Contents

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title: "Entrega-2"
author: "Ivan Cala Mesa - Pau Bosch Ribalta"
date: "May 1, 2023"
output:
pdf_document:
toc: yes
toc_depth: 4
html_document:
toc: yes
toc_depth: '4'
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fontsize: 18pt
classoption: a4paper
editor_options:
chunk_output_type: console

R Markdown

Obtenim les dades i les classifiquem:

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

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

llmout<-which(df$mout=="Yes")

df$default <- NULL
```

Anàlisis CA

Transformació de la variable duration

Anàlisis PCA

```r
# Load the required packages
library(dplyr)
```

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

## The following object is masked from 'package:car':
##
##     recode

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

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

```r
library(factoextra)
library(FactoMineR)

# Select numeric variables
df_numeric <- select(df, which(sapply(df, is.numeric)))

# Remove na_count variable
df_numeric <- df_numeric[, -which(names(df_numeric) == "na_count")]

# Create data frame for supplementary variables
df_numeric$y <- ifelse(df$y == "yes", 1, 0)

# Perform PCA with y as a supplementary variable
pca_result <- PCA(df_numeric, quanti.sup = c(8), graph = FALSE,
                  ind.sup=llmout)
```

1. Eigenvalues and dominant axes. How many axes we have to interpret?

Kaiser's rule suggests that we should interpret all the axes with an eigenvalue greater than 1, while the elbow rule suggests that we should interpret the first few axes up to the point where the eigenvalues start to level off.

```
library(FactoMineR)
library(factoextra)
# extract the eigenvalues
# Extract the eigenvalues and dominant axes
eigenvalues <- pca_result$eig
eigenvalues
```

```
##        eigenvalue percentage of variance cumulative percentage of variance
## comp 1 4.973512074            62.16890092                          62.16890
## comp 2 1.492165287            18.65206608                          80.82097
## comp 3 0.939017632            11.73772040                          92.55869
## comp 4 0.318668804             3.98336005                          96.54205
## comp 5 0.190015615             2.37519519                          98.91724
## comp 6 0.069761561             0.87201952                          99.78926
## comp 7 0.011142093             0.13927616                          99.92854
## comp 8 0.005716934             0.07146167                         100.00000
```

```
eigenvalues[1:8,1]
```

```
##      comp 1      comp 2      comp 3      comp 4      comp 5      comp 6
## 4.973512074 1.492165287 0.939017632 0.318668804 0.190015615 0.069761561
##      comp 7      comp 8
## 0.011142093 0.005716934
```

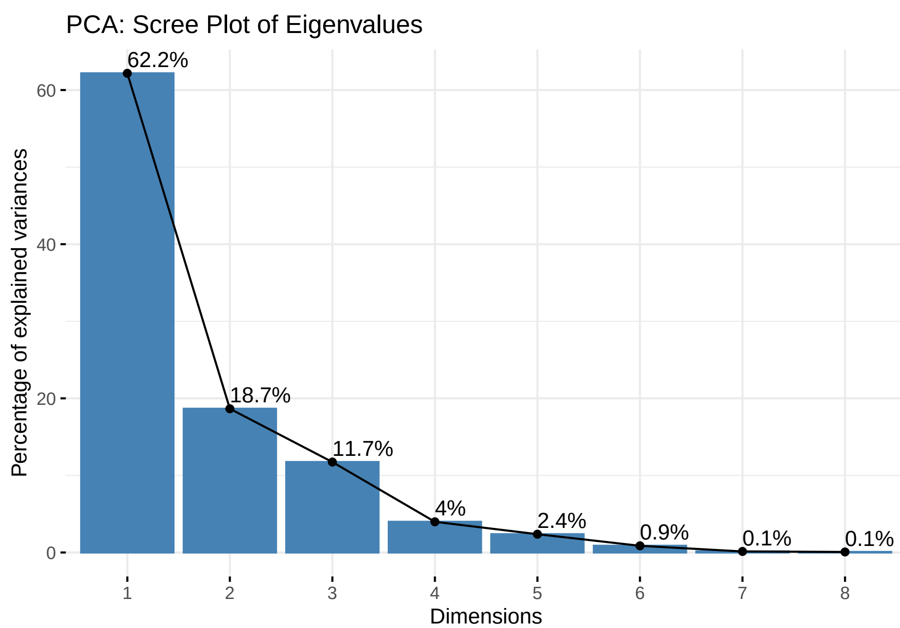
```
kaiser_num_axes = length(which(eigenvalues[1:8,1]>1))
# print the results
cat("Number of axes to interpret using Kaiser's rule:",
    kaiser_num_axes, "\n")
```

```
## Number of axes to interpret using Kaiser's rule: 2
```

According to Kaiser's rule, only 2 axes should be considered for the analysis.

```
#dev.off()  # Close any previous plot windows
#fviz_pca_biplot(pca_result, col.var = "contrib",
#                gradient.cols = c("#00AFBB", "#E7B800", "#FC4E07"),
                #show.points = TRUE, show.labels = FALSE, label.size = 0)
```

```r
# creates a scree plot that shows the proportion of
# variance explained by each axis.
fviz_eig(pca_result, addlabels = TRUE) +
  ggtitle("PCA: Scree Plot of Eigenvalues") +
  scale_shape_manual(values = c(16, 17, 15)) +
  scale_color_manual(values = c("#FFA500", "#008000", "#0000FF"))
```

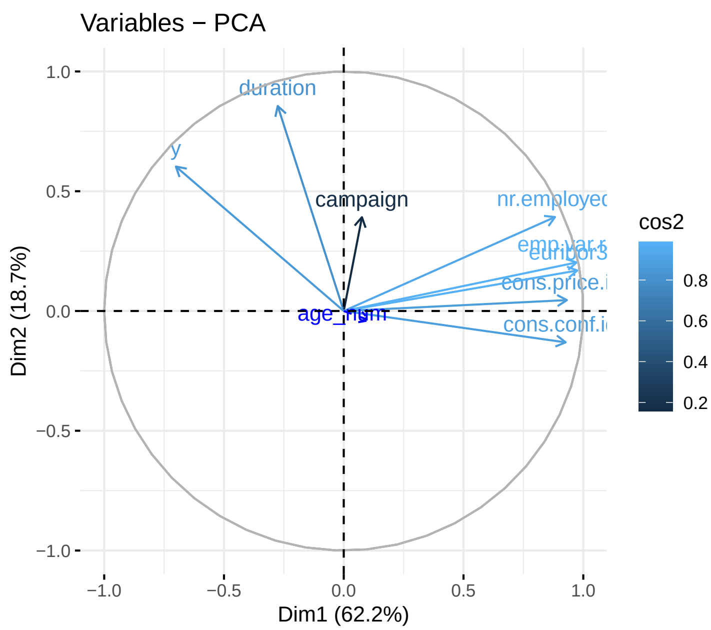


The scree plot created by fviz_eig() function shows the proportion of variance explained by each axis. The x-axis represents the axis number, and the y-axis represents the proportion of variance explained by that axis. In general, we want to retain as many axes as necessary to explain a reasonable proportion of the variance in the data. We can use Kaiser's rule or the elbow rule to determine the number of axes to retain.

It can be observed a significant change in slope from dimension 2 onward, which, according to the elbow rule, means that for this analysis we should consider only the first 2 dimensions.

Both rules suggest that only the first 2 axes are to be considered.

```r
# creates a correlation circle plot that shows the
# correlation between each variable and each axis.
fviz_pca_var(pca_result, col.var = "cos2", col.ind = "black")
```

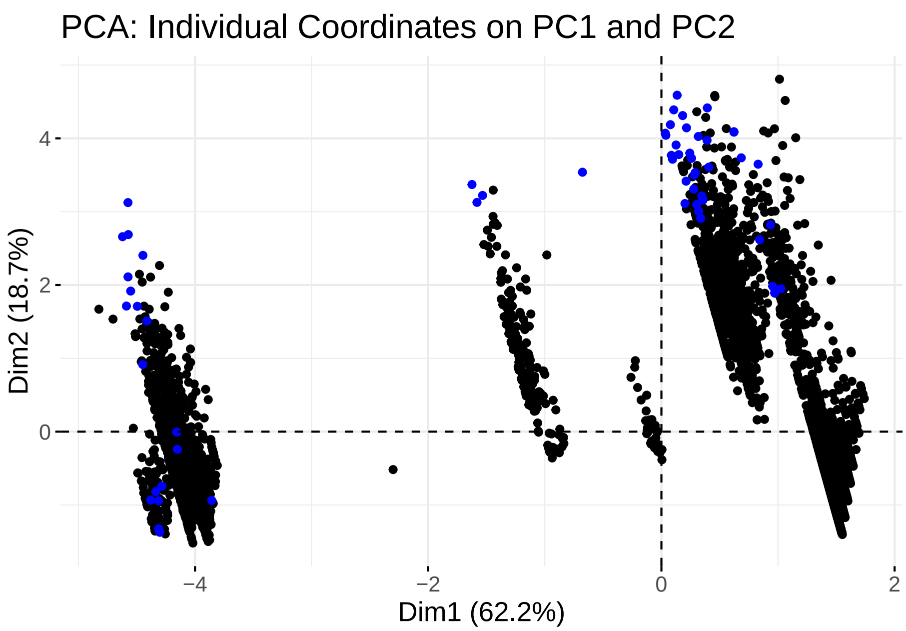


The correlation circle plot created by fviz_pca_var() function shows the correlation between each variable and each axis. The x-axis and y-axis represent the first two axes, and the location of each variable on the plot represents its correlation with those axes. The length of the vector for each variable represents the correlation between that variable and the origin (i.e., the center of the plot). The angle between the vectors represents the correlation between the two variables. We can use this plot to identify which variables are most strongly associated with each axis and which variables are strongly correlated with each other.

2. Individuals point of view

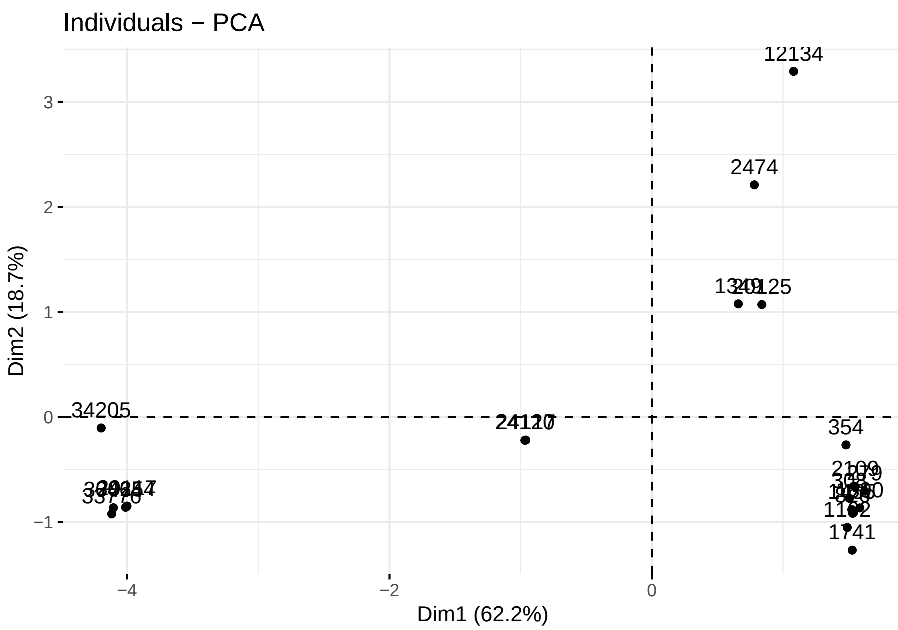
```
library(ggplot2)
# Extract the individual coordinates and squared distances
# from the PCA result
ind_coord <- get_pca_ind(pca_result)$coord
ind_dist <- get_pca_ind(pca_result)$cos2

# Plot the individual coordinates on the first two axes
fviz_pca_ind(pca_result, axes = 1:2, show.labels = FALSE,
             labelsize = 0) +
  ggtitle("PCA: Individual Coordinates on PC1 and PC2") +
  theme(text = element_text(size = 14)) +
```

```
  scale_shape_manual(values = c(16, 17, 15)) +
  scale_color_gradient2(low="darkslateblue", mid="white",
                        high="red", midpoint=0.5)
```



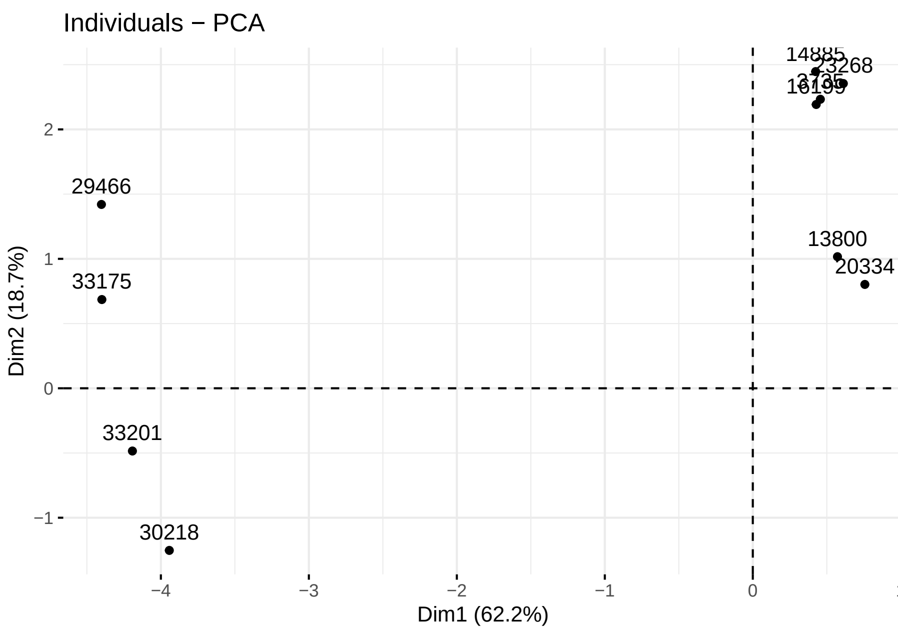
In dimension 1:

```
# Select the 100 most extreme individuals based on
# the first principal component
rang1 <- order(pca_result$ind$coord[, 1])
contrib.extremes1 <- c(row.names(df)[rang1[1:10]],
                      row.names(df)[rang1[
                        (length(rang1) - 9):length(rang1)]])

fviz_pca_ind(pca_result, select.ind = list(names=contrib.extremes1))
```



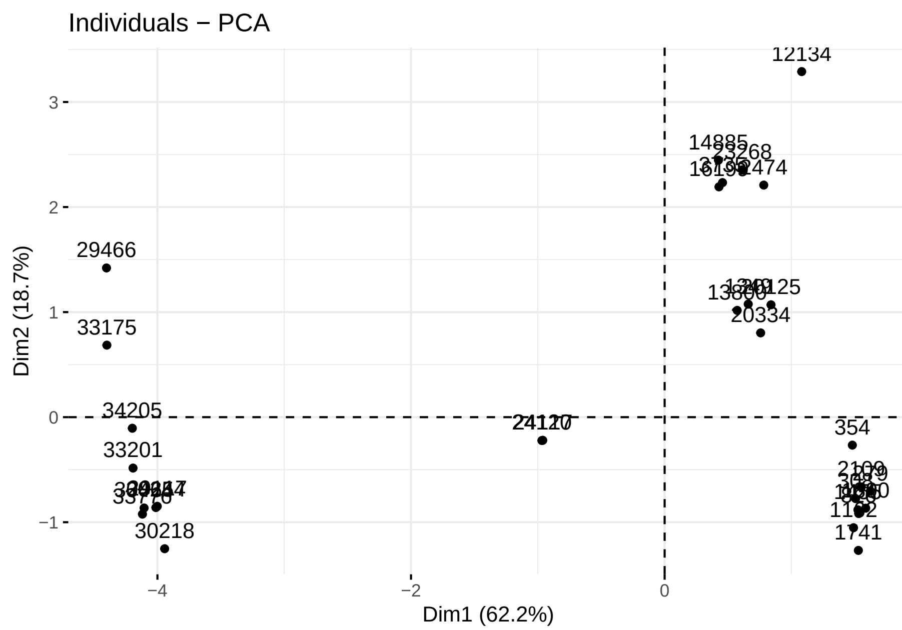
In dimension 2:

