retired                       9.268293 10.795455  4.1115122
## education=education-university.degree  5.051151 44.886364 31.3678299
## job=job-student                      10.000000  5.681818  2.0056157
## month=month-nov                       5.719921 16.477273 10.1684717
## job=job-housemaid                     8.148148  6.250000  2.7075812
```

```
## job=job-admin.                            4.494382 31.818182 24.9899719
## poutcome=poutcome-failure                 5.241090 14.204545  9.5667870
## education=education-basic.9y              2.086050  9.090909 15.3830726
## job=job-services                          1.405622  3.977273  9.9879663
## job=job-blue-collar                       1.964133 13.068182 23.4857601
## month=month-jul                           1.326900  6.250000 16.6265544
## month=month-may                           1.378518 13.636364 34.9177698
## y=y-no                                    1.603071 40.340909 88.8287204
## poutcome=poutcome-nonexistent             0.000000  0.000000 87.3044525
##                                                p.value     v.test
## poutcome=poutcome-success                3.881038e-254  34.051314
## y=y-yes                                   2.249261e-57  15.964754
## month=month-oct                           6.983202e-10   6.166468
## month=month-mar                           5.595931e-09   5.828406
## month=month-sep                           7.963183e-06   4.466171
## month=month-dec                           2.444489e-05   4.219865
## job=job-retired                           1.204719e-04   3.845164
## education=education-university.degree     1.343088e-04   3.818421
## job=job-student                           3.281252e-03   2.940082
## month=month-nov                           8.467352e-03   2.632843
## job=job-housemaid                         1.043595e-02   2.561039
## job=job-admin.                            3.744524e-02   2.080876
## poutcome=poutcome-failure                 4.315053e-02   2.022250
## education=education-basic.9y              1.353542e-02  -2.469362
## job=job-services                          3.081976e-03  -2.959441
## job=job-blue-collar                       4.706686e-04  -3.496917
## month=month-jul                           3.415301e-05  -4.143845
## month=month-may                           1.098069e-10  -6.452794
## y=y-no                                    2.249261e-57 -15.964754
## poutcome=poutcome-nonexistent            7.847689e-169 -27.695786
##
## $`2`
##                                             Cla/Mod    Mod/Cla     Global
## job=job-retired                           40.975610 26.8370607  4.1115122
## month=month-oct                           58.762887 18.2108626  1.9454473
## y=y-yes                                   18.312388 32.5878594 11.1712796
## month=month-sep                           55.737705 10.8626198  1.2234256
## poutcome=poutcome-failure                 18.867925 28.7539936  9.5667870
## month=month-dec                           61.538462  5.1118211  0.5214601
## month=month-aug                           10.329986 23.0031949 13.9791416
## education=education-basic.4y              10.318949 17.5718850 10.6899318
## education=education-university.degree      8.056266 40.2555911 31.3678299
## month=month-mar                           16.666667  3.5143770  1.3237064
## housing=housing-yes                        7.192661 62.6198083 54.6530285
## poutcome=poutcome-success                  1.923077  0.9584665  3.1287605
## housing=housing-no                         5.174701 37.3801917 45.3469715
## job=job-entrepreneur                       1.298701  0.6389776  3.0886482
## education=education-high.school            4.515599 17.5718850 24.4283995
## month=month-jun                            3.374233  7.0287540 13.0766145
## job=job-services                           2.208835  3.5143770  9.9879663
## education=education-basic.9y               2.346806  5.7507987 15.3830726
## month=month-jul                            2.412545  6.3897764 16.6265544
## poutcome=poutcome-nonexistent              5.053986 70.2875399 87.3044525
## job=job-blue-collar                        1.707942  6.3897764 23.4857601
```

```
## y=y-no                                   4.764055 67.4121406 88.8287204
## month=month-may                          1.608271  8.9456869 34.9177698
##                                             p.value     v.test
## job=job-retired                          3.206853e-50  14.901828
## month=month-oct                          6.590944e-45  14.061041
## y=y-yes                                  3.834595e-26  10.576387
## month=month-sep                          8.371333e-26  10.502960
## poutcome=poutcome-failure                9.880353e-24  10.042825
## month=month-dec                          1.246107e-13   7.411785
## month=month-aug                          8.737157e-06   4.446276
## education=education-basic.4y             1.483350e-04   3.793840
## education=education-university.degree    6.031404e-04   3.430198
## month=month-mar                          3.078719e-03   2.959767
## housing=housing-yes                      3.315110e-03   2.936900
## poutcome=poutcome-success                1.178823e-02  -2.518421
## housing=housing-no                       3.315110e-03  -2.936900
## job=job-entrepreneur                     3.124217e-03  -2.955244
## education=education-high.school          2.715285e-03  -2.998257
## month=month-jun                          4.715598e-04  -3.496412
## job=job-services                         1.072126e-05  -4.402091
## education=education-basic.9y             6.730357e-08  -5.398225
## month=month-jul                          3.048594e-08  -5.538623
## poutcome=poutcome-nonexistent            1.400973e-16  -8.264657
## job=job-blue-collar                      1.157386e-16  -8.287413
## y=y-no                                   3.834595e-26 -10.576387
## month=month-may                          5.102772e-28 -10.973892
##
## $`3`
##                                    Cla/Mod    Mod/Cla     Global
## month=month-apr                  87.741935 23.5497835  6.2174087
## month=month-may                  39.402642 59.3939394 34.9177698
## poutcome=poutcome-failure        59.329140 24.5021645  9.5667870
## job=job-student                  60.000000  5.1948052  2.0056157
## month=month-mar                  60.606061  3.4632035  1.3237064
## y=y-yes                          33.572711 16.1904762 11.1712796
## housing=housing-yes              25.614679 60.4329004 54.6530285
## job=job-blue-collar              26.985482 27.3593074 23.4857601
## education=education-high.school  26.026273 27.4458874 24.4283995
## education=education-basic.9y     26.075619 17.3160173 15.3830726
## month=month-dec                   7.692308  0.1731602  0.5214601
## month=month-oct                  14.432990  1.2121212  1.9454473
## job=job-management               18.734793  6.6666667  8.2430806
## job=job-housemaid                12.592593  1.4718615  2.7075812
## job=job-technician               18.718593 12.9004329 15.9647012
## education=education-basic.4y     16.510319  7.6190476 10.6899318
## housing=housing-no               20.212295 39.5670996 45.3469715
## y=y-no                           21.855949 83.8095238 88.8287204
## job=job-retired                   6.341463  1.1255411  4.1115122
## month=month-jun                  12.269939  6.9264069 13.0766145
## poutcome=poutcome-success         1.282051  0.1731602  3.1287605
## month=month-nov                   3.353057  1.4718615 10.1684717
## poutcome=poutcome-nonexistent    19.986216 75.3246753 87.3044525
## month=month-aug                   1.865136  1.1255411 13.9791416
## month=month-jul                   1.809409  1.2987013 16.6265544
```