```
# Select the 10 most extreme individuals based on the
# second principal component
rang2 <- order(pca_result$ind$coord[, 2])
contrib.extremes2 <- row.names(df)[rang2[1:10]]
fviz_pca_ind(pca_result, select.ind = list(names=contrib.extremes2))
```



Between both dimensions:

```
# Combine the two sets of extreme individuals
contrib.extremes <- unique(c(contrib.extremes1, contrib.extremes2))

# Plot the extreme individuals
fviz_pca_ind(pca_result, select.ind = list(names = contrib.extremes))
```



We can now have a look at them:

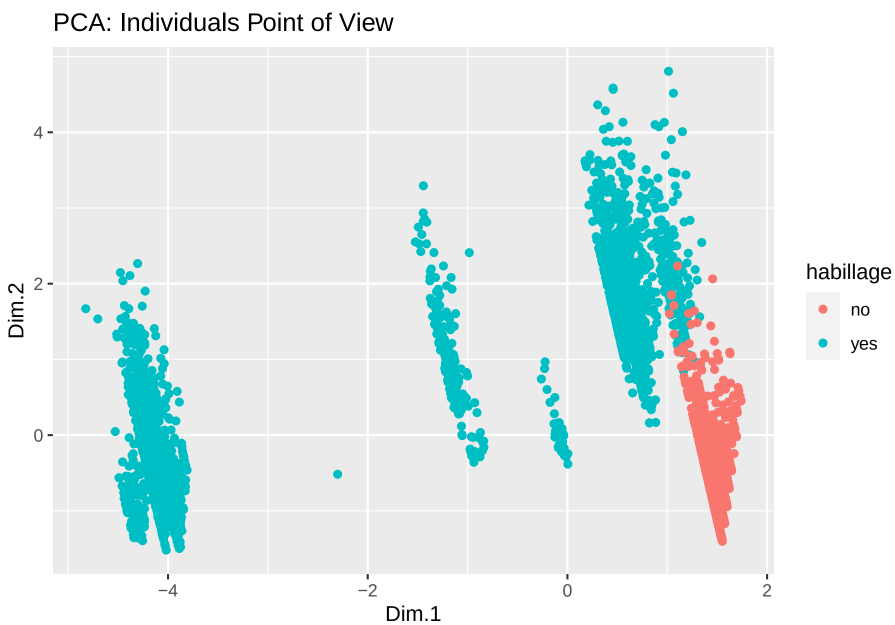
```
rang <- order(pca_result$ind$coord)
df[which(row.names(df) %in% row.names(df)[rang[length(rang)]]), 1:length(df)]
```

```
##  [1] age            job            marital        education      housing
##  [6] loan           contact        month          day_of_week    duration
## [11] campaign       previous       poutcome       emp.var.rate   cons.price.idx
## [16] cons.conf.idx  euribor3m      nr.employed    y              age_num
## [21] na_count       mout
## <0 rows> (or 0-length row.names)
```

```
df[which(row.names(df) %in% row.names(df)[rang[1]]),1:length(df)]
```

```
##               age        job marital           education housing loan   contact
## 24120 Jove-Adult technician  single professional.course     yes   no telephone
##       month day_of_week duration campaign previous    poutcome emp.var.rate
## 24120   nov         fri      160        1       No nonexistent         -0.1
##       cons.price.idx cons.conf.idx euribor3m nr.employed   y age_num na_count
## 24120           93.2           -42     4.223      5195.8 yes      35        0
##       mout
## 24120   No
```

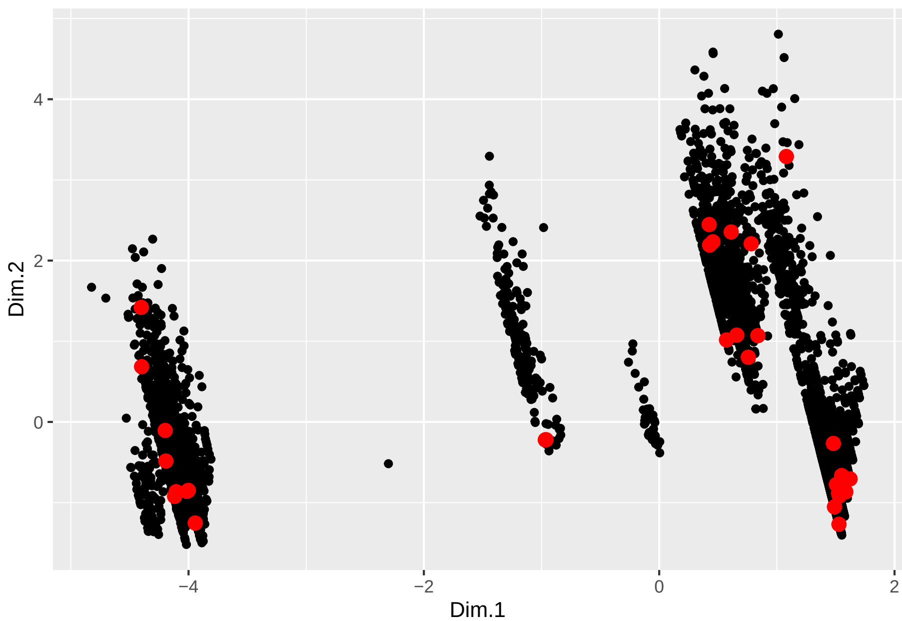
```r
# Create a factor variable for the color-coded target variable
habillage <- factor(df[-c(llmout),"y"])

# Plot the individuals with color-coded target variable
ggplot(data = data.frame(ind_coord, habillage),
       aes(x = Dim.1, y = Dim.2, color = habillage)) +
  geom_point() +
  ggtitle("PCA: Individuals Point of View")
```



- This plot shows the positions of the individuals in the first two principal components. Each individual is represented by a point, and the color of the point represents the value of the categorical target variable.
- The x-axis represents the first principal component, and the y-axis represents the second principal component. These two components together explain the most variance in the data.
- The plot can help identify patterns or clusters of individuals in the data. For example, if individuals with the same value of the target variable tend to cluster together, this could indicate a relationship between the target variable and the principal components.

As can be seen in the graphs, the groups of outliers from Dimension are relatively close to each other(forming clusters), but with a variety of isolated points in relation to the others. As for the Dimension 2 outliers, a single cluster of outliers is formed, and with a variety of isolated points all around.

```r
# Identify extreme individuals
extreme_ind <- ind_coord[which(row.names(ind_coord) %in% contrib.extremes), ]
# Plot the extreme individuals on the first two axes
ggplot(data = data.frame(ind_coord), aes(x = Dim.1, y = Dim.2)) +
  geom_point() +
  geom_point(data = data.frame(extreme_ind), color = "red", size = 3)
```




```r
  ggtitle("Extreme Individuals")
```

```
## $title
## [1] "Extreme Individuals"
##
## attr(,"class")
## [1] "labels"
```

- This plot shows the positions of the extreme individuals on the first two principal components. Each extreme individual is represented by a red point, and the non-extreme individuals are represented by black points.
- The plot can help identify individuals that are outliers in the data or have extreme values on one or more of the principal components. These individuals may have a large influence on the PCA results and should be examined further to understand their characteristics and potential impact on the analysis.

3. Interpreting the axes: Variables point of view

The variance plot and contribution plot created by fviz_contrib() function show the contribution of each variable to each axis. In the variance plot, the x-axis represents the axis number, and the y-axis represents the contribution of each variable to that axis. In the contribution plot, the x-axis represents the variable name, and the y-axis represents the contribution of each variable to each axis. The contribution of each variable to each axis is measured by the squared correlation between the variable and the axis. We can use these plots to identify the variables that are most strongly associated with each axis.

```
round(cbind(pca_result$var$coord[,1:2],
            pca_result$var$cos2[,1:2],pca_result$var$contrib[,1:2]),2)
```

```
##                 Dim.1 Dim.2 Dim.1 Dim.2 Dim.1 Dim.2
## duration        -0.28  0.86  0.08  0.73  1.53 49.09
## campaign         0.08  0.39  0.01  0.15  0.12 10.28
## emp.var.rate     0.97  0.20  0.94  0.04 18.99  2.75
## cons.price.idx   0.93  0.05  0.87  0.00 17.46  0.14
## cons.conf.idx    0.93 -0.13  0.86  0.02 17.26  1.15
## euribor3m        0.98  0.17  0.95  0.03 19.13  1.92
## nr.employed      0.88  0.39  0.78  0.15 15.64 10.31
## y               -0.70  0.60  0.49  0.36  9.88 24.37
```

```
round(cbind(pca_result$var$cos2[,1:2],pca_result$var$contrib[,1:2]),2)
```

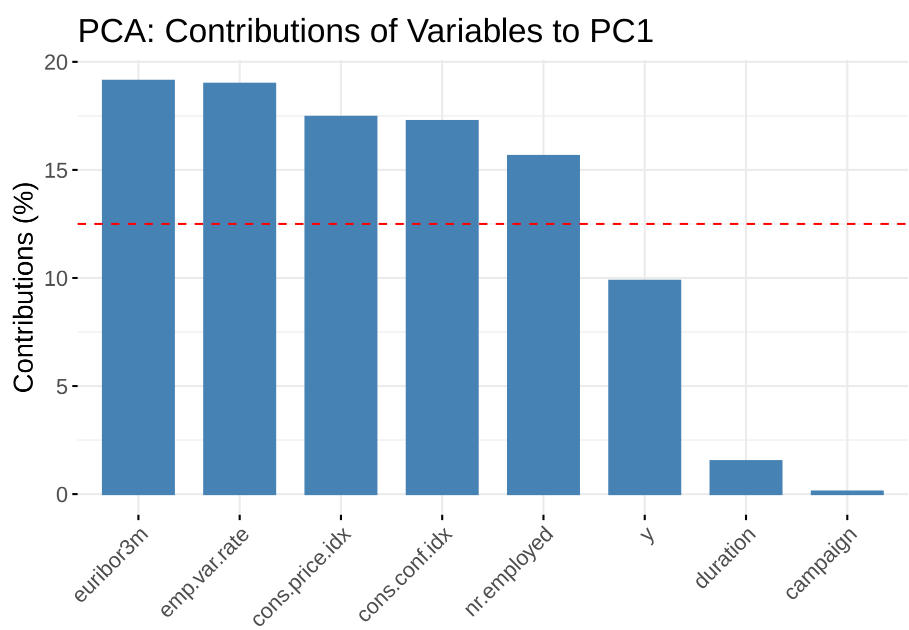
```
##                 Dim.1 Dim.2 Dim.1 Dim.2
## duration         0.08  0.73  1.53 49.09
## campaign         0.01  0.15  0.12 10.28
## emp.var.rate     0.94  0.04 18.99  2.75
## cons.price.idx   0.87  0.00 17.46  0.14
## cons.conf.idx    0.86  0.02 17.26  1.15
## euribor3m        0.95  0.03 19.13  1.92
## nr.employed      0.78  0.15 15.64 10.31
## y                0.49  0.36  9.88 24.37
```

```
# dimdes easies this description from the variables
dimdesc_result<-dimdesc(pca_result)
###

# Print the dimension description results
print(dimdesc_result$Dim.1)
```

```
##
```

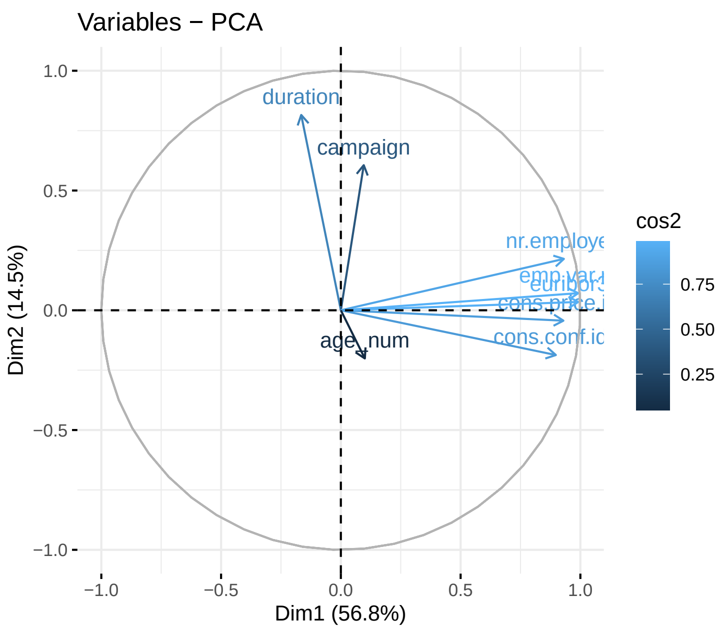
```
## Link between the variable and the continuous variables (R-square)
## =================================================================================
##                 correlation      p.value
## euribor3m        0.97529121 0.000000e+00
## emp.var.rate     0.97184563 0.000000e+00
## cons.price.idx   0.93185862 0.000000e+00
## cons.conf.idx    0.92652247 0.000000e+00
## nr.employed      0.88208006 0.000000e+00
## age_num          0.10632665 6.755390e-14
## campaign         0.07593983 9.101419e-08
## duration        -0.27570140 6.993054e-87
## y               -0.70084769 0.000000e+00
```

```r
# creates a variance plot that shows the contribution
# of each variable to each axis, and a contribution plot
# that shows the most contributing variables to each axis.
fviz_contrib(pca_result, choice = "var", axes = 1) +
  ggtitle("PCA: Contributions of Variables to PC1") +
  theme(text = element_text(size = 14)) +
  scale_shape_manual(values = c(16, 17, 15)) +
  scale_color_manual(values = c("#FFA500", "#008000", "#0000FF"))
```

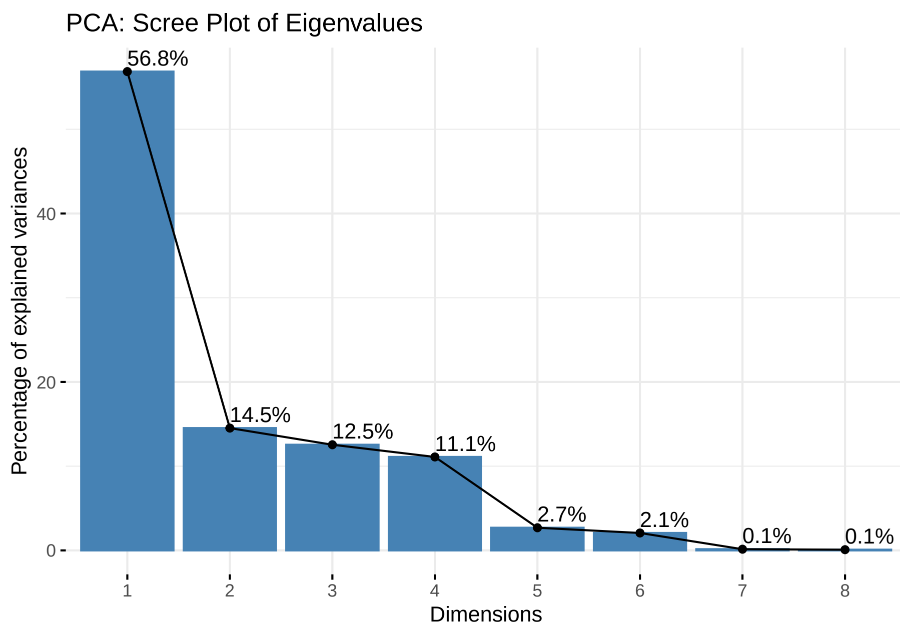


4. Perform a PCA taking into account also supplementary variables

```
temp_cont = c("duration","campaign","emp.var.rate",
              "cons.price.idx","cons.conf.idx",
              "euribor3m","nr.employed","age_num")
temp_dis = var_dis[2:11]
pca_result2 = PCA(df[,c(temp_dis, var_res, temp_cont)],
                  quali.sup = 1:11, graph = FALSE)
fviz_pca_var(pca_result2, col.var = "cos2", col.ind = "black")
```




```
fviz_eig(pca_result2, addlabels = TRUE) +
  ggtitle("PCA: Scree Plot of Eigenvalues") +
  scale_shape_manual(values = c(16, 17, 15)) +
  scale_color_manual(values = c("#FFA500", "#008000", "#0000FF"))
```



As it can be observed, there is a slight change in the weight of contributions from different dimensions, as well as from some variables, as subtly appreciated in the first plot. Throughout the process, various tests were performed, such as modifying the way the 'y' variable is presented, such as passing it as a supplementary continuous (boolean) variable instead of a categorical one, resulting in some changes, although not very significant. In conclusion, there have been changes in the weights, although not significant enough to significantly alter the workflow dynamics.

Clustering PCA

K-Means classification

```
prc<-pca_result$ind$coord[,1:2] # 3 components principals (kaiser)
dim(prc)
```

```
## [1] 4940    2
```

Classification

```r
# coordenates are real - Euclidean metric
dist<-dist(prc)
#caclulate the distances, it turns into a matrix
kc<-kmeans(dist, 5, iter.max=30, trace=TRUE)
```

```
## KMNS(*, k=5): iter=  1, indx=8
##  QTRAN(): istep=4940, icoun=6
##  QTRAN(): istep=9880, icoun=12
##  QTRAN(): istep=14820, icoun=4
##  QTRAN(): istep=19760, icoun=22
##  QTRAN(): istep=24700, icoun=175
##  QTRAN(): istep=29640, icoun=1941
##  QTRAN(): istep=34580, icoun=1597
##  QTRAN(): istep=39520, icoun=2611
##  QTRAN(): istep=44460, icoun=2640
##  QTRAN(): istep=49400, icoun=4426
## KMNS(*, k=5): iter=  2, indx=3
##  QTRAN(): istep=4940, icoun=10
##  QTRAN(): istep=9880, icoun=38
##  QTRAN(): istep=14820, icoun=62
##  QTRAN(): istep=19760, icoun=2
##  QTRAN(): istep=24700, icoun=18
##  QTRAN(): istep=29640, icoun=20
##  QTRAN(): istep=34580, icoun=297
##  QTRAN(): istep=39520, icoun=44
##  QTRAN(): istep=44460, icoun=1196
## KMNS(*, k=5): iter=  3, indx=4940
```

We see from the output that in 3 iterations it has converged. We now procceed to save in the data frame the number of clusters.

```r
df$claKM = df_numeric$claKM

df_numeric <- df_numeric[-c(llmout),]

df_numeric$claKM<-0
df_numeric$claKM<-kc$cluster
df_numeric$claKM<-factor(df_numeric$claKM)

dim(df_numeric)
```

```
## [1] 4940   10
```

```r
cat.res <-catdes(df_numeric,grep("^claKM$", colnames(df_numeric)))
```

The output shows the results of a cluster analysis based on the K-means algorithm. The analysis was carried out using eight quantitative variables and a categorical variable 'y' representing whether or not the client subscribed to a product.

The first table shows the Eta squared value and p-value for each variable in relation to the cluster variable. The Eta squared value indicates the proportion of variance explained by the cluster variable, and the p-value indicates the statistical significance of the relationship between the variables. The link between the cluster variable and the quantitative variables shows that all the variables have a strong association with the cluster variable, with eta2 values ranging from 0.012 to 0.989. This suggests that the clustering analysis is effective in capturing the differences between the clusters.

The second table provides a detailed description of each cluster based on the quantitative variables. The analysis resulted in five distinct clusters.

Cluster 1: This group of customers represents a large proportion of the data set, with the highest contributions in all variables except for age_num and campaign. They have longer duration of calls, higher number of contacts, and have subscribed to the product, suggesting that they are more likely to become loyal customers. They are also sensitive to changes in economic factors such as employment variation rate, consumer price index, and euribor3m.

Cluster 2: This cluster consists of customers who are not very responsive to marketing campaigns, as they have a lower number of contacts and subscribe to the product less frequently. However, they are highly sensitive to changes in economic factors such as consumer confidence index, consumer price index, euribor3m, employment variation rate, and number of employees. This suggests that they might be highly influenced by external economic factors.

Cluster 3: This group of customers are highly responsive to marketing campaigns, with the highest number of contacts and subscriptions. They are also highly sensitive to changes in economic factors such as euribor3m, employment variation rate, and number of employees. This suggests that they are more likely to be early adopters and respond positively to new product launches.

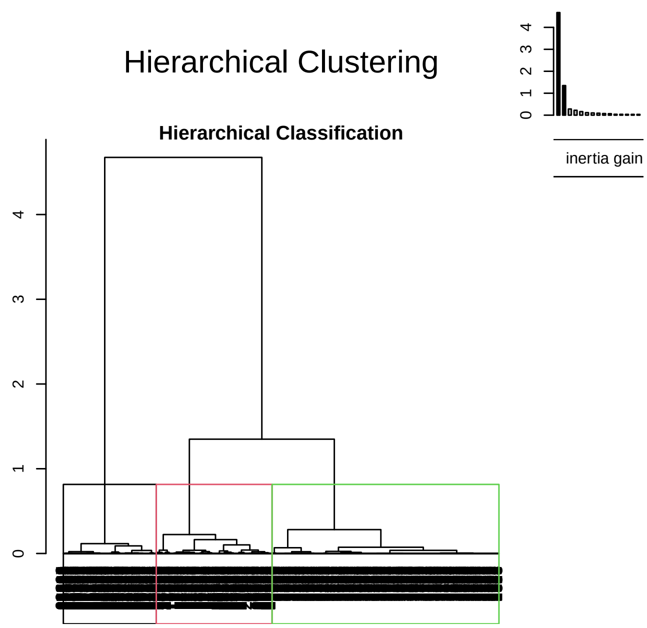
Cluster 4: This cluster consists of customers who are highly sensitive to changes in consumer price index, consumer confidence index, number of employees, employment variation rate, and euribor3m. They have a higher number of contacts and have subscribed to the product, but their duration of calls is lower than that of cluster 1.

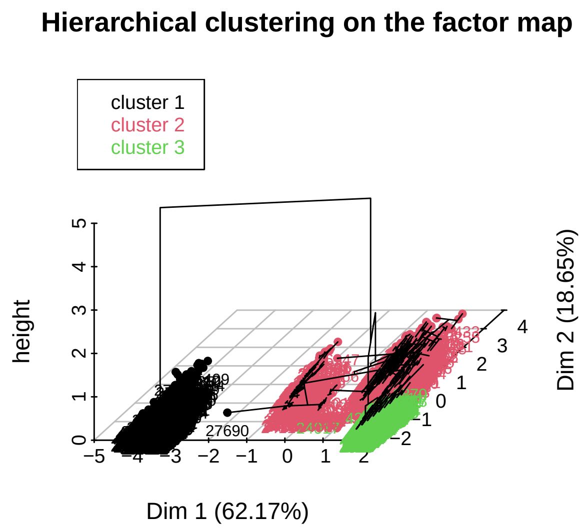
Cluster 5: This group of customers are less likely to subscribe to the product, but they are highly sensitive to changes in economic factors such as number of employees, employment variation rate, euribor3m, and consumer price index.

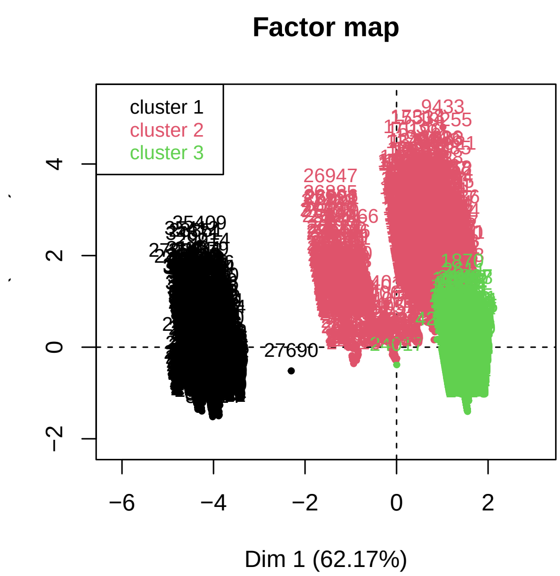
They also have a higher duration of calls and number of contacts, suggesting that they might be interested in the product but have not yet been convinced to subscribe.

Hierarchical clustering

```
# Perform hierarchical clustering on the first two principal components
#hclust_result <- hclust(dist(pca_result$ind$coord[, 1:2]))

# Visualize the results using a dendrogram
#fviz_dend(hclust_result, cex = 0.5, k = 2)

# Cut the dendrogram into three clusters
#cut_result <- cutree(hclust_result, k = w)

# Describe the clusters
#summary(cut_result)

res.hcpc <- HCPC(pca_result,nb.clust = -1, order = TRUE)
```





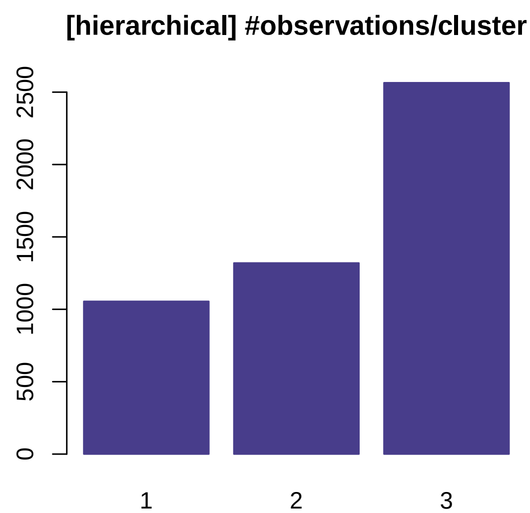



```
table(res.hcpc$data.clust$clust)
```

```
##
##      1      2      3
```

```
## 1055 1320 2565
```

```r
barplot(table(res.hcpc$data.clust$clust),
        col="darkslateblue", border="darkslateblue",
        main="[hierarchical] #observations/cluster")
```




```r
  # categorical variables which characterizes the clusters
```

```r
res.hcpc$desc.var$quanti.var     # description of each cluster by the categories
```

```
##                     Eta2      P-value
## duration       0.48037755 0.000000e+00
## emp.var.rate   0.94469043 0.000000e+00
## cons.price.idx 0.79574759 0.000000e+00
## cons.conf.idx  0.86711351 0.000000e+00
## euribor3m      0.98754043 0.000000e+00
## nr.employed    0.95914529 0.000000e+00
## y              0.98239602 0.000000e+00
## campaign       0.01561385 1.345944e-17
## age_num        0.01355134 2.359805e-15
```

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