```
##                                       p.value     v.test
## month=month-apr                  8.449977e-140  25.170408
## month=month-may                   6.491023e-85  19.526860
## poutcome=poutcome-failure         2.400092e-72  17.988443
## job=job-student                   1.919893e-15   7.946413
## month=month-mar                   7.101962e-11   6.518488
## y=y-yes                           2.708602e-09   5.948349
## housing=housing-yes               6.372241e-06   4.513646
## job=job-blue-collar               4.638064e-04   3.500833
## education=education-high.school   6.941146e-03   2.699655
## education=education-basic.9y      3.965890e-02   2.057284
## month=month-dec                   4.946472e-02  -1.964564
## month=month-oct                   3.354840e-02  -2.125458
## job=job-management                2.394486e-02  -2.258013
## job=job-housemaid                 1.872587e-03  -3.109730
## job=job-technician                9.690944e-04  -3.299349
## education=education-basic.4y      7.133660e-05  -3.971783
## housing=housing-no                6.372241e-06  -4.513646
## y=y-no                            2.708602e-09  -5.948349
## job=job-retired                   5.601283e-11  -6.554008
## month=month-jun                   6.684182e-14  -7.493929
## poutcome=poutcome-success         8.577891e-16  -8.045664
## month=month-nov                   7.092964e-39 -13.041624
## poutcome=poutcome-nonexistent     4.123377e-39 -13.082912
## month=month-aug                   3.750561e-66 -17.179978
## month=month-jul                   1.381625e-80 -19.011049
##
## $`4`
##                                        Cla/Mod    Mod/Cla    Global
## month=month-nov                      84.615385 99.7674419 10.168472
## y=y-no                                9.415218 96.9767442 88.828720
## job=job-management                   17.761557 16.9767442  8.243081
## poutcome=poutcome-failure            16.561845 18.3720930  9.566787
## job=job-entrepreneur                 23.376623  8.3720930  3.088648
## education=education-university.degree 11.700767 42.5581395 31.367830
## job=job-unemployed                   16.393443  4.6511628  2.446851
## job=job-self-employed                14.189189  4.8837209  2.968311
## job=job-admin.                        7.223114 20.9302326 24.989972
## job=job-student                       3.000000  0.6976744  2.005616
## education=education-basic.9y          6.258149 11.1627907 15.383073
## month=month-sep                       0.000000  0.0000000  1.223426
## month=month-mar                       0.000000  0.0000000  1.323706
## job=job-blue-collar                   6.233988 16.9767442 23.485760
## poutcome=poutcome-nonexistent         8.063405 81.6279070 87.304452
## month=month-oct                       0.000000  0.0000000  1.945447
## poutcome=poutcome-success             0.000000  0.0000000  3.128761
## y=y-yes                               2.333932  3.0232558 11.171280
## month=month-apr                       0.000000  0.0000000  6.217409
## month=month-jun                       0.000000  0.0000000 13.076615
## month=month-aug                       0.000000  0.0000000 13.979142
## month=month-jul                       0.000000  0.0000000 16.626554
## month=month-may                       0.000000  0.0000000 34.917770
##                                          p.value     v.test
## month=month-nov                     0.000000e+00        Inf
```

```
## y=y-no                                1.445137e-10   6.411058
## job=job-management                    6.094995e-10   6.187954
## poutcome=poutcome-failure             3.411201e-09   5.910476
## job=job-entrepreneur                  1.906432e-08   5.620285
## education=education-university.degree 3.261080e-07   5.107698
## job=job-unemployed                    5.040211e-03   2.804453
## job=job-self-employed                 2.256934e-02   2.280647
## job=job-admin.                        3.956647e-02  -2.058247
## job=job-student                       2.833524e-02  -2.192613
## education=education-basic.9y          8.935086e-03  -2.614528
## month=month-sep                       3.940443e-03  -2.882891
## month=month-mar                       2.495043e-03  -3.023942
## job=job-blue-collar                   6.095792e-04  -3.427316
## poutcome=poutcome-nonexistent         4.218766e-04  -3.526007
## month=month-oct                       1.451605e-04  -3.799206
## poutcome=poutcome-success             6.138981e-07  -4.986793
## y=y-yes                               1.445137e-10  -6.411058
## month=month-apr                       2.792982e-13  -7.304018
## month=month-jun                       3.466586e-28 -11.008782
## month=month-aug                       3.067865e-30 -11.426923
## month=month-jul                       2.141900e-36 -12.598870
## month=month-may                       1.367297e-85 -19.606258
##
## $`5`
##                                         Cla/Mod      Mod/Cla     Global
## poutcome=poutcome-nonexistent           29.129336 100.00000000 87.3044525
## month=month-aug                         52.367288  28.78548896 13.9791416
## month=month-may                         34.462952  47.31861199 34.9177698
## y=y-no                                  27.387672  95.66246057 88.8287204
## education=education-basic.4y            38.836773  16.32492114 10.6899318
## education=education-professional.course 30.406504  14.74763407 12.3345367
## loan=loan-no                            26.179749  87.06624606 84.5768151
## job=job-retired                         33.658537   5.44164038  4.1115122
## housing=housing-no                      26.890756  47.94952681 45.3469715
## job=job-housemaid                       33.333333   3.54889590  2.7075812
## job=job-blue-collar                     27.754056  25.63091483 23.4857601
## housing=housing-yes                     24.220183  52.05047319 54.6530285
## job=job-unemployed                      17.213115   1.65615142  2.4468512
## job=job-admin.                          22.953451  22.55520505 24.9899719
## education=education-high.school         22.495895  21.60883281 24.4283995
## loan=loan-yes                           21.326398  12.93375394 15.4231849
## month=month-dec                          0.000000   0.00000000  0.5214601
## education=education-university.degree   21.419437  26.41955836 31.3678299
## month=month-sep                          0.000000   0.00000000  1.2234256
## month=month-mar                          0.000000   0.00000000  1.3237064
## month=month-jun                         15.644172   8.04416404 13.0766145
## job=job-student                          2.000000   0.15772871  2.0056157
## month=month-oct                          1.030928   0.07886435  1.9454473
## poutcome=poutcome-success                0.000000   0.00000000  3.1287605
## y=y-yes                                  9.874327   4.33753943 11.1712796
## month=month-apr                          0.000000   0.00000000  6.2174087
## poutcome=poutcome-failure                0.000000   0.00000000  9.5667870
## month=month-nov                          0.000000   0.00000000 10.1684717
##                                             p.value     v.test
```