```
## $`1`
##                   v.test Mean in category Overall mean sd in category
## y              38.338282         1.000000    0.4771255     0.00000000
## duration        8.866357       537.192355  451.5148423   329.95927318
## campaign       -4.762643         1.882851    2.0659116     1.23327956
## age_num        -6.479975        38.331754   40.0534413    11.74491465
## cons.conf.idx  -61.197160       -46.999242  -39.5948381     1.14605418
## cons.price.idx -61.496214        92.963010   93.7237951     0.09580868
## nr.employed    -66.750380      5099.173175 5177.9568016     2.37566471
## emp.var.rate   -68.306030        -1.798483    0.4769231     0.04923657
## euribor3m      -69.834889         1.379672    4.1040802     0.13067118
##                Overall sd      p.value
## y               0.4994765 0.000000e+00
## duration      353.8929338 7.557823e-19
## campaign        1.4076541 1.910738e-06
## age_num         9.7304136 9.173795e-11
## cons.conf.idx   4.4310744 0.000000e+00
## cons.price.idx  0.4530683 0.000000e+00
## nr.employed    43.2247469 0.000000e+00
## emp.var.rate    1.2199729 0.000000e+00
## euribor3m       1.4287293 0.000000e+00
##
## $`2`
##                  v.test Mean in category Overall mean sd in category
## y              43.138393        0.9848485    0.4771255      0.1221554
## duration       42.672278      807.3636565  451.5148423    319.4681962
## nr.employed    36.933342     5215.5750758 5177.9568016     16.7671936
## euribor3m      21.271137        4.8202045    4.1040802      0.2855248
## emp.var.rate   21.176161        1.0856818    0.4769231      0.5523088
## campaign        8.501825        2.3479160    2.0659116      1.6933763
## cons.price.idx  7.787766       93.8069379   93.7237951      0.3867083
## age_num        -2.701203       39.4340909   40.0534413      9.2679092
## cons.conf.idx  -2.750672      -39.8820455  -39.5948381      2.9500288
##                Overall sd       p.value
## y               0.4994765  0.000000e+00
## duration      353.8929338  0.000000e+00
## nr.employed    43.2247469 1.348324e-298
## euribor3m       1.4287293 2.101252e-100
## emp.var.rate    1.2199729  1.584309e-99
## campaign        1.4076541  1.866331e-17
## cons.price.idx  0.4530683  6.820447e-15
## age_num         9.7304136  6.908905e-03
## cons.conf.idx   4.4310744  5.947320e-03
```

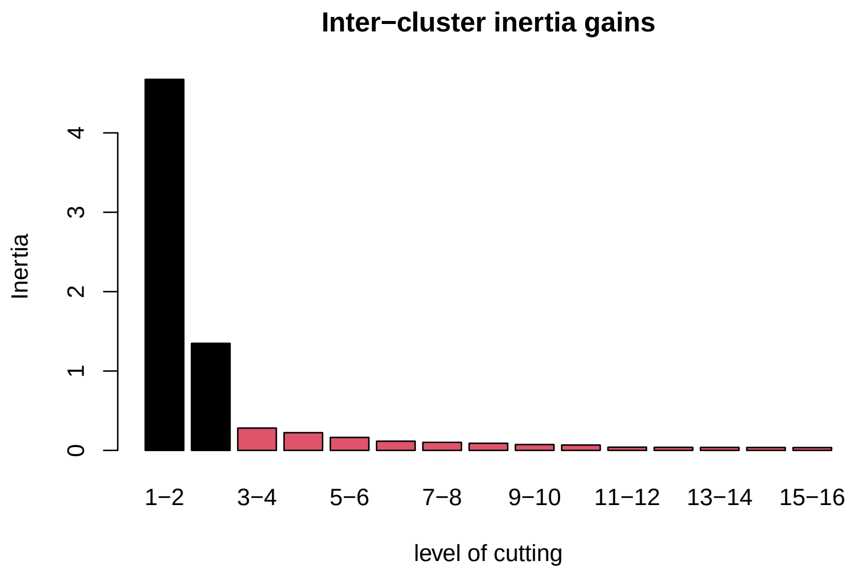
```
##
## $`3`
##                     v.test Mean in category Overall mean sd in category
## cons.conf.idx   52.633125    -3.640156e+01  -39.5948381   7.896445e-02
## cons.price.idx  43.544978     9.399392e+01   93.7237951   3.869258e-03
## euribor3m       38.443129     4.856114e+00    4.1040802   2.362042e-03
## emp.var.rate    37.273199     1.099532e+00    0.4769231   2.368934e-02
## nr.employed     22.041713     5.191002e+03 5177.9568016   9.475734e-02
## age_num          7.707540     4.108031e+01   40.0534413   8.884695e+00
## campaign        -3.623146     1.996080e+00    2.0659116   1.286602e+00
## duration       -45.065648     2.331483e+02  451.5148423   1.674289e+02
## y              -69.652814     7.797271e-04    0.4771255   2.791271e-02
##                 Overall sd       p.value
## cons.conf.idx    4.4310744  0.000000e+00
## cons.price.idx   0.4530683  0.000000e+00
## euribor3m        1.4287293  0.000000e+00
## emp.var.rate     1.2199729 4.461163e-304
## nr.employed     43.2247469 1.147149e-107
## age_num          9.7304136  1.282658e-14
## campaign         1.4076541  2.910411e-04
## duration       353.8929338  0.000000e+00
## y                0.4994765  0.000000e+00
```

Per a relitzar la descripció dels grups d'individus, hem de realitzar una agrupació jeràrquica dels components principals (HCPC).

Agafem 3 clusters, ja que són els que ens indica el propi HCPC que hem d'incloure degut a la inèrcia acumulada d'aquests.

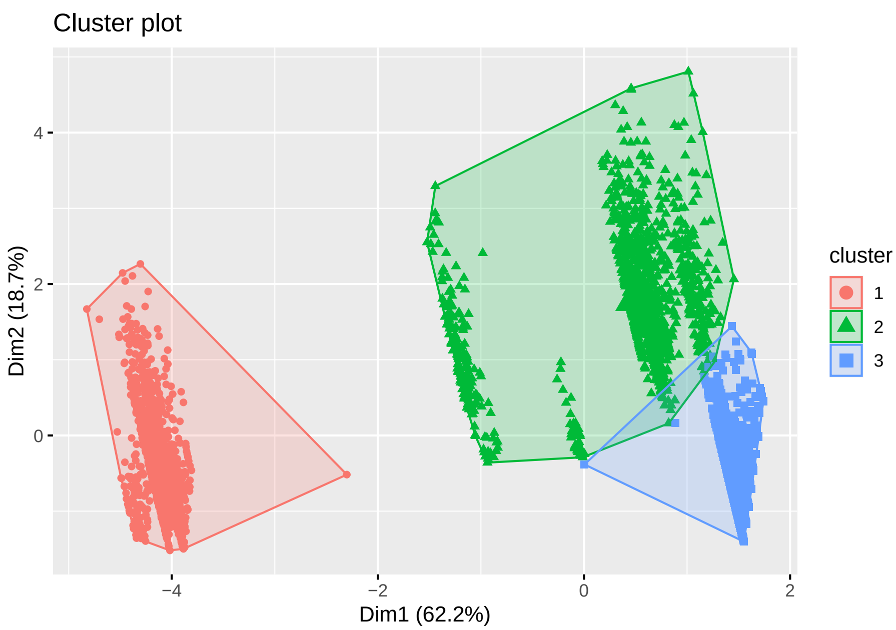
A la següent gràfica es pot veure les inèrcies per cada parella de clusters. Veiem que les més significatives són de la 1 a la 2 i en menor mesura la 3 (les que ens recomanava agafar el HCPC).

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



A continuació imprimirem en un factor map tots els individus agrupats amb els diferents clusters que tenim. Podem veure com el cluster 1 esta completament difgerenciat de la resta, i el cluster 2 està disper i te punts desviats que provoquen que abarquin molta superfície sense individus.

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



A continuació durem a terme la descripció de clusters envers les variables i categories més rellevants en ells.

Primer de tot veiem les variables més relacionades amb tots els clusters:

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

```
##
## Link between the cluster variable and the quantitative variables
## ================================================================
##                     Eta2      P-value
## duration       0.48037755 0.000000e+00
## emp.var.rate   0.94469043 0.000000e+00
## cons.price.idx 0.79574759 0.000000e+00
## cons.conf.idx  0.86711351 0.000000e+00
## euribor3m      0.98754043 0.000000e+00
## nr.employed    0.95914529 0.000000e+00
## y              0.98239602 0.000000e+00
## campaign       0.01561385 1.345944e-17
## age_num        0.01355134 2.359805e-15
##
## Description of each cluster by quantitative variables
## =====================================================
## $`1`
##                   v.test Mean in category Overall mean sd in category
```

```
## y               38.338282         1.000000    0.4771255     0.00000000
## duration         8.866357       537.192355  451.5148423   329.95927318
## campaign        -4.762643         1.882851    2.0659116     1.23327956
## age_num         -6.479975        38.331754   40.0534413    11.74491465
## cons.conf.idx  -61.197160       -46.999242  -39.5948381     1.14605418
## cons.price.idx -61.496214        92.963010   93.7237951     0.09580868
## nr.employed    -66.750380      5099.173175 5177.9568016     2.37566471
## emp.var.rate   -68.306030        -1.798483    0.4769231     0.04923657
## euribor3m      -69.834889         1.379672    4.1040802     0.13067118
##                 Overall sd      p.value
## y                0.4994765 0.000000e+00
## duration       353.8929338 7.557823e-19
## campaign         1.4076541 1.910738e-06
## age_num          9.7304136 9.173795e-11
## cons.conf.idx    4.4310744 0.000000e+00
## cons.price.idx   0.4530683 0.000000e+00
## nr.employed     43.2247469 0.000000e+00
## emp.var.rate     1.2199729 0.000000e+00
## euribor3m        1.4287293 0.000000e+00
##
## $`2`
##                   v.test Mean in category Overall mean sd in category
## y              43.138393        0.9848485    0.4771255      0.1221554
## duration       42.672278      807.3636565  451.5148423    319.4681962
## nr.employed    36.933342     5215.5750758 5177.9568016     16.7671936
## euribor3m      21.271137        4.8202045    4.1040802      0.2855248
## emp.var.rate   21.176161        1.0856818    0.4769231      0.5523088
## campaign        8.501825        2.3479160    2.0659116      1.6933763
## cons.price.idx  7.787766       93.8069379   93.7237951      0.3867083
## age_num        -2.701203       39.4340909   40.0534413      9.2679092
## cons.conf.idx  -2.750672      -39.8820455  -39.5948381      2.9500288
##                 Overall sd       p.value
## y                0.4994765  0.000000e+00
## duration       353.8929338  0.000000e+00
## nr.employed     43.2247469 1.348324e-298
## euribor3m        1.4287293 2.101252e-100
## emp.var.rate     1.2199729  1.584309e-99
## campaign         1.4076541  1.866331e-17
## cons.price.idx   0.4530683  6.820447e-15
## age_num          9.7304136  6.908905e-03
## cons.conf.idx    4.4310744  5.947320e-03
##
## $`3`
##                   v.test Mean in category Overall mean sd in category
## cons.conf.idx  52.633125    -3.640156e+01  -39.5948381   7.896445e-02
## cons.price.idx 43.544978     9.399392e+01   93.7237951   3.869258e-03
```

```
## euribor3m       38.443129     4.856114e+00    4.1040802   2.362042e-03
## emp.var.rate    37.273199     1.099532e+00    0.4769231   2.368934e-02
## nr.employed     22.041713     5.191002e+03 5177.9568016   9.475734e-02
## age_num          7.707540     4.108031e+01   40.0534413   8.884695e+00
## campaign        -3.623146     1.996080e+00    2.0659116   1.286602e+00
## duration       -45.065648     2.331483e+02  451.5148423   1.674289e+02
## y              -69.652814     7.797271e-04    0.4771255   2.791271e-02
##                 Overall sd       p.value
## cons.conf.idx    4.4310744  0.000000e+00
## cons.price.idx   0.4530683  0.000000e+00
## euribor3m        1.4287293  0.000000e+00
## emp.var.rate     1.2199729 4.461163e-304
## nr.employed     43.2247469 1.147149e-107
## age_num          9.7304136  1.282658e-14
## campaign         1.4076541  2.910411e-04
## duration       353.8929338  0.000000e+00
## y                0.4994765  0.000000e+00
```

The analysis is based on a cluster analysis and its description in terms of quantitative variables. In this case, eight variables have been used for the analysis. The table describes the link between the cluster variable and the quantitative variables, followed by the description of each cluster individually.

The variable "y" (customer subscription to the product) has a very strong relationship with the cluster variables in all three groups, with an Eta2 relationship of 98%, 98%, and 98% respectively. This indicates that customer subscription is an important factor in the separation of clusters.

Cluster 1 is described by a high level of call duration, a low number of campaigns, high consumer confidence, a low consumer price index, low consumer confidence index, and a low number of employees and employment rate variation. This group represents a small proportion of customers but stands out for its high call duration, which may indicate high-quality interaction between the customer and the company.

Cluster 2 is characterized by an extremely high call duration, a high employment rate, high employment rate variation, high euribor value, and positive employment rate variation. This group also has a high product subscription rate, indicating that this group is an attractive target for advertising campaigns.

Cluster 3 is described by low call duration, low product subscription rate, high consumer confidence index, high consumer price index, and high number of employees. This group represents the majority of customers. The low call duration and low number of subscriptions may suggest that this group is less receptive to advertising campaigns, although their high consumer confidence may be an opportunity for brand building and customer loyalty.

Anàlisis CA

Transformació de la variable duration

```
df$duration_fact <- cut(df$duration,
              breaks = c(0, 10, 30, 60, 300, 900, 1800, max(df$duration)),
              labels = c("extr.curt", "molt.curta", "curta",
                         "normal", "llarga", "molt.llarga", "extr.llarga"))
df$duration_fact <- as.factor(df$duration_fact)

summary(df$duration_fact)
```

```
##   extr.curt  molt.curta       curta      normal      llarga molt.llarga
##           8          59         124        2128        2001         652
## extr.llarga
##          28
```

Eigenvalues and dominant axes analysis

Realitzarem l'anàlisis per la target (duration_fact) i per les variables categòriques job i education

Duration_fact - job Realitzem la taula que relaciona les dues variables i fem l'anàlisis de correspondència (CA).

```
tab1 <- table(df[,c("duration_fact", "job")])
tab1
```

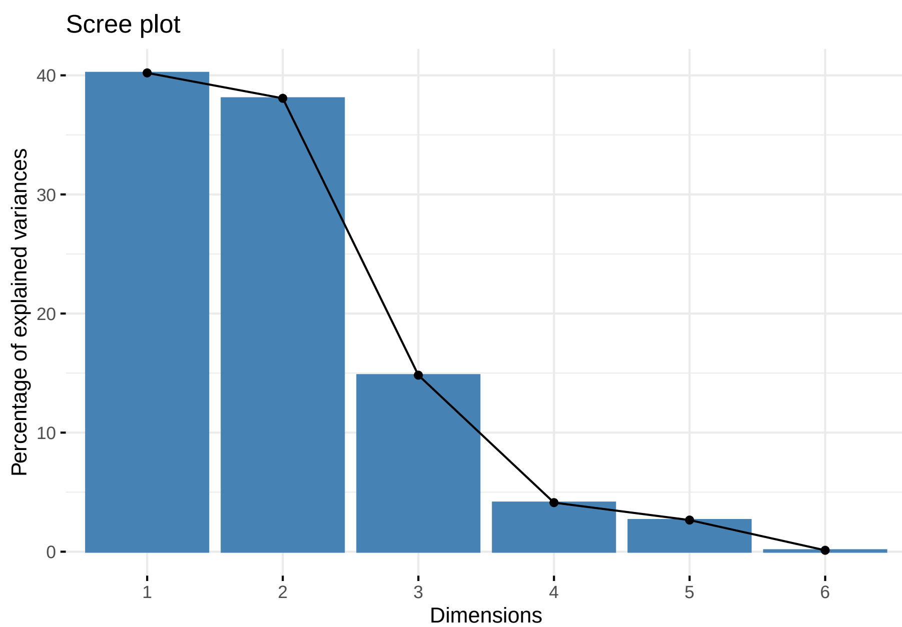
```
##              job
## duration_fact admin. blue-collar management self-employed services technician
##   extr.curt        3           3          1             0        0          1
##   molt.curta      14          22          5             1        6          6
##   curta           25          44          5             9       11         18
##   normal         468         549        168           143      227        317
##   llarga         488         492        151           145      220        313
##   molt.llarga    166         171         48            52       65         95
##   extr.llarga      5          11          1             2        1          6
##              job
## duration_fact unemployed
##   extr.curt            0
##   molt.curta           5
##   curta               12
```

```
##    normal              256
##    llarga              192
##    molt.llarga          55
##    extr.llarga           2
```

```
res.ca1 <- CA(tab1, graph = F)
```

Seguidament triarem les dimensions que hem d'agafar, gràficament i a partir dels eigenvalues.

```
fviz_eig(res.ca1)
```




```
mm <- mean(res.ca1$eig[,1])
ll<- which(as.data.frame(res.ca1$eig[,1])>mm)
length(ll) #Número dimensions
```

```
## [1] 2
```

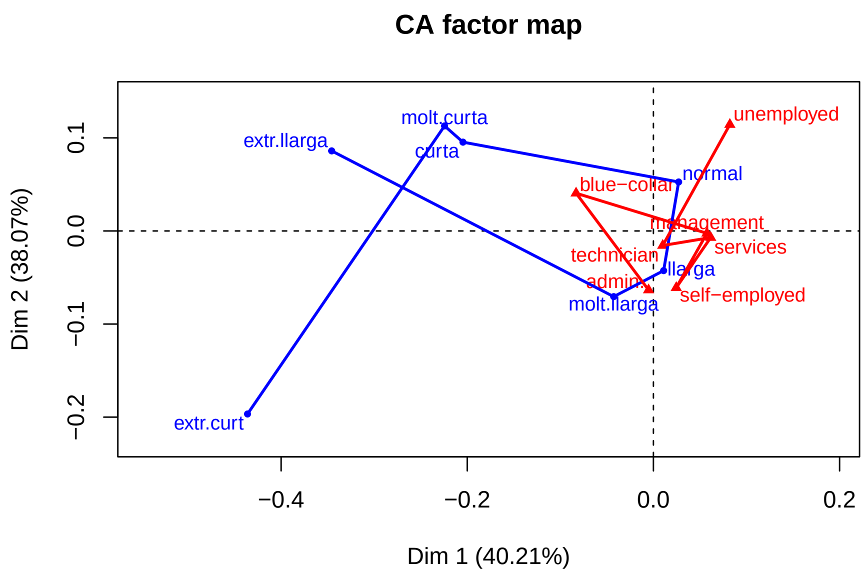
```
res.ca1$eig[length(ll),3]
```

```
## [1] 78.27887
```

Gràficament, per la regla del colze, veiem que la dimensió on hi ha un canvi important de la corva és la 2. A més, per Kaiser, agafem totes les dimensions amb els eigenvalues els quals superin la mitjana de tots els eigenvalues, i també ens surten dues dimensions.

Amb dues dimensions representem un 78.2788744%, un percentatge prou considerable.