```
## poutcome=poutcome-nonexistent           5.289007e-88  19.886855
## month=month-aug                         1.191159e-61  16.567794
## month=month-may                         3.493765e-26  10.585108
## y=y-no                                  2.522644e-22   9.718174
## education=education-basic.4y            5.108301e-13   7.222387
## education=education-professional.course 2.901818e-03   2.977952
## loan=loan-no                            3.988941e-03   2.879035
## job=job-retired                         7.243663e-03   2.685430
## housing=housing-no                      3.131061e-02   2.153103
## job=job-housemaid                       3.740547e-02   2.081311
## job=job-blue-collar                     3.801325e-02   2.074712
## housing=housing-yes                     3.131061e-02  -2.153103
## job=job-unemployed                      3.030370e-02  -2.166098
## job=job-admin.                          1.971720e-02  -2.331686
## education=education-high.school         6.416463e-03  -2.725703
## loan=loan-yes                           3.988941e-03  -2.879035
## month=month-dec                         4.751074e-04  -3.494412
## education=education-university.degree   9.020632e-06  -4.439409
## month=month-sep                         1.482866e-08  -5.663534
## month=month-mar                         3.344948e-09  -5.913706
## month=month-jun                         1.357270e-10  -6.420613
## job=job-student                         8.674956e-11  -6.488405
## month=month-oct                         1.130837e-11  -6.788783
## poutcome=poutcome-success               5.633481e-21  -9.396637
## y=y-yes                                 2.522644e-22  -9.718174
## month=month-apr                         9.931295e-42 -13.533406
## poutcome=poutcome-failure               3.651539e-65 -17.047444
## month=month-nov                         1.753726e-69 -17.619231
##
## $`6`
##                                    Cla/Mod     Mod/Cla     Global
## month=month-jul                  62.243667  35.8084663 16.6265544
## poutcome=poutcome-nonexistent    33.103607 100.0000000 87.3044525
## month=month-jun                  57.055215  25.8154060 13.0766145
## y=y-no                           30.571235  93.9625260 88.8287204
## job=job-services                 36.746988  12.6995142  9.9879663
## housing=housing-no               31.357806  49.2019431 45.3469715
## education=education-basic.9y     33.898305  18.0430257 15.3830726
## education=education-high.school  32.266010  27.2727273 24.4283995
## job=job-technician               32.035176  17.6960444 15.9647012
## job=job-blue-collar              31.255337  25.3990285 23.4857601
## job=job-management               22.627737   6.4538515  8.2430806
## housing=housing-yes              26.862385  50.7980569 54.6530285
## job=job-student                  14.000000   0.9715475  2.0056157
## month=month-dec                   0.000000   0.0000000  0.5214601
## month=month-oct                   6.185567   0.4163775  1.9454473
## education=education-basic.4y     18.011257   6.6620402 10.6899318
## month=month-sep                   0.000000   0.0000000  1.2234256
## month=month-mar                   0.000000   0.0000000  1.3237064
## y=y-yes                          15.619390   6.0374740 11.1712796
## month=month-may                  20.964963  25.3296322 34.9177698
## poutcome=poutcome-success         0.000000   0.0000000  3.1287605
## job=job-retired                   0.000000   0.0000000  4.1115122
## month=month-apr                   0.000000   0.0000000  6.2174087
```

```
## poutcome=poutcome-failure        0.000000   0.0000000  9.5667870
## month=month-nov                  0.000000   0.0000000 10.1684717
##                                      p.value     v.test
## month=month-jul                 2.193896e-108  22.116481
## poutcome=poutcome-nonexistent   2.146626e-102  21.485087
## month=month-jun                  5.177232e-59  16.198381
## y=y-no                           1.177463e-14   7.718457
## job=job-services                 6.653178e-05   3.988360
## housing=housing-no               4.994477e-04   3.481052
## education=education-basic.9y     1.044519e-03   3.278253
## education=education-high.school  3.082735e-03   2.959365
## job=job-technician               3.462568e-02   2.112709
## job=job-blue-collar              4.313066e-02   2.022442
## job=job-management               2.864908e-03  -2.981873
## housing=housing-yes              4.994477e-04  -3.481052
## job=job-student                  4.497429e-04  -3.509031
## month=month-dec                  1.370593e-04  -3.813416
## month=month-oct                  2.045152e-08  -5.608138
## education=education-basic.4y     1.058277e-09  -6.100363
## month=month-sep                  7.911717e-10  -6.146689
## month=month-mar                  1.400443e-10  -6.415845
## y=y-yes                          1.177463e-14  -7.718457
## month=month-may                  3.650636e-20  -9.197885
## poutcome=poutcome-success        2.829400e-24 -10.165406
## job=job-retired                  7.352963e-32 -11.746586
## month=month-apr                  1.961207e-48 -14.624460
## poutcome=poutcome-failure        9.590135e-76 -18.417043
## month=month-nov                  8.816429e-81 -19.034599
##
## $`7`
##                                  Cla/Mod     Mod/Cla    Global      p.value
## poutcome=poutcome-nonexistent 4.6634505 100.0000000 87.304452 5.792869e-13
## month=month-jul               8.0820265  33.0049261 16.626554 5.404009e-09
## month=month-jun               8.2822086  26.6009852 13.076615 1.418693e-07
## y=y-no                        4.4027997  96.0591133 88.828720 2.087025e-04
## month=month-aug               5.7388809  19.7044335 13.979142 2.141058e-02
## housing=housing-no            4.6881911  52.2167488 45.346972 4.567393e-02
## housing=housing-yes           3.5596330  47.7832512 54.653028 4.567393e-02
## month=month-oct               0.0000000   0.0000000  1.945447 1.704213e-02
## poutcome=poutcome-success     0.0000000   0.0000000  3.128761 1.374795e-03
## y=y-yes                       1.4362657   3.9408867 11.171280 2.087025e-04
## month=month-apr               0.3225806   0.4926108  6.217409 2.660092e-05
## month=month-nov               0.5917160   1.4778325 10.168472 6.310181e-07
## month=month-may               2.1826536  18.7192118 34.917770 2.409376e-07
## poutcome=poutcome-failure     0.0000000   0.0000000  9.566787 8.711382e-10
##                                  v.test
## poutcome=poutcome-nonexistent  7.205271
## month=month-jul                5.834228
## month=month-jun                5.262811
## y=y-no                         3.708243
## month=month-aug                2.300665
## housing=housing-no             1.998394
## housing=housing-yes           -1.998394
## month=month-oct               -2.385798
```

```
## poutcome=poutcome-success     -3.199891
## y=y-yes                       -3.708243
## month=month-apr               -4.200770
## month=month-nov               -4.981474
## month=month-may               -5.164612
## poutcome=poutcome-failure     -6.131391
```

Sobre les variables quantitatives (numeriques)

A continuacio es realitzara una altra descripcio dels diferents clusters formats pero basant-nos en les variables quantitatives (numeriques), les quals han estat utilitzades en el PCA. En el primer output es poden veure les que han estat "p-provades" com a globalment relacionades amb la clusteritzacio, mentres que el detall es pot veure en el segon output.

El **primer cluster** esta caracteritzat per individus (sempre respecte la mitja global) mes contactats en campanyes anteriors (previous) i menys en l'actual (campaign); aixi com individus que han estat contactats molt mes recentment (pdays). La duracio de les trucades en aquest cluster esta 35 segons per sobra la mitja global, aixi com tambe podem veure lleugers esbiaixos en els indicadors socioeconomics (valors baixos de euribor3m, emp.var.rate, nr.employed i cons.conf.idx). El **segon cluster** te una mitjana d'edat 12 anys per sobre la mitjana global, si be tambe una major desvacio estandard dins la categoria; a part d'un esbiaix similar a l'anterior amb els indicadors socioeconomics. El **tercer cluster** es similar al cluster 2 pero amb una mitja d'edat 4 anys per sota de la global; a mes en aquest grup la duracio de les trucades esta per sobra la mitja per 14 segons. Els quatre altres clusters contenen nomes individus els quals no han estat contactats abans per cap altra campanya (mitja de pdays=19.0 amb un sd de 0) i els seus indicadors socioeconomics tenen un comportament similar en l'esbiaix. El **quart cluster** pero, a diferencia dels altres tres, no mostra una mitja de 0.0 en la variable "previous", el que fa pensar que aquests individus han estat contactat abans pero no necessariament per a una campanya d'un producte. La duracio en aquest cluster es 30 segons per sota la mitja global. Entre els **cinque cluster** i **sise cluster** la diferencia principal esta en l'edat, que que el cinque agrupa individus per sobre la mitja i el sise per sota. Per ultim, el **sete cluster** destaca per a una mitja de duracio de les trucades extremadament curta (65 segons per sota la mitja global), aixi com per un numero de vegades que l'individu ha estat contactat en l'actual campanya molt per sobre de la mitja global (11.3 respecte 2.5).

```
# Numeric (quantitative) variables globally related to clustering partition:
res.hcpc$desc.var$quanti.var
```

```
##                       Eta2     P-value
## age            0.335988921 0.00000e+00
## campaign       0.540040103 0.00000e+00
## pdays          0.925018800 0.00000e+00
## previous       0.465947411 0.00000e+00
## emp.var.rate   0.960040097 0.00000e+00
## cons.price.idx 0.614485994 0.00000e+00
## cons.conf.idx  0.503365350 0.00000e+00
## euribor3m      0.988716657 0.00000e+00
## nr.employed    0.879442070 0.00000e+00
## duration       0.006588486 1.08361e-05
```

```
res.hcpc$desc.var$quanti
```

```
## $`1`
##                    v.test Mean in category  Overall mean sd in category
## previous        43.973874         1.687500    0.15984757      0.8848873
## cons.conf.idx    8.805587       -37.359091  -40.42591256      6.5879649
## age              3.296336        42.619318   40.06799037     14.8938468
## duration         2.067896       285.897727  250.62194144    213.7620565
```

```
## campaign        -3.562842         1.880682    2.53512993      1.3282215
## cons.price.idx  -7.388255        93.253477   93.57245006      0.7521195
## emp.var.rate   -19.367388        -2.208523    0.06446049      0.8800737
## euribor3m      -20.279982         1.006216    3.61448034      0.6758827
## nr.employed    -25.213543      5032.493750 5166.47621340     52.1226287
## pdays          -67.905435         5.738636   18.52647413      3.5659192
##                 Overall sd       p.value
## previous         0.4691873  0.000000e+00
## cons.conf.idx    4.7037753  1.301691e-18
## age             10.4532458  9.795477e-04
## duration       230.3904064  3.864981e-02
## campaign         2.4808187  3.668615e-04
## cons.price.idx   0.5830800  1.487681e-13
## emp.var.rate     1.5850448  1.454512e-83
## euribor3m        1.7370025  1.932036e-91
## nr.employed     71.7679377 2.845704e-140
## pdays            2.5433666  0.000000e+00
##
## $`2`
##                    v.test Mean in category  Overall mean sd in category
## cons.conf.idx   25.044818      -33.9789137  -40.42591256      6.3573009
## age             19.567738       51.2619808   40.06799037     16.7801531
## previous         7.959341        0.3642173    0.15984757      0.6047713
## pdays            3.149566       18.9648562   18.52647413      0.4099927
## campaign        -5.588859        1.7763578    2.53512993      1.2567327
## cons.price.idx -26.189093       92.7367668   93.57245006      0.5664489
## euribor3m      -28.684949        0.8877157    3.61448034      0.2248025
## nr.employed    -31.489513     5042.7990415 5166.47621340     36.8870017
## emp.var.rate   -32.543552       -2.7584665    0.06446049      0.6816163
##                Overall sd       p.value
## cons.conf.idx   4.7037753 1.988210e-138
## age            10.4532458  2.913265e-85
## previous        0.4691873  1.729578e-15
## pdays           2.5433666  1.635132e-03
## campaign        2.4808187  2.285660e-08
## cons.price.idx  0.5830800 3.537697e-151
## euribor3m       1.7370025 5.878957e-181
## nr.employed    71.7679377 1.209022e-217
## emp.var.rate    1.5850448 2.583254e-232
##
## $`3`
##                    v.test Mean in category  Overall mean sd in category
## previous         8.754589        0.2658009    0.15984757      0.4829555
## pdays            7.006604       18.9861472   18.52647413      0.3326118
## duration         2.386888      264.8069264  250.62194144    234.8283557
## campaign        -5.291156        2.1965368    2.53512993      1.6640810
## age            -13.956513       36.3047619   40.06799037      8.5250191
## cons.price.idx -35.103266       93.0444814   93.57245006      0.3872219
## cons.conf.idx  -42.294031      -45.5575758  -40.42591256      3.1552802
## nr.employed    -43.023029     5086.8302165 5166.47621340     33.6303225
## emp.var.rate   -46.855120       -1.8512554    0.06446049      0.3273476
## euribor3m      -52.114578        1.2794519    3.61448034      0.1767441
##                 Overall sd       p.value
## previous         0.4691873  2.048491e-18
```

```
## pdays            2.5433666  2.441716e-12
## duration       230.3904064  1.699168e-02
## campaign         2.4808187  1.215453e-07
## age             10.4532458  2.871432e-44
## cons.price.idx   0.5830800 6.010017e-270
## cons.conf.idx    4.7037753  0.000000e+00
## nr.employed     71.7679377  0.000000e+00
## emp.var.rate     1.5850448  0.000000e+00
## euribor3m        1.7370025  0.000000e+00
##
## $`4`
##                    v.test Mean in category  Overall mean sd in category
## nr.employed      8.848963     5195.7546512 5166.47621340   9.392794e-01
## euribor3m        6.251387        4.1150930    3.61448034   7.151549e-02
## pdays            4.038403       19.0000000   18.52647413   0.000000e+00
## emp.var.rate    -2.253765       -0.1002326    0.06446049   4.816817e-03
## duration        -2.828692      220.5767442  250.62194144   2.118224e+02
## campaign        -5.593856        1.8953488    2.53512993   1.308550e+00
## cons.conf.idx   -7.300497      -42.0090698  -40.42591256   1.878559e-01
## cons.price.idx -13.893678       93.1989674   93.57245006   2.138667e-02
##                Overall sd      p.value
## nr.employed     71.767938 8.833617e-19
## euribor3m        1.737002 4.068245e-10
## pdays            2.543367 5.381623e-05
## emp.var.rate     1.585045 2.421094e-02
## duration       230.390406 4.673870e-03
## campaign         2.480819 2.220806e-08
## cons.conf.idx    4.703775 2.867066e-13
## cons.price.idx   0.583080 6.918945e-44
##
## $`5`
##                    v.test Mean in category  Overall mean sd in category
## emp.var.rate    31.018314         1.256861    0.06446049     0.15450722
## euribor3m       30.778624         4.911099    3.61448034     0.05291853
## age             28.431726        47.276025   40.06799037     6.83638157
## nr.employed     25.303757      5210.519322 5166.47621340    18.52135643
## cons.conf.idx   23.501417       -37.744874  -40.42591256     2.61453060
## cons.price.idx  20.434823        93.861426   93.57245006     0.29713094
## pdays            7.676659        19.000000   18.52647413     0.00000000
## campaign        -3.366631         2.332570    2.53512993     1.51977446
## previous       -14.047446         0.000000    0.15984757     0.00000000
##                Overall sd       p.value
## emp.var.rate    1.5850448 3.053044e-211
## euribor3m       1.7370025 5.064155e-208
## age            10.4532458 8.199565e-178
## nr.employed    71.7679377 2.904135e-141
## cons.conf.idx   4.7037753 3.944955e-122
## cons.price.idx  0.5830800  8.198980e-93
## pdays           2.5433666  1.632909e-14
## campaign        2.4808187  7.609255e-04
## previous        0.4691873  7.986314e-45
##
## $`6`
##                    v.test Mean in category  Overall mean sd in category
```