```
plot( res.ca1, cex=0.8, graph.type = "classic" )
lines( res.ca1$row$coord[,1], res.ca1$row$coord[,2], col="blue", lwd = 2 )
lines( res.ca1$col$coord[,1], res.ca1$col$coord[,2], col="red", lwd = 2 )
```



Tal i com podem veure a la gràfica, hi ha diverses categories amb valors molt similars, que, per tant, podriem considerar-les com a una sola. Per exemple la duration_fact curta i molt.curta tenen quasibé el mateix valor, la resta de categories tenen prou discrepància. Mencionar que en la variable job, tenim dues altres categories amb valors molt similars, que són services i self-employed.

Podem observar que les feines amb posicions superiors tendeixen a estar més estona a la trucada, mentres que els unemployed estan totalment separats.

Duration_fact - Education Igual que amb la parella anterior, realitzem la taula que relaciona les dues variables i fem l'anàlisis de correspondència (CA).

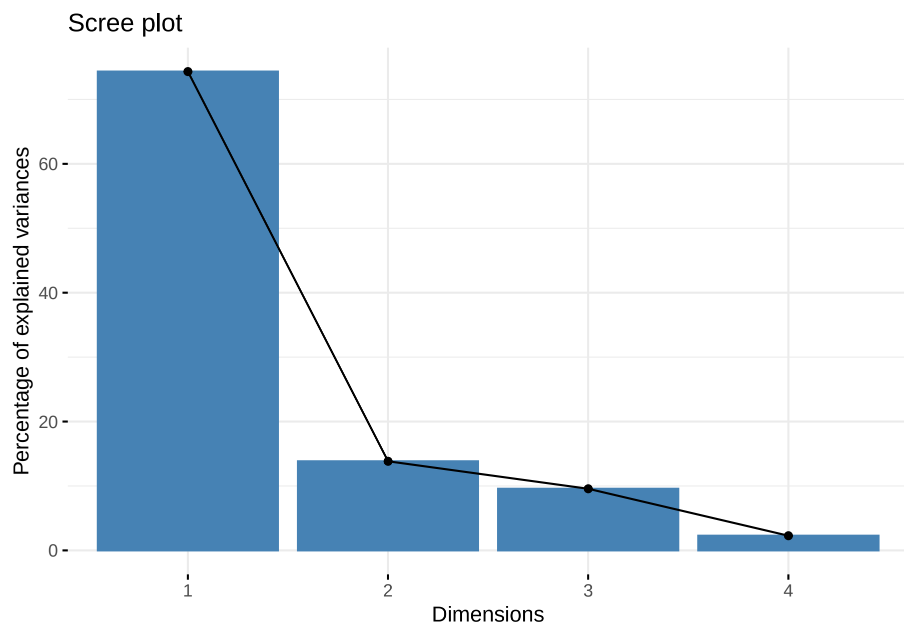
```r
df$education <- factor(df$education, levels = c( "illiterate", "basic",
                                                  "high.school",
                                                  "professional.course",
                                                  "university.degree"))
tab2 <- table(df[,c("duration_fact", "education")])
tab2
```

```
##              education
## duration_fact illiterate basic high.school professional.course
##   extr.curt            0     4           1                   1
##   molt.curta           0    26          16                   5
##   curta                0    57          26                  15
##   normal               0   769         529                 283
##   llarga               2   669         475                 250
##   molt.llarga          0   230         159                  73
##   extr.llarga          0    12           6                   5
##              education
## duration_fact university.degree
##   extr.curt                   2
##   molt.curta                 12
##   curta                      26
##   normal                    547
##   llarga                    605
##   molt.llarga               190
##   extr.llarga                 5
```

```r
res.ca2 <- CA(tab2, graph = F)
```

Seguidament triarem les dimensions que hem d'agafar, gràficament i a partir dels eigenvalues.

```r
fviz_eig(res.ca2)
```




```r
mm <- mean(res.ca2$eig[,1])
ll<- which(as.data.frame(res.ca2$eig[,1])>mm)
length(ll) #Número dimensions
```

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

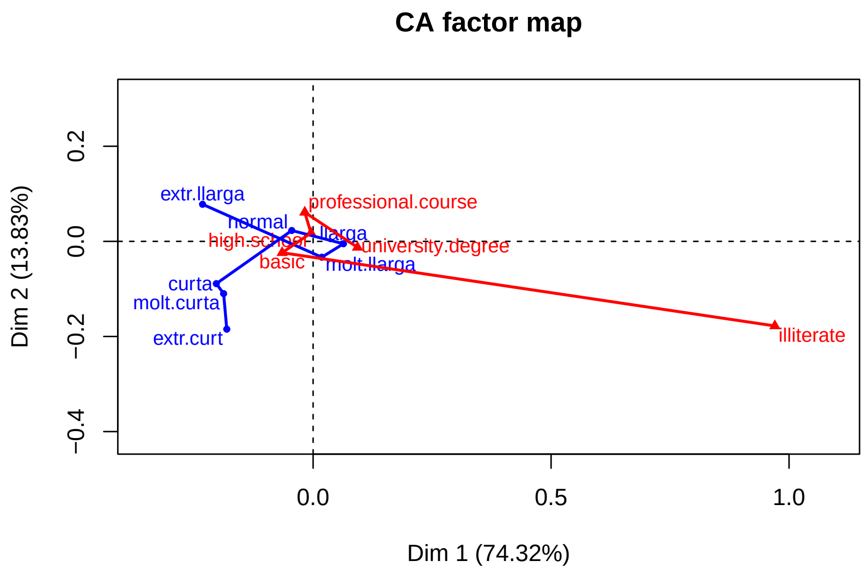
```r
res.ca2$eig[length(ll),3]
```

```
## [1] 74.3226
```

Gràficament, per la regla del colze, veiem que la dimensió on hi ha un canvi important de la corva és la 1. A més, per Kaiser, agafem totes les dimensions amb els eigenvalues els quals superin la mitjana de tots els eigenvalues, i també ens surt una sola dimensió.

Amb aquesta dimensions representem un 74.3226032%, de nou un percentatge prou considerable.

```r
plot( res.ca2, cex=0.8, graph.type = "classic" )
lines( res.ca2$row$coord[,1], res.ca2$row$coord[,2], col="blue", lwd = 2 )
lines( res.ca2$col$coord[,1], res.ca2$col$coord[,2], col="red", lwd = 2 )
```



De la mateixa forma que hem vist amb la parella de variables anterior, aquí tornem a veure que les categories de duration_fact curta i molt.curta tenen valors molt similars. A més, veiem que llarga i molt.llarga també els passa el mateix.

Ens podem fixar també amb que la categoria de education illiterate està molt separada de la resta, cosa que té molt de sentit. De la mateixa manera podem veure que els nivells d'estudi més alts estan relacionats amb les trucades més llargues.

Anàlisis MCA

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

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

En aquest primer punt haurem d'escollir les dimensions que agafem per fer l'anàlisis a partir dels eigenvalues. Per a triar les dimensions durem a terme dos mètodes, el de Kaiser i el de la regla del colze:

Regla de Kaiser La regla de Kaiser ens diu que haurem d'agafar totes aquelles dimensions amb el valor del eigenvalue superior al de la mitjana d'eigenvalues de totes les dimensions.

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

```
##
## Call:
## MCA(X = df[, c(var_res, var_con[2], var_dis[1:11])], ind.sup = llmout,
##      quanti.sup = 2, quali.sup = 1, graph = F)
##
##
## Eigenvalues
##                        Dim.1   Dim.2   Dim.3   Dim.4   Dim.5   Dim.6   Dim.7
## Variance               0.216   0.175   0.147   0.142   0.135   0.122   0.115
## % of var.              7.200   5.838   4.900   4.740   4.493   4.076   3.848
## Cumulative % of var.   7.200  13.037  17.938  22.678  27.171  31.248  35.095
##                        Dim.8   Dim.9  Dim.10  Dim.11  Dim.12  Dim.13  Dim.14
## Variance               0.107   0.102   0.099   0.098   0.096   0.095   0.094
## % of var.              3.574   3.416   3.316   3.279   3.197   3.151   3.117
## Cumulative % of var.  38.669  42.085  45.401  48.680  51.877  55.028  58.145
##                       Dim.15  Dim.16  Dim.17  Dim.18  Dim.19  Dim.20  Dim.21
## Variance               0.092   0.091   0.090   0.088   0.087   0.084   0.082
## % of var.              3.077   3.034   2.989   2.934   2.884   2.815   2.724
## Cumulative % of var.  61.222  64.257  67.246  70.180  73.064  75.879  78.603
##                       Dim.22  Dim.23  Dim.24  Dim.25  Dim.26  Dim.27  Dim.28
## Variance               0.081   0.080   0.077   0.076   0.068   0.060   0.055
## % of var.              2.688   2.677   2.582   2.538   2.266   2.001   1.831
## Cumulative % of var.  81.291  83.968  86.550  89.088  91.354  93.355  95.186
##                       Dim.29  Dim.30  Dim.31  Dim.32  Dim.33
## Variance               0.050   0.043   0.030   0.019   0.002
## % of var.              1.661   1.428   1.009   0.647   0.070
## Cumulative % of var.  96.846  98.274  99.283  99.930 100.000
##
## Categories (the 12 first)
##                     Dim.1     ctr    cos2  v.test     Dim.2     ctr    cos2
## Jove           |   0.877   1.101   0.027  11.565 |  -0.711   0.892   0.018
## Jove-Adult     |   0.038   0.042   0.003   3.964 |  -0.058   0.119   0.007
## Adult          |  -0.239   0.662   0.022 -10.349 |   0.244   0.851   0.023
## Gran           |   1.597   0.652   0.016   8.772 |  -0.551   0.096   0.002
## admin.         |   0.438   1.896   0.059  17.051 |  -0.458   2.554   0.064
## blue-collar    |  -0.667   4.847   0.155 -27.700 |   0.674   6.101   0.159
## management     |   0.132   0.056   0.001   2.664 |  -0.397   0.621   0.013
## self-employed  |   0.111   0.036   0.001   2.140 |  -0.222   0.180   0.004
## services       |  -0.192   0.165   0.004  -4.650 |   0.020   0.002   0.000
```

```
## technician    |   0.362   0.838   0.023  10.764 |  -0.129   0.131   0.003
## unemployed    |   0.170   0.125   0.003   4.036 |  -0.036   0.007   0.000
## divorced      |   0.010   0.000   0.000   0.235 |  -0.179   0.175   0.004
##                v.test     Dim.3     ctr    cos2  v.test
## Jove           -9.373 |  -0.520   0.569   0.010  -6.859 |
## Jove-Adult     -5.989 |  -0.220   2.056   0.106 -22.849 |
## Adult          10.565 |   0.517   4.535   0.101  22.345 |
## Gran           -3.024 |   4.408   7.298   0.119  24.216 |
## admin.        -17.818 |  -0.540   4.236   0.090 -21.025 |
## blue-collar    27.984 |   0.623   6.208   0.135  25.862 |
## management     -7.998 |   0.121   0.068   0.001   2.430 |
## self-employed  -4.294 |   0.290   0.366   0.006   5.611 |
## services        0.480 |  -1.350  11.974   0.217 -32.712 |
## technician     -3.835 |  -0.098   0.089   0.002  -2.901 |
## unemployed     -0.861 |   0.919   5.360   0.097  21.841 |
## divorced       -4.321 |  -0.013   0.001   0.000  -0.318 |
##
## Categorical variables (eta2)
##                 Dim.1 Dim.2 Dim.3
## age           | 0.058 0.038 0.234 |
## job           | 0.189 0.185 0.458 |
## marital       | 0.104 0.084 0.090 |
## education     | 0.203 0.215 0.427 |
## housing       | 0.030 0.005 0.025 |
## loan          | 0.002 0.001 0.000 |
## contact       | 0.528 0.049 0.109 |
## month         | 0.488 0.135 0.152 |
## day_of_week   | 0.062 0.014 0.025 |
## previous      | 0.327 0.594 0.030 |
## poutcome      | 0.384 0.606 0.067 |
##
## Supplementary categories
##                   Dim.1    cos2  v.test     Dim.2    cos2  v.test     Dim.3
## y_no          |  -0.585   0.375 -43.036 |   0.192   0.040  14.131 |  -0.241
## y_yes         |   0.641   0.375  43.036 |  -0.210   0.040 -14.131 |   0.264
##                  cos2  v.test
## y_no            0.064 -17.713 |
## y_yes           0.064  17.713 |
##
## Supplementary categorical variables (eta2)
##                 Dim.1 Dim.2 Dim.3
## y             | 0.375 0.040 0.064 |
##
## Supplementary continuous variable
##                  Dim.1    Dim.2    Dim.3
## duration      |  0.252 | -0.131 |  0.140 |
```

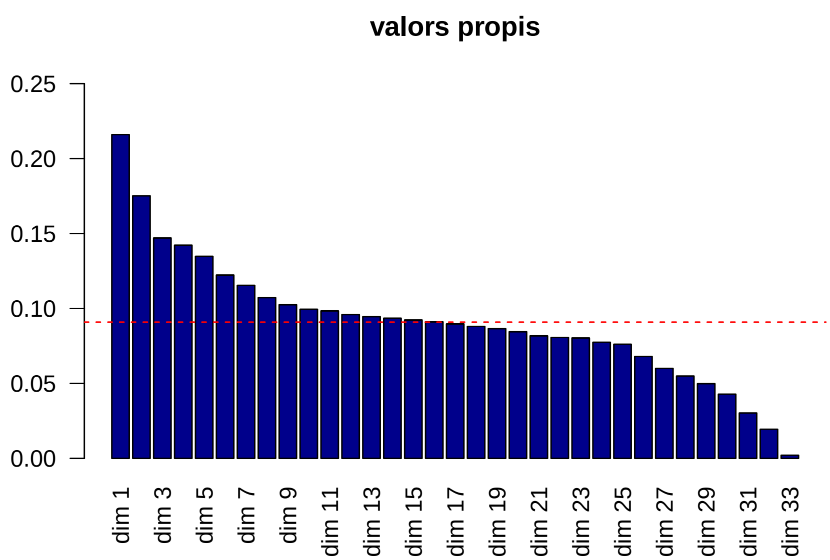
```r
mm <- mean(res.mca$eig[,1])
ll<- which(as.data.frame(res.mca$eig[,1])>mm)
length(ll) #Número dimensions
```

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

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

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

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

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



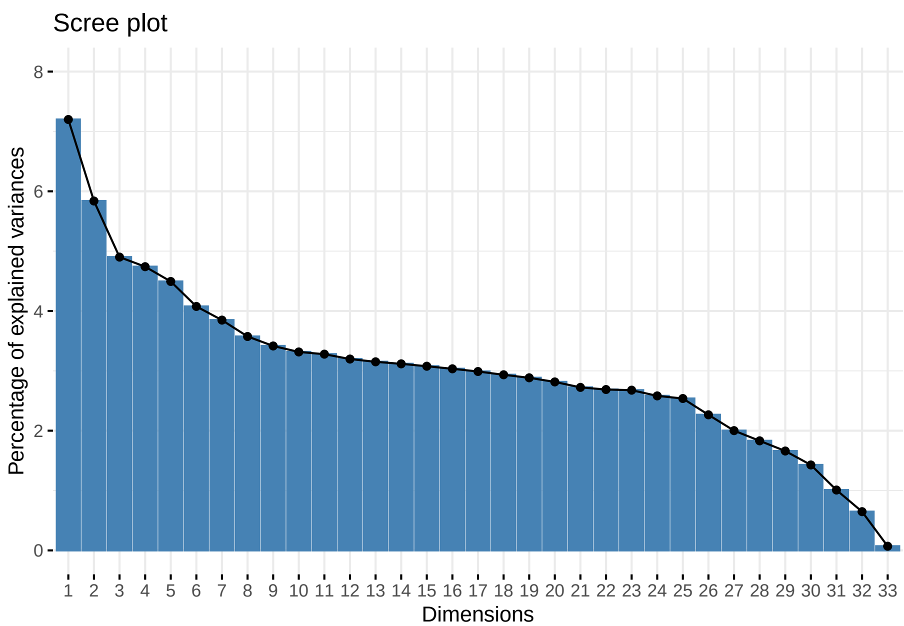
Per la regla de Kaiser ens surten 16 dimensions, però el percentatge explicat és 64.2566121%, un percentatge que considerem baix.

Regla del colze La regla del colze ens diu que hem d'agafar la dimensió la qual fa variar la corva de la gràfica que ens indica el valor propi de cada dimensió:

```
res.mca$eig
```

```
##         eigenvalue percentage of variance cumulative percentage of variance
## dim 1  0.215985532              7.1995177                          7.199518
## dim 2  0.175136654              5.8378885                         13.037406
## dim 3  0.147012791              4.9004264                         17.937833
## dim 4  0.142213865              4.7404622                         22.678295
## dim 5  0.134796116              4.4932039                         27.171499
## dim 6  0.122285019              4.0761673                         31.247666
## dim 7  0.115427448              3.8475816                         35.095247
## dim 8  0.107226255              3.5742085                         38.669456
## dim 9  0.102473603              3.4157868                         42.085243
## dim 10 0.099474533              3.3158178                         45.401061
## dim 11 0.098357758              3.2785919                         48.679652
## dim 12 0.095920509              3.1973503                         51.877003
## dim 13 0.094527756              3.1509252                         55.027928
## dim 14 0.093515471              3.1171824                         58.145110
## dim 15 0.092316196              3.0772065                         61.222317
## dim 16 0.091028857              3.0342952                         64.256612
## dim 17 0.089676076              2.9892025                         67.245815
## dim 18 0.088030654              2.9343551                         70.180170
## dim 19 0.086521870              2.8840623                         73.064232
## dim 20 0.084453327              2.8151109                         75.879343
## dim 21 0.081712085              2.7237362                         78.603079
## dim 22 0.080640389              2.6880130                         81.291092
## dim 23 0.080312899              2.6770966                         83.968189
## dim 24 0.077456392              2.5818797                         86.550068
## dim 25 0.076140285              2.5380095                         89.088078
## dim 26 0.067968101              2.2656034                         91.353681
## dim 27 0.060034342              2.0011447                         93.354826
## dim 28 0.054925787              1.8308596                         95.185686
## dim 29 0.049820820              1.6606940                         96.846380
## dim 30 0.042831485              1.4277162                         98.274096
## dim 31 0.030266658              1.0088886                         99.282984
## dim 32 0.019421634              0.6473878                         99.930372
## dim 33 0.002088834              0.0696278                        100.000000
```

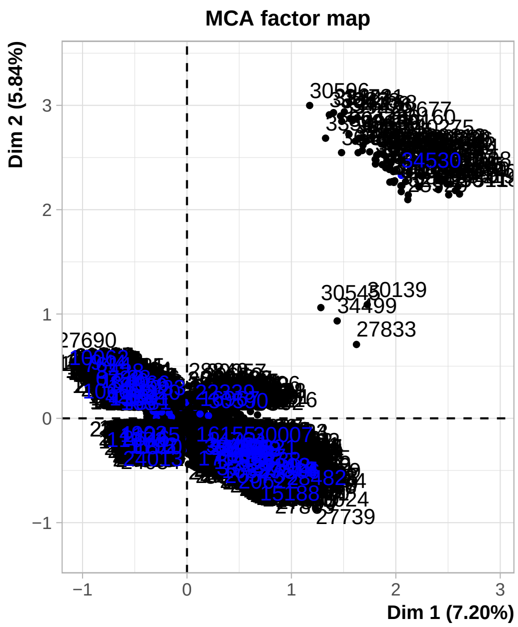
```
fviz_screeplot(res.mca,
               ylim = c(0, 8),
               ncp = 33)
```



En el nostre cas, agafarem la primera dimensió que té un percentatge acomulat de variança més gran de 85%, la dimensió 24. Podem veure gràficament com aquesta dimensió és la última que manté una corva de valor propi constant i que ens explica suficient variança, a partir de la dimensió 25 la corva canvia la seva linealitat.

2. Individuals point of view

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



Podem distingir dos grups diferenciats d'individus, un a l'origen de coordenades i l'altre al primer quadrant, i un grup molt petit d'individus entre ells. Tal i com veiem a la gràfica, el grup del primer quadrant té una contribució molt superior als altres tan en la dimensió 1 com en la 2.

A continuació veurem els 10 individus que més contribueixen a explicar la primera dimensió i quins valors tenen en les diferents variables:

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

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

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

```
##               age          job marital           education housing loan
## 30189 Jove-Adult        admin.  single         high.school     yes   no
## 30315 Jove-Adult        admin. married   university.degree     yes   no
```

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

Seguidament veurem la mateixa informació però per la segona dimensió:

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

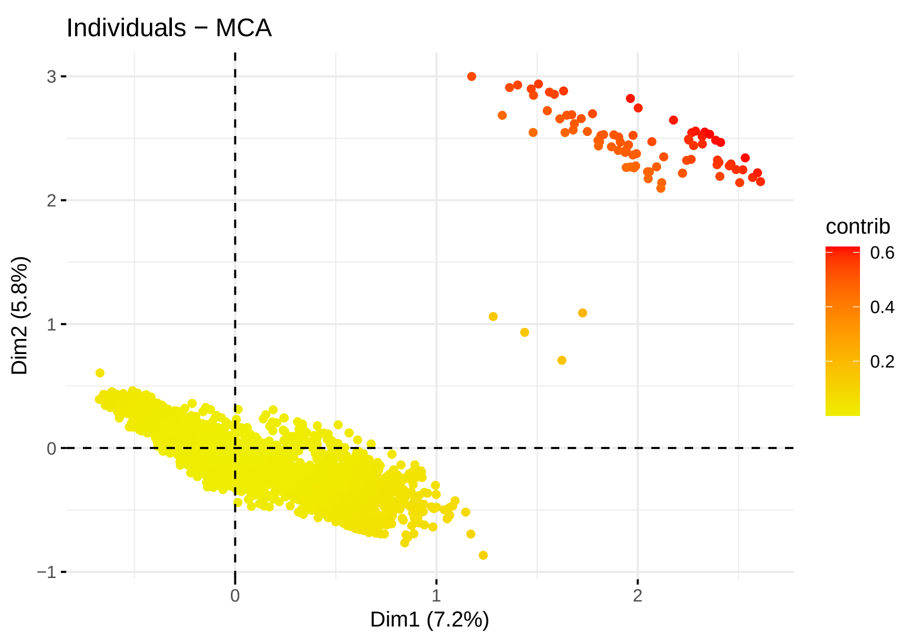
```
##    30596    34731    32721    33383    30473    28168    34408    34276 
## 2.998819 2.937982 2.930081 2.909436 2.898307 2.882058 2.872351 2.854547 
##    35942    28677 
## 2.846646 2.821221
```

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

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

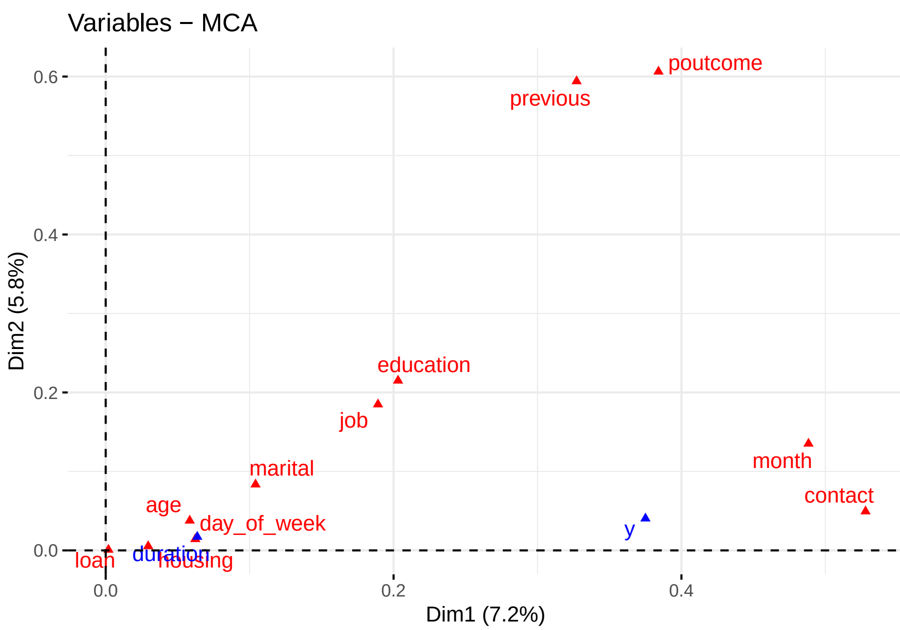
A la següent gràfica podrem veure sobre sobre el pla quins individus son els més contributius (marcats en vermell) i els menys (en groc).

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

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



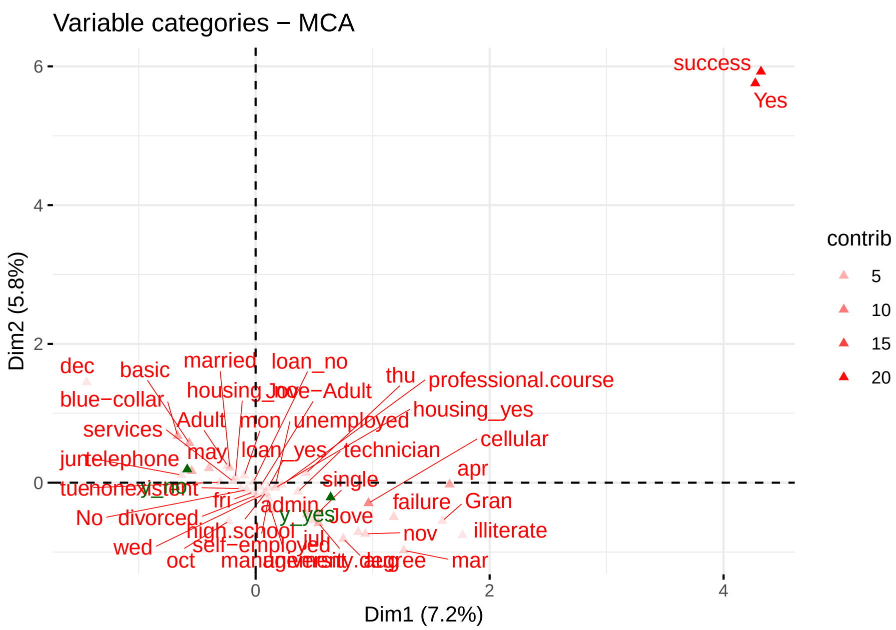
3. Interpreting map of categories

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



Podem veure que contribueixen en gran mesura les variables previous i poutcome per ambdues dimensions, mentres que per la dimensió 1 també contribueixen month i contact. Education i job tenen una contribució en les dues dimensions en menor mesura de les mencionades anteriorment.

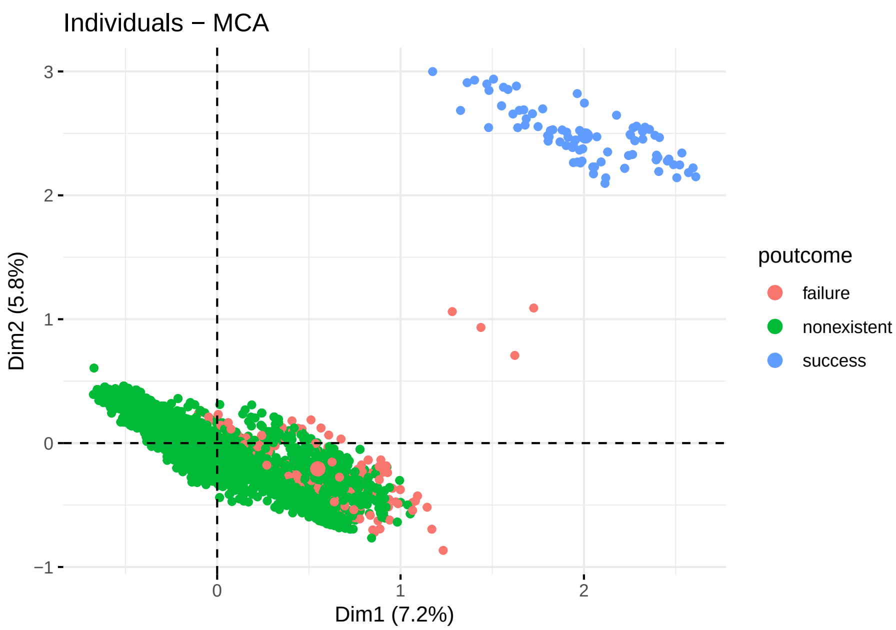
```
fviz_mca_var(res.mca,
             alpha.var="contrib",
             repel = T)
```



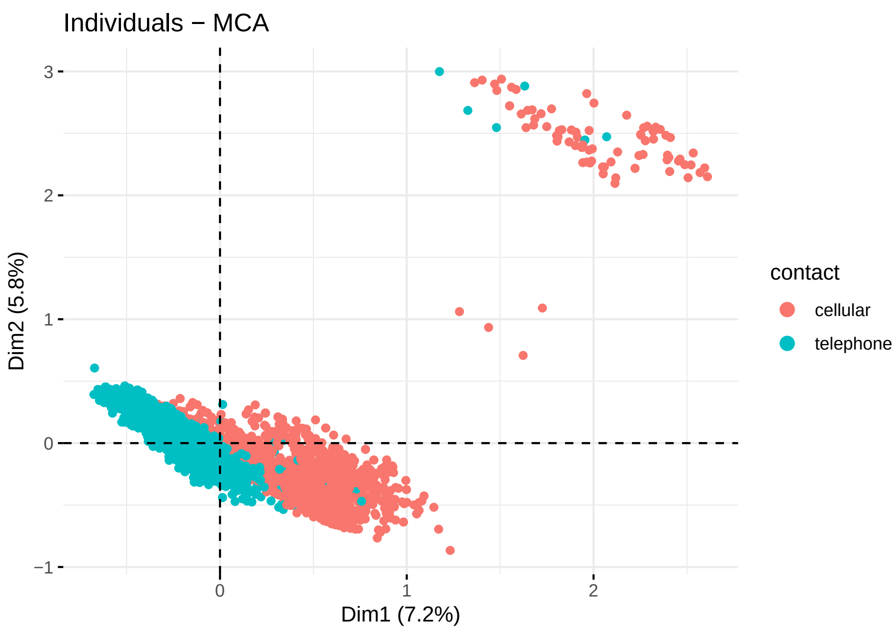
Les categories més contributives en ambdues dimensions són "success" (categoria de "poutcome", variable que hem vist que contribuia en les dues dimensions) i "yes" (categoria de previous que també contribuia en les dues dimensions), la resta de categories no són tan determinants.

Representarem les categories de les variables més representatives: poutcome, month i contact (com que poutcome i previous estan relacionades, sols imprimirem la més significativa, és a dir, poutcome).

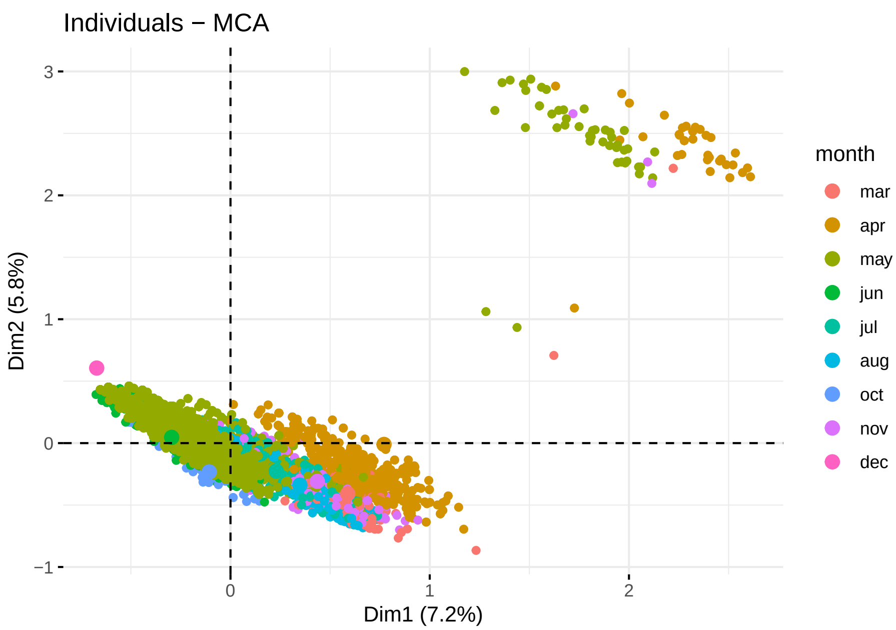
```
# A l'hora de fer les gràfiques per individus i categories, posarem
# com a invisible els individus suplementaris per no tenir-los en compte
# (individus amb outliers multivariants)
fviz_mca_ind(res.mca,
             label="none",
             invisible=c("ind.sup"),
             geom = c("point"),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




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




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



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

4. Interpreting the axes association to factor map

Per auquest punt durem a terme una descripció de dimensions a través de la funció dimdesc per poder veure les variables i categories més relacionades amb cada dimensió. Realitzarem l'anàlisis amb profunditat de les tres primeres dimensions ja que són les més rellevants.