```
## emp.var.rate    35.593579         1.317765    0.06446049     0.15938206
## cons.price.idx  34.404615        94.018094   93.57245006     0.31164559
## euribor3m       34.019646         4.927205    3.61448034     0.04863405
## nr.employed     32.673604      5218.568217 5166.47621340    16.19038972
## pdays            8.380911        19.000000   18.52647413     0.00000000
## cons.conf.idx    3.801019       -40.028730  -40.42591256     2.94116617
## campaign        -6.468091         2.178667    2.53512993     1.37338503
## previous       -15.336148         0.000000    0.15984757     0.00000000
## age            -27.777266        33.617627   40.06799037     5.41378149
##                Overall sd       p.value
## emp.var.rate    1.5850448 1.761028e-277
## cons.price.idx  0.5830800 2.151036e-259
## euribor3m       1.7370025 1.141427e-253
## nr.employed    71.7679377 3.704005e-234
## pdays           2.5433666  5.251979e-17
## cons.conf.idx   4.7037753  1.441025e-04
## campaign        2.4808187  9.924849e-11
## previous        0.4691873  4.384517e-53
## age            10.4532458 8.165488e-170
##
## $`7`
##                   v.test Mean in category Overall mean sd in category
## campaign       51.681982        11.349754 2.535130e+00      4.2854821
## emp.var.rate   11.261387         1.291626 6.446049e-02      0.3725545
## nr.employed    10.764761      5219.589655 5.166476e+03     18.9160146
## euribor3m      10.662441         4.887768 3.614480e+00      0.3732829
## cons.price.idx  9.771322        93.964148 9.357245e+01      0.3729365
## pdays           2.708103        19.000000 1.852647e+01      0.0000000
## duration       -4.128695       185.226601 2.506219e+02    230.3643674
## previous       -4.955532         0.000000 1.598476e-01      0.0000000
##                 Overall sd      p.value
## campaign         2.4808187 0.000000e+00
## emp.var.rate     1.5850448 2.035309e-29
## nr.employed     71.7679377 5.049245e-27
## euribor3m        1.7370025 1.525396e-26
## cons.price.idx   0.5830800 1.494883e-22
## pdays            2.5433666 6.766903e-03
## duration       230.3904064 3.648276e-05
## previous         0.4691873 7.213279e-07
```

Descripcio dels clusters mitjancant individus

Aqui descrivim els clusters mitjancant els individus, concretament ens centrarem en els individus que estan al centre de gravetat del cluster (para-parangons) i els que estan mes allunyats de la resta de clusters, es a dir, els mes propis del cluster en questio i menys dels altres (dist-especifics). En les seguents grafiques es poden veure representats en blau els parangons i en taronja els individus especifics per a cada cluster de la classificacio.

```
# Description of the clusters by individuals:
names(res.hcpc$desc.ind)
```

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

```
res.hcpc$desc.ind$para #parangons of each clusters
```

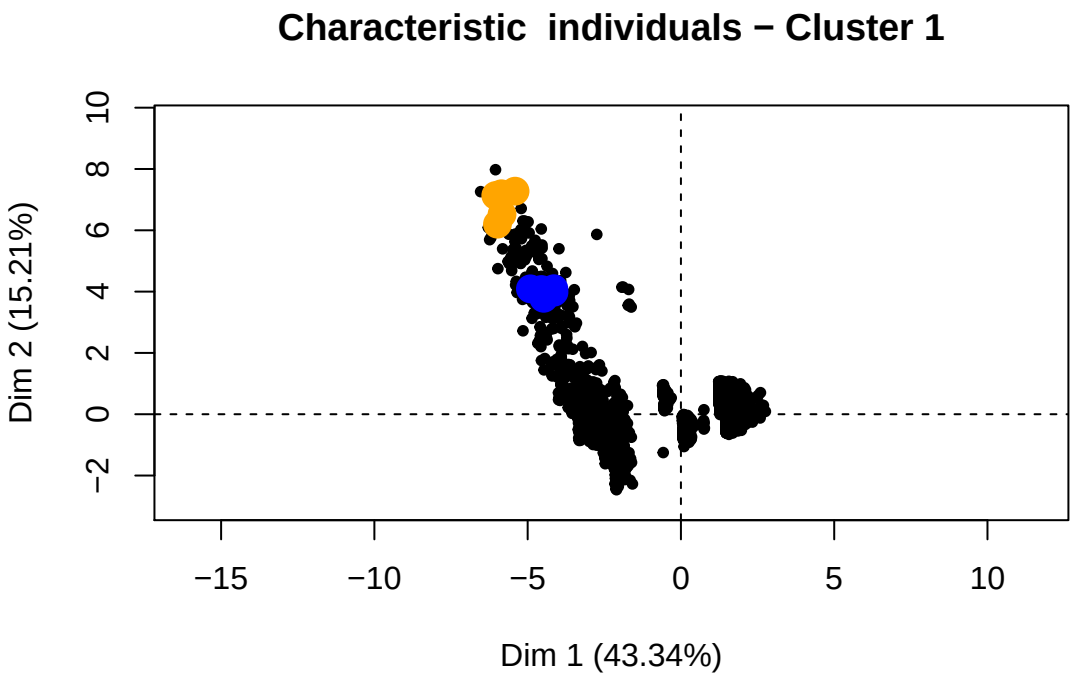
```
## Cluster: 1
```