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

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

Dimensió 1

```
##                    R2       p.value
## y         0.374987432  0.000000e+00
## contact   0.527902185  0.000000e+00
## month     0.488263590  0.000000e+00
```

```
## previous    0.327162493  0.000000e+00
## poutcome    0.384056740  0.000000e+00
## education   0.203105403 2.555766e-241
## job         0.189176924 2.541743e-220
## marital     0.104098708 1.426304e-118
## day_of_week 0.062267605  1.968206e-67
## age         0.058376451  4.596511e-64
## housing     0.029524225  4.813177e-34
## loan        0.001906531  2.143411e-03
```

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

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

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

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

```
##                                 Estimate       p.value
## poutcome=success              1.17531597  0.000000e+00
## previous=Yes                  1.01047661  0.000000e+00
## month=apr                     0.64675641  0.000000e+00
## contact=cellular              0.35132508  0.000000e+00
## y=y_yes                       0.28488898  0.000000e+00
## education=university.degree   0.05900022 2.383815e-128
## marital=single                0.19670535 2.666734e-114
## job=admin.                    0.18013247  4.137677e-67
## day_of_week=thu               0.19339224  6.660628e-53
## month=mar                     0.46472456  6.802393e-45
## month=nov                     0.31200496  1.079628e-39
## month=aug                     0.22458575  4.665454e-37
## housing=housing_yes           0.07985867  4.813177e-34
## age=Jove                      0.14354196  2.506712e-31
## job=technician                0.14485506  2.581261e-27
## month=jul                     0.10589318  1.029731e-24
## age=Gran                      0.47806017  1.307906e-18
## job=unemployed                0.05540381  5.365573e-05
## loan=loan_yes                 0.02895621  2.143411e-03
## job=management                0.03794035  7.710261e-03
```

```
## education=illiterate            0.63136693  1.235638e-02
## day_of_week=wed                 0.02407510  2.879632e-02
## job=self-employed               0.02795219  3.237426e-02
## loan=loan_no                   -0.02895621  2.143411e-03
## education=high.school          -0.14980519  4.746968e-04
## day_of_week=mon                -0.05256369  3.291634e-04
## age=Jove-Adult                 -0.24629074  7.288918e-05
## job=services                   -0.11268984  3.254931e-06
## education=professional.course -0.08612124  1.676784e-09
## month=jun                      -0.41903271  1.194469e-18
## age=Adult                      -0.37531139  2.372548e-25
## day_of_week=tue                -0.14817144  8.073767e-34
## housing=housing_no             -0.07985867  4.813177e-34
## poutcome=failure               -0.28388793  1.169020e-65
## marital=married                -0.15185866  6.566766e-96
## job=blue-collar                -0.33359402 2.665337e-183
## education=basic                -0.45444072 1.483351e-208
## poutcome=nonexistent           -0.89142804  0.000000e+00
## previous=No                    -1.01047661  0.000000e+00
## month=may                      -0.30916544  0.000000e+00
## contact=telephone              -0.35132508  0.000000e+00
## y=y_no                         -0.28488898  0.000000e+00
```

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

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

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

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

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

Dimensió 2

```
##                       R2       p.value
## previous    0.5940564621  0.000000e+00
```

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

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

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

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

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

```
##                                Estimate       p.value
## poutcome=success             1.73394719  0.000000e+00
## previous=Yes                 1.22612449  0.000000e+00
## education=basic              0.31810208 9.138533e-212
## job=blue-collar              0.31488937 2.189283e-187
## month=may                    0.17499654 1.506661e-102
## marital=married              0.14623996  1.751311e-89
## contact=telephone            0.09681807  2.166185e-56
## y=y_no                       0.08423522  3.143042e-46
## age=Adult                    0.21471233  2.315031e-26
## age=Jove-Adult               0.08827440  1.987533e-09
## education=high.school        0.01860896  9.527271e-09
## housing=housing_no           0.03060577  2.667713e-07
## day_of_week=thu              0.06294006  9.326999e-07
## day_of_week=mon              0.04771803  1.318104e-04
## loan=loan_no                 0.01714975  4.355077e-02
## loan=loan_yes               -0.01714975  4.355077e-02
## age=Gran                    -0.11796644  2.483794e-03
## month=oct                   -0.14489659  3.614771e-04
```

```
## job=technician                -0.02121630  1.242614e-04
## day_of_week=fri               -0.05220759  1.885359e-05
## job=self-employed             -0.06021933  1.728930e-05
## marital=divorced              -0.01775560  1.526968e-05
## housing=housing_yes           -0.03060577  2.667713e-07
## day_of_week=wed               -0.06639553  4.421294e-08
## poutcome=failure              -0.95300863  1.250230e-12
## job=management                -0.13337023  1.030364e-15
## age=Jove                      -0.18502029  4.814380e-21
## month=nov                     -0.22143499  4.994564e-25
## month=mar                     -0.32129786  3.766175e-27
## month=jul                     -0.13918909  2.462041e-29
## month=aug                     -0.25156750  4.941531e-43
## y=y_yes                       -0.08423522  3.143042e-46
## contact=cellular              -0.09681807  2.166185e-56
## job=admin.                    -0.15882870  2.586561e-73
## marital=single                -0.12848436  1.929238e-79
## poutcome=nonexistent          -0.78093856 6.075965e-139
## education=university.degree -0.16532509 8.613027e-153
## previous=No                   -1.22612449  0.000000e+00
```

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

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

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

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

Dimensió 3

```
##                    R2       p.value
## job         0.45767503  0.000000e+00
## education   0.42707963  0.000000e+00
## age         0.23380846 9.505926e-285
## month       0.15175628 5.160481e-170
## contact     0.10850285 2.414833e-125
```

```
## marital     0.09033880 3.122212e-102
## poutcome    0.06740715  1.530758e-75
## y           0.06352746  1.877783e-72
## previous    0.03006950  1.190896e-34
## housing     0.02525844  2.622655e-29
## day_of_week 0.02524322  2.528430e-26
```

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

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

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

```
##                                 Estimate       p.value
## education=basic               0.03036553  0.000000e+00
## job=blue-collar               0.24075041 2.869731e-158
## age=Gran                      1.28909975 9.665342e-138
## contact=cellular              0.13140691 2.414833e-125
## job=unemployed                0.35425607 4.453087e-111
## marital=married               0.11728914  2.174045e-83
## y=y_yes                       0.09674160  1.877783e-72
## month=apr                     0.18403860  6.229941e-69
## poutcome=failure              0.41986805  1.832819e-43
## previous=No                   0.25273932  1.190896e-34
## housing=housing_yes           0.06093985  2.622655e-29
## month=aug                     0.11799097  2.284992e-25
## month=nov                     0.09532077  7.725177e-15
## month=jul                     0.01548543  5.942950e-13
## day_of_week=wed               0.07781044  2.614175e-11
## day_of_week=thu               0.07066121  4.948072e-11
## job=self-employed             0.11327939  1.918956e-08
## month=mar                     0.06475565  1.590061e-07
## education=illiterate          1.06838259  1.358657e-06
## poutcome=nonexistent          0.04610141  3.030347e-06
## job=management                0.04816927  1.506661e-02
## education=university.degree -0.25750295  4.547814e-02
## day_of_week=tue              -0.02438976  1.598485e-02
## job=technician               -0.03553068  3.713086e-03
## month=jun                    -0.20722310  1.264593e-03
## day_of_week=mon              -0.04162443  9.623346e-05
```

```
## day_of_week=fri              -0.08245746  1.849777e-11
## age=Jove                     -0.60057120  6.233578e-12
## month=oct                    -0.64919397  3.733186e-19
## housing=housing_no           -0.06093985  2.622655e-29
## previous=Yes                 -0.25273932  1.190896e-34
## poutcome=success             -0.46596946  6.149424e-36
## y=y_no                       -0.09674160  1.877783e-72
## marital=single               -0.15058853  1.507932e-98
## job=admin.                   -0.20528163 1.083739e-102
## month=may                    -0.20002879 4.193292e-107
## age=Adult                    -0.20294259 1.890559e-116
## age=Jove-Adult               -0.48558596 5.626479e-122
## contact=telephone            -0.13140691 2.414833e-125
## job=services                 -0.51564283 3.571756e-264
## education=high.school        -0.62594578  0.000000e+00
```

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

- Gran de age (1.289)
- illiterate de education (1.068)
- oct de month (-0.649)

5. Perform a MCA taking into account also supplementary variables

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

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

Igual que hem fet a l'apartat anterior, realitzarem una nova descripció de dimensions per veure les variacions.

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

```r
res.des_sup
```

```
## $`Dim 1`
##
## Link between the variable and the continuous variables (R-square)
```

```
## ================================================================================
##                 correlation       p.value
## duration          0.2522384  1.453834e-72
## nr.employed      -0.4591929 2.942456e-256
## emp.var.rate     -0.5906105  0.000000e+00
## euribor3m        -0.5952353  0.000000e+00
## cons.conf.idx    -0.6546221  0.000000e+00
## cons.price.idx   -0.6697710  0.000000e+00
##
## Link between the variable and the categorical variable (1-way anova)
## =============================================
##                      R2       p.value
## y           0.374987432  0.000000e+00
## contact     0.527902185  0.000000e+00
## month       0.488263590  0.000000e+00
## previous    0.327162493  0.000000e+00
## poutcome    0.384056740  0.000000e+00
## education   0.203105403 2.555766e-241
## job         0.189176924 2.541743e-220
## marital     0.104098708 1.426304e-118
## day_of_week 0.062267605  1.968206e-67
## age         0.058376451  4.596511e-64
## housing     0.029524225  4.813177e-34
## loan        0.001906531  2.143411e-03
##
## Link between variable abd the categories of the categorical variables
## ================================================================
##                                 Estimate       p.value
## poutcome=success              1.17531597  0.000000e+00
## previous=Yes                  1.01047661  0.000000e+00
## month=apr                     0.64675641  0.000000e+00
## contact=cellular              0.35132508  0.000000e+00
## y=y_yes                       0.28488898  0.000000e+00
## education=university.degree   0.05900022 2.383815e-128
## marital=single                0.19670535 2.666734e-114
## job=admin.                    0.18013247  4.137677e-67
## day_of_week=thu               0.19339224  6.660628e-53
## month=mar                     0.46472456  6.802393e-45
## month=nov                     0.31200496  1.079628e-39
## month=aug                     0.22458575  4.665454e-37
## housing=housing_yes           0.07985867  4.813177e-34
## age=Jove                      0.14354196  2.506712e-31
## job=technician                0.14485506  2.581261e-27
## month=jul                     0.10589318  1.029731e-24
## age=Gran                      0.47806017  1.307906e-18
## job=unemployed                0.05540381  5.365573e-05
```

```
## loan=loan_yes                 0.02895621  2.143411e-03
## job=management                0.03794035  7.710261e-03
## education=illiterate          0.63136693  1.235638e-02
## day_of_week=wed               0.02407510  2.879632e-02
## job=self-employed             0.02795219  3.237426e-02
## loan=loan_no                 -0.02895621  2.143411e-03
## education=high.school        -0.14980519  4.746968e-04
## day_of_week=mon              -0.05256369  3.291634e-04
## age=Jove-Adult               -0.24629074  7.288918e-05
## job=services                 -0.11268984  3.254931e-06
## education=professional.course -0.08612124  1.676784e-09
## month=jun                    -0.41903271  1.194469e-18
## age=Adult                    -0.37531139  2.372548e-25
## day_of_week=tue              -0.14817144  8.073767e-34
## housing=housing_no           -0.07985867  4.813177e-34
## poutcome=failure             -0.28388793  1.169020e-65
## marital=married              -0.15185866  6.566766e-96
## job=blue-collar              -0.33359402 2.665337e-183
## education=basic              -0.45444072 1.483351e-208
## poutcome=nonexistent         -0.89142804  0.000000e+00
## previous=No                  -1.01047661  0.000000e+00
## month=may                    -0.30916544  0.000000e+00
## contact=telephone            -0.35132508  0.000000e+00
## y=y_no                       -0.28488898  0.000000e+00
##
## $`Dim 2`
##
## Link between the variable and the continuous variables (R-square)
## =================================================================================
##                correlation      p.value
## cons.price.idx  0.09636262 1.145336e-11
## cons.conf.idx   0.09399734 3.601633e-11
## campaign       -0.04611342 1.186972e-03
## nr.employed    -0.09247914 7.404675e-11
## duration       -0.13111935 2.174986e-20
##
## Link between the variable and the categorical variable (1-way anova)
## =============================================
##                      R2       p.value
## previous    0.5940564621  0.000000e+00
## poutcome    0.6062924147  0.000000e+00
## education   0.2149866672 2.160555e-257
## job         0.1848775504 1.122408e-214
## month       0.1351545003 2.072247e-149
## marital     0.0835207347  3.160431e-94
## contact     0.0494419477  2.166185e-56
```

```
## y           0.0404296938  3.143042e-46
## age         0.0377013815  7.044337e-41
## day_of_week 0.0142988220  1.337097e-14
## housing     0.0053479661  2.667713e-07
## loan        0.0008247522  4.355077e-02
##
## Link between variable abd the categories of the categorical variables
## ================================================================
##                                 Estimate       p.value
## poutcome=success              1.73394719  0.000000e+00
## previous=Yes                  1.22612449  0.000000e+00
## education=basic               0.31810208 9.138533e-212
## job=blue-collar               0.31488937 2.189283e-187
## month=may                     0.17499654 1.506661e-102
## marital=married               0.14623996  1.751311e-89
## contact=telephone             0.09681807  2.166185e-56
## y=y_no                        0.08423522  3.143042e-46
## age=Adult                     0.21471233  2.315031e-26
## age=Jove-Adult                0.08827440  1.987533e-09
## education=high.school         0.01860896  9.527271e-09
## housing=housing_no            0.03060577  2.667713e-07
## day_of_week=thu               0.06294006  9.326999e-07
## day_of_week=mon               0.04771803  1.318104e-04
## loan=loan_no                  0.01714975  4.355077e-02
## loan=loan_yes                -0.01714975  4.355077e-02
## age=Gran                     -0.11796644  2.483794e-03
## month=oct                    -0.14489659  3.614771e-04
## job=technician               -0.02121630  1.242614e-04
## day_of_week=fri              -0.05220759  1.885359e-05
## job=self-employed            -0.06021933  1.728930e-05
## marital=divorced             -0.01775560  1.526968e-05
## housing=housing_yes          -0.03060577  2.667713e-07
## day_of_week=wed              -0.06639553  4.421294e-08
## poutcome=failure             -0.95300863  1.250230e-12
## job=management               -0.13337023  1.030364e-15
## age=Jove                     -0.18502029  4.814380e-21
## month=nov                    -0.22143499  4.994564e-25
## month=mar                    -0.32129786  3.766175e-27
## month=jul                    -0.13918909  2.462041e-29
## month=aug                    -0.25156750  4.941531e-43
## y=y_yes                      -0.08423522  3.143042e-46
## contact=cellular             -0.09681807  2.166185e-56
## job=admin.                   -0.15882870  2.586561e-73
## marital=single               -0.12848436  1.929238e-79
## poutcome=nonexistent         -0.78093856 6.075965e-139
## education=university.degree -0.16532509 8.613027e-153
```

```
## previous=No                 -1.22612449  0.000000e+00
##
## $`Dim 3`
##
## Link between the variable and the continuous variables (R-square)
## =================================================================================
##                correlation      p.value
## duration         0.1400398 4.646852e-23
## nr.employed     -0.1218646 8.315456e-18
## emp.var.rate    -0.1844349 4.757303e-39
## euribor3m       -0.1954924 9.525318e-44
## cons.conf.idx   -0.2419309 9.945248e-67
## cons.price.idx  -0.2519419 2.158776e-72
##
## Link between the variable and the categorical variable (1-way anova)
## =============================================
##                     R2       p.value
## job         0.45767503  0.000000e+00
## education   0.42707963  0.000000e+00
## age         0.23380846 9.505926e-285
## month       0.15175628 5.160481e-170
## contact     0.10850285 2.414833e-125
## marital     0.09033880 3.122212e-102
## poutcome    0.06740715  1.530758e-75
## y           0.06352746  1.877783e-72
## previous    0.03006950  1.190896e-34
## housing     0.02525844  2.622655e-29
## day_of_week 0.02524322  2.528430e-26
##
## Link between variable abd the categories of the categorical variables
## ================================================================
##                                Estimate       p.value
## education=basic              0.03036553  0.000000e+00
## job=blue-collar              0.24075041 2.869731e-158
## age=Gran                     1.28909975 9.665342e-138
## contact=cellular             0.13140691 2.414833e-125
## job=unemployed               0.35425607 4.453087e-111
## marital=married              0.11728914  2.174045e-83
## y=y_yes                      0.09674160  1.877783e-72
## month=apr                    0.18403860  6.229941e-69
## poutcome=failure             0.41986805  1.832819e-43
## previous=No                  0.25273932  1.190896e-34
## housing=housing_yes          0.06093985  2.622655e-29
## month=aug                    0.11799097  2.284992e-25
## month=nov                    0.09532077  7.725177e-15
## month=jul                    0.01548543  5.942950e-13
```

```
## day_of_week=wed               0.07781044  2.614175e-11
## day_of_week=thu               0.07066121  4.948072e-11
## job=self-employed             0.11327939  1.918956e-08
## month=mar                     0.06475565  1.590061e-07
## education=illiterate          1.06838259  1.358657e-06
## poutcome=nonexistent          0.04610141  3.030347e-06
## job=management                0.04816927  1.506661e-02
## education=university.degree -0.25750295  4.547814e-02
## day_of_week=tue              -0.02438976  1.598485e-02
## job=technician               -0.03553068  3.713086e-03
## month=jun                    -0.20722310  1.264593e-03
## day_of_week=mon              -0.04162443  9.623346e-05
## day_of_week=fri              -0.08245746  1.849777e-11
## age=Jove                     -0.60057120  6.233578e-12
## month=oct                    -0.64919397  3.733186e-19
## housing=housing_no           -0.06093985  2.622655e-29
## previous=Yes                 -0.25273932  1.190896e-34
## poutcome=success             -0.46596946  6.149424e-36
## y=y_no                       -0.09674160  1.877783e-72
## marital=single               -0.15058853  1.507932e-98
## job=admin.                   -0.20528163 1.083739e-102
## month=may                    -0.20002879 4.193292e-107
## age=Adult                    -0.20294259 1.890559e-116
## age=Jove-Adult               -0.48558596 5.626479e-122
## contact=telephone            -0.13140691 2.414833e-125
## job=services                 -0.51564283 3.571756e-264
## education=high.school        -0.62594578  0.000000e+00
```