```
##     31670     30284     37727     36469     30158
## 0.3892465 0.6099896 0.6405242 0.6517560 0.6658754
## ------------------------------------------------------------
## Cluster: 2
##     38732     38503     37268     39000     37397
## 0.4162434 0.5086237 0.5839632 0.5993900 0.6629911
## ------------------------------------------------------------
## Cluster: 3
##     36703     36516     36745     36444     36765
## 0.2333947 0.2626528 0.2918447 0.3074016 0.4287422
## ------------------------------------------------------------
## Cluster: 4
##     27423     26065     25081     25324     26601
## 0.2429945 0.2473604 0.2495809 0.2495809 0.2519679
## ------------------------------------------------------------
## Cluster: 5
##     19520     19421     20018     23464     23491
## 0.1425541 0.1427061 0.1428585 0.1431648 0.1434728
## ------------------------------------------------------------
## Cluster: 6
##     12276     14034     16531     16228     18537
## 0.2192499 0.2196483 0.2196483 0.2199155 0.2247631
## ------------------------------------------------------------
## Cluster: 7
##     20528     15744     21650     23413     21920
## 0.1715338 0.1947761 0.2990218 0.3655228 0.3672151
```

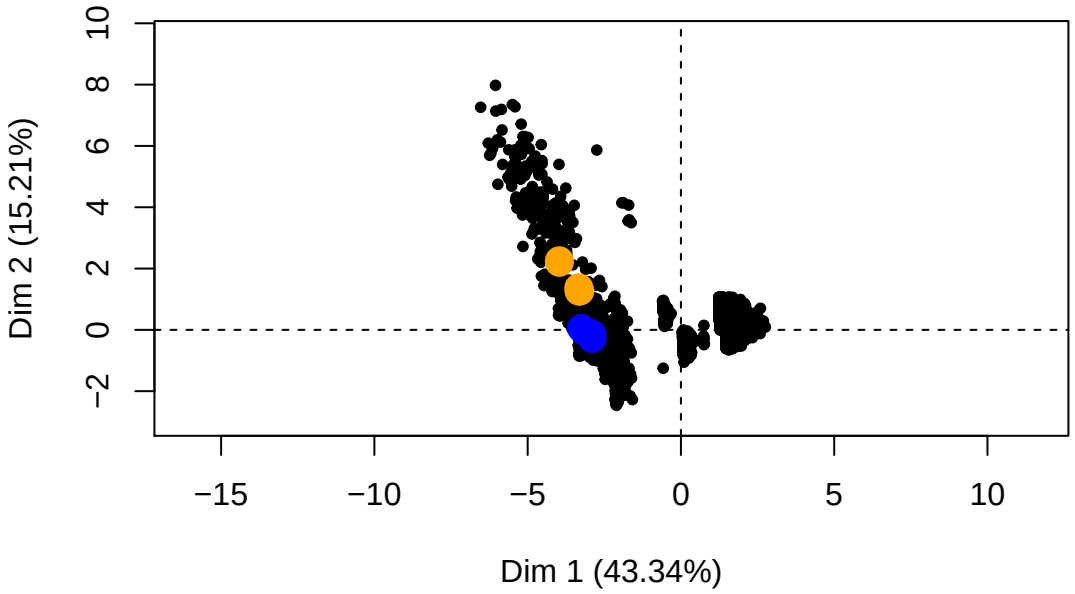
```
res.hcpc$desc.ind$dist #specific individuals
```

```
## Cluster: 1
##     40258     39828     40592     39359     39659
## 10.171491 10.130157  9.325015  9.035001  9.033797
## ------------------------------------------------------------
## Cluster: 2
##    38207    38192    38185    38558    38253
## 6.441959 6.210520 6.144412 6.115588 6.069564
## ------------------------------------------------------------
## Cluster: 3
##    27734    34291    40877    27890    33321
## 4.536960 4.490433 4.483955 4.461203 4.400579
## ------------------------------------------------------------
## Cluster: 4
##    26974    26571    27451    25845    26975
## 2.669911 2.636325 2.431859 2.426201 2.423020
## ------------------------------------------------------------
## Cluster: 5
##    22846      743    22712    22178    20336
## 2.849191 2.722699 2.706876 2.651221 2.651213
## ------------------------------------------------------------
## Cluster: 6
##    18411    11796     8740     8085    11253
## 2.757309 2.704960 2.704805 2.689915 2.651787
## ------------------------------------------------------------
## Cluster: 7
##    18712     8993    15581    17458    18417
```

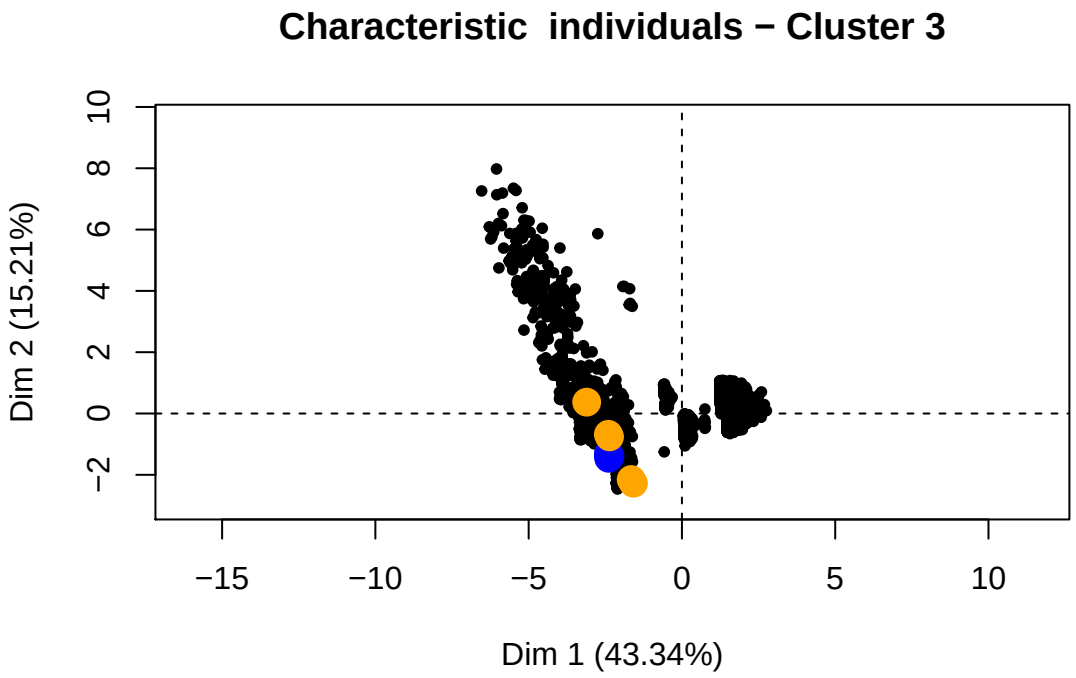
```
## 9.054553 8.685034 8.669008 8.303776 8.273290
#Characteristic individuals - as many as clusters
para1<-which(rownames(res.pca$ind$coord)%in%names(res.hcpc$desc.ind$para[[1]]))
para2<-which(rownames(res.pca$ind$coord)%in%names(res.hcpc$desc.ind$para[[2]]))
para3<-which(rownames(res.pca$ind$coord)%in%names(res.hcpc$desc.ind$para[[3]]))
para4<-which(rownames(res.pca$ind$coord)%in%names(res.hcpc$desc.ind$para[[4]]))
para5<-which(rownames(res.pca$ind$coord)%in%names(res.hcpc$desc.ind$para[[5]]))
para6<-which(rownames(res.pca$ind$coord)%in%names(res.hcpc$desc.ind$para[[6]]))
para7<-which(rownames(res.pca$ind$coord)%in%names(res.hcpc$desc.ind$para[[7]]))

dist1<-which(rownames(res.pca$ind$coord)%in%names(res.hcpc$desc.ind$dist[[1]]))
dist2<-which(rownames(res.pca$ind$coord)%in%names(res.hcpc$desc.ind$dist[[2]]))
dist3<-which(rownames(res.pca$ind$coord)%in%names(res.hcpc$desc.ind$dist[[3]]))
dist4<-which(rownames(res.pca$ind$coord)%in%names(res.hcpc$desc.ind$dist[[4]]))
dist5<-which(rownames(res.pca$ind$coord)%in%names(res.hcpc$desc.ind$dist[[5]]))
dist6<-which(rownames(res.pca$ind$coord)%in%names(res.hcpc$desc.ind$dist[[6]]))
dist7<-which(rownames(res.pca$ind$coord)%in%names(res.hcpc$desc.ind$dist[[7]]))

df$clust<-factor(res.hcpc$data.clust$clust)

#cluster as variable suplementaria
res.pca<-PCA(df[,c("duration", "clust", vars_con)], quanti.sup=1,quali.sup=2,ncp=4, graph=FALSE)

#? habillage
#color the individuals among a categorical variable (give the number/name of the categorical variable)

plot.PCA(res.pca, label="none", invisible="quali", title="Characteristic  individuals - Cluster 1")
#pintar "para" del cluster 1
points(res.pca$ind$coord[para1,1], res.pca$ind$coord[para1,2], col="blue", cex=2, pch=16)
#pintar "dist" del cluster 1
points(res.pca$ind$coord[dist1,1], res.pca$ind$coord[dist1,2], col="orange", cex=2, pch=16)
```



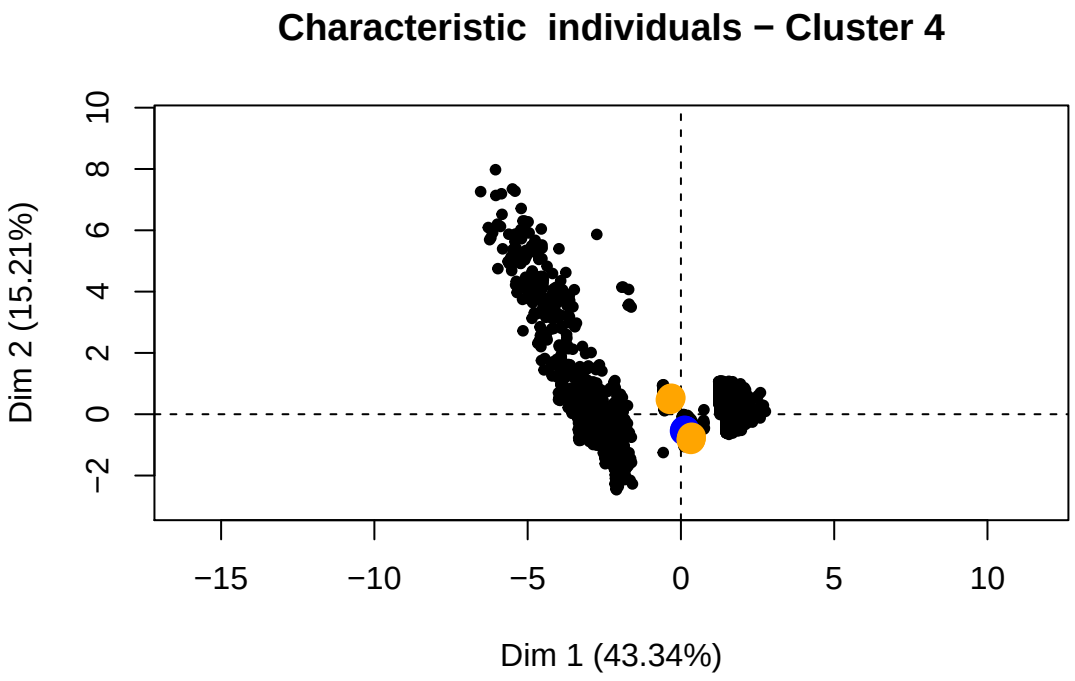

```
plot.PCA(res.pca, label="none", invisible="quali", title="Characteristic  individuals - Cluster 2")
points(res.pca$ind$coord[para2,1], res.pca$ind$coord[para2,2], col="blue", cex=2, pch=16)
points(res.pca$ind$coord[dist2,1], res.pca$ind$coord[dist2,2], col="orange", cex=2, pch=16)
```



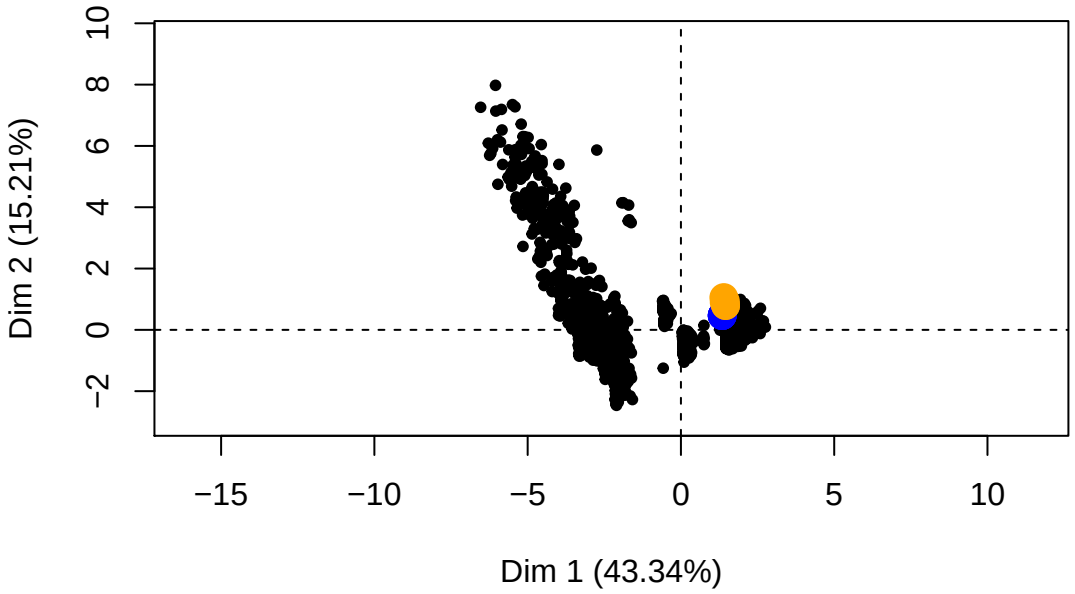
```
plot.PCA(res.pca, label="none", invisible="quali", title="Characteristic  individuals - Cluster 3")
points(res.pca$ind$coord[para3,1], res.pca$ind$coord[para3,2], col="blue", cex=2, pch=16)
points(res.pca$ind$coord[dist3,1], res.pca$ind$coord[dist3,2], col="orange", cex=2, pch=16)
```



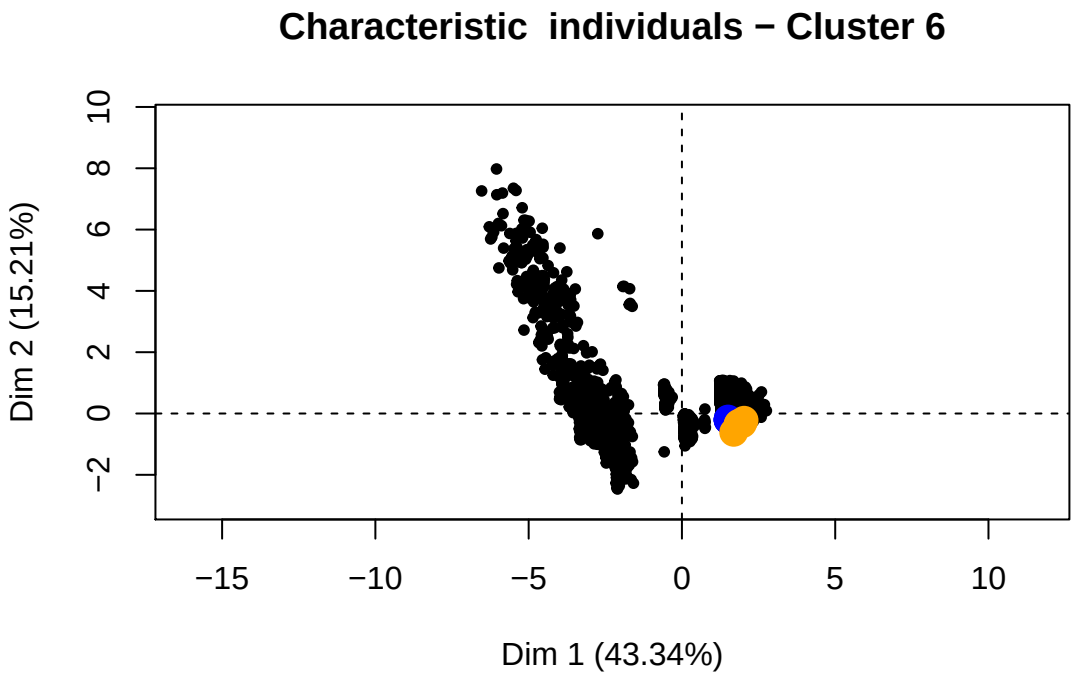

```
plot.PCA(res.pca, label="none", invisible="quali", title="Characteristic  individuals - Cluster 4")
points(res.pca$ind$coord[para4,1], res.pca$ind$coord[para4,2], col="blue", cex=2, pch=16)
points(res.pca$ind$coord[dist4,1], res.pca$ind$coord[dist4,2], col="orange", cex=2, pch=16)
```



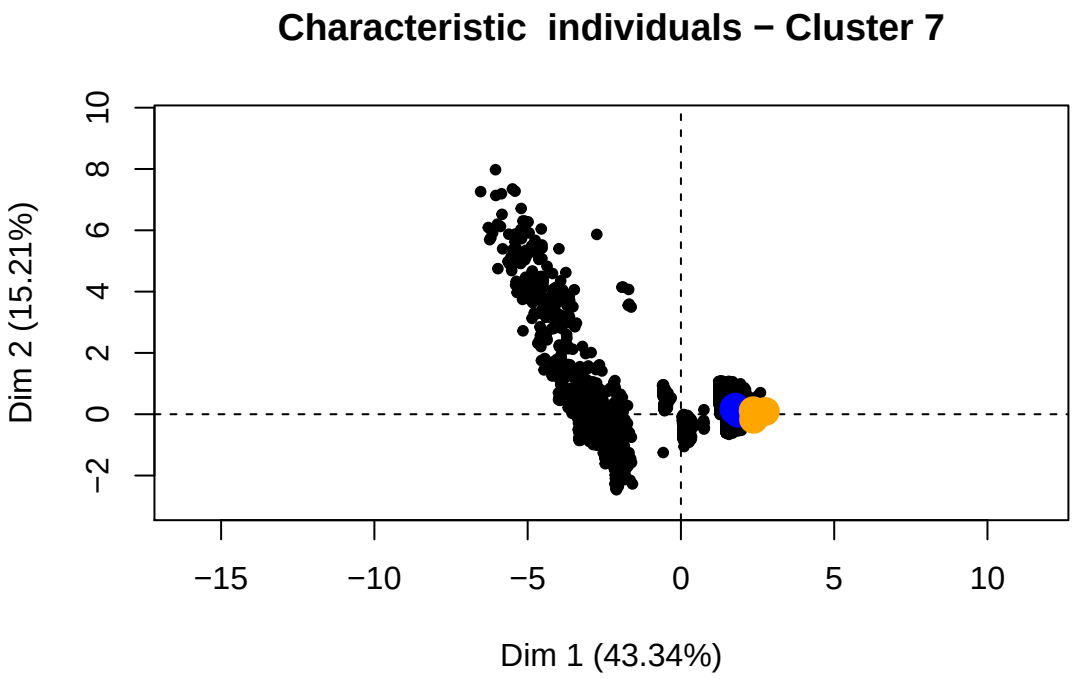

```
plot.PCA(res.pca, label="none", invisible="quali", title="Characteristic  individuals - Cluster 5")
points(res.pca$ind$coord[para5,1], res.pca$ind$coord[para5,2], col="blue", cex=2, pch=16)
points(res.pca$ind$coord[dist5,1], res.pca$ind$coord[dist5,2], col="orange", cex=2, pch=16)
```



```
plot.PCA(res.pca, label="none", invisible="quali", title="Characteristic  individuals - Cluster 6")
points(res.pca$ind$coord[para6,1], res.pca$ind$coord[para6,2], col="blue", cex=2, pch=16)
points(res.pca$ind$coord[dist6,1], res.pca$ind$coord[dist6,2], col="orange", cex=2, pch=16)
```




```
plot.PCA(res.pca, label="none", invisible="quali", title="Characteristic  individuals - Cluster 7")
points(res.pca$ind$coord[para7,1], res.pca$ind$coord[para7,2], col="blue", cex=2, pch=16)
points(res.pca$ind$coord[dist7,1], res.pca$ind$coord[dist7,2], col="orange", cex=2, pch=16)
```


Characteristic individuals − Cluster 7
Dim 2 (15.21%)
10
8
6
4
2
0
−2
−15
−10
−5
0
5
10
Dim 1 (43.34%)