Per cada dimensió podem veure les correlacions que hi ha amb les variables continues, la majoria d'aquestes són índex econòmics que contribueixen de forma negativa a les dimensions.

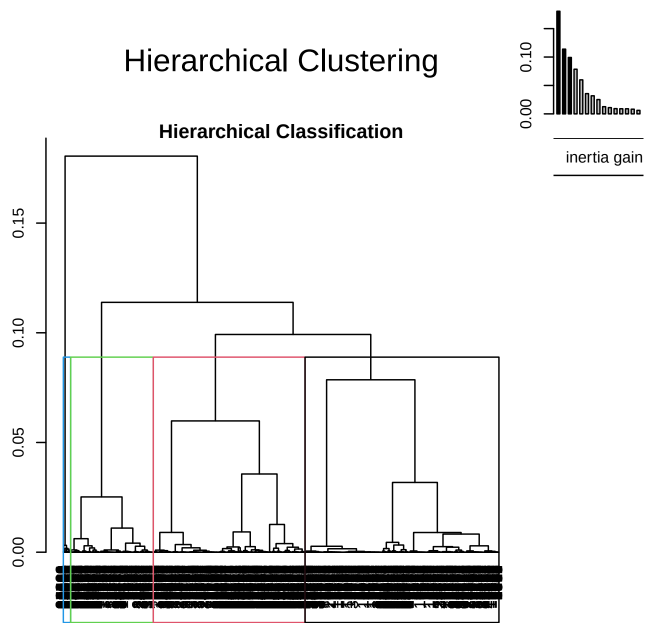
Tant per variables com per categories, el fet d'incloure les variables continues com a suplementàries no ha variat el seu resultat ni contribució.

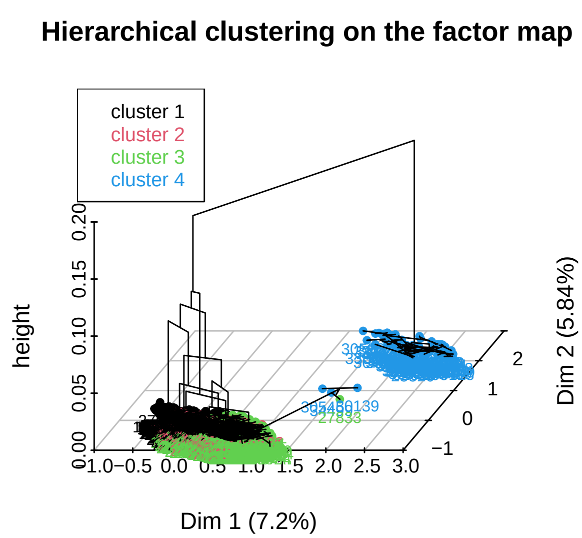
Clustering MCA

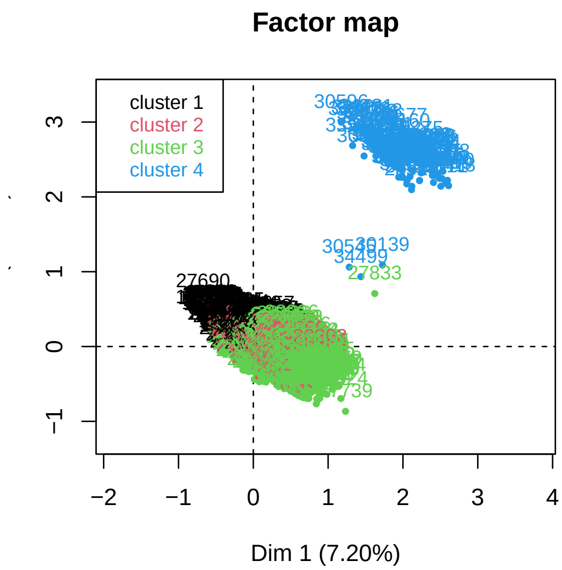
Description of clusters

Per a relitzar la descripció dels grups d'individus, hem de realitzar una agrupació jeràrquica dels components principals (HCPC).

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


Hierarchical Clustering
Hierarchical Classification
inertia gain
0.00
0.05
0.10
0.15

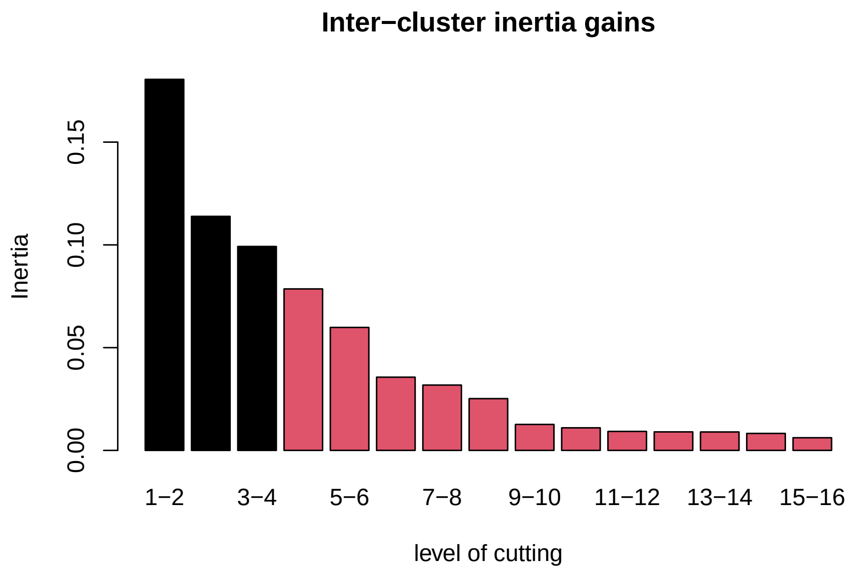

Hierarchical clustering on the factor map
cluster 1
cluster 2
cluster 3
cluster 4
height
Dim 1 (7.2%)
Dim 2 (5.84%)



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

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

```
plot(res.hcpc_mca, choice = "bar")
```



A continuació imprimirem en un factor map tots els individus agrupats amb els diferents clusters que tenim. Podem veure com el cluster 1, 3 i 4 estan completament difgerenciats, però el cluster 2 està dispers amb el primer i tercer. També observem com els clusters 3 i 4 tenen punts molt desviats que provoquen que abarquin molta superfície sense individus.

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

A continuació durem a terme la descripció de clusters envers les variables i categories més rellevants en ells.

Primer de tot veiem les variables més relacionades amb tots els clusters:

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

```
##                   p.value df
## job          0.000000e+00 18
## education    0.000000e+00 12
## previous     0.000000e+00  3
## poutcome     0.000000e+00  6
## month       2.749774e-235 24
## contact     9.965243e-211  3
## y           4.828120e-166  3
## marital      2.045561e-64  6
## age          6.296158e-21  9
## day_of_week  5.642845e-12 12
## housing      6.548853e-12  3
```

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

- job
- education

- poutcome
- month

Seguidament podem veure, per cadascun dels 4 clusters escollits, les categories que els conformen. Aquests valors els relacionarem amb les variables que hem vist que estan més relacionades per veure'n les seves categories exactes:

```
res.hcpc_mca$desc.var$category
```

```
## $`1`
##                              Cla/Mod      Mod/Cla     Global       p.value
## education=basic            86.133487  66.56291685 35.1821862  0.000000e+00
## job=blue-collar            90.532081  51.44508671 25.8704453  0.000000e+00
## contact=telephone          60.247462  84.43752779 63.8056680 9.477077e-177
## month=may                  57.993351  85.32681192 66.9838057 3.520823e-146
## y=y_no                     62.098335  71.32058693 52.2874494 1.785644e-135
## marital=married            53.888000  74.87772343 63.2591093  4.968708e-55
## job=services               76.571429  17.87461094 10.6275304  6.875358e-53
## poutcome=nonexistent       47.500536  98.44375278 94.3522267  7.002413e-34
## education=high.school      59.367194  31.70297910 24.3117409  1.989472e-28
## previous=No                46.342469 100.00000000 98.2388664  5.871416e-24
## housing=housing_no         50.695012  55.13561583 49.5141700  4.920995e-13
## age=Adult                  50.221239  30.28012450 27.4493927  4.717230e-05
## month=jun                  58.152174   4.75767008  3.7246964  4.860564e-04
## day_of_week=tue            49.832776  26.50066696 24.2105263  6.050054e-04
## loan=loan_no               46.290170  87.10538017 85.6680162  8.287388e-03
## month=oct                  29.268293   0.53357048  0.8299595  3.542951e-02
## day_of_week=wed            42.227378  16.18497110 17.4493927  3.217246e-02
## loan=loan_yes              40.960452  12.89461983 14.3319838  8.287388e-03
## marital=divorced           39.196941   9.11516229 10.5870445  2.047602e-03
## age=Jove                   32.738095   2.44553135  3.4008097  6.343174e-04
## day_of_week=thu            40.081384  17.51889729 19.8987854  1.232443e-04
## month=jul                  33.587786   5.86927523  7.9554656  5.715705e-07
## age=Gran                    3.333333   0.04446421  0.6072874  3.092767e-07
## job=self-employed          29.106628   4.49088484  7.0242915  9.457441e-11
## housing=housing_yes        40.457097  44.86438417 50.4858300  4.920995e-13
## poutcome=failure           17.857143   1.55624722  3.9676113  1.144982e-16
## poutcome=success            0.000000   0.00000000  1.6801619  7.070463e-23
## previous=Yes                0.000000   0.00000000  1.7611336  5.871416e-24
## month=mar                   2.542373   0.13339262  2.3886640  4.227342e-27
## month=nov                   8.556150   0.71142730  3.7854251  2.406330e-29
## month=aug                  11.567164   1.37839040  5.4251012  1.103349e-34
## job=management             15.466667   2.57892397  7.5910931  1.622807e-37
## marital=single             27.863777  16.00711427 26.1538462  2.705281e-51
## job=admin.                 23.123382  11.91640729 23.4615385  5.726114e-72
```

```
## month=apr                        6.378132   1.24499778  8.8866397  3.025751e-80
## y=y_yes                         27.365295  28.67941307 47.7125506 1.785644e-135
## education=professional.course    1.437700   0.40017786 12.6720648 2.460003e-162
## contact=cellular                19.574944  15.56247221 36.1943320 9.477077e-177
## job=technician                   2.002670   0.66696309 15.1619433 1.377363e-190
## education=university.degree      2.184996   1.33392619 27.7935223  0.000000e+00
##                                     v.test
## education=basic                        Inf
## job=blue-collar                        Inf
## contact=telephone                28.345623
## month=may                        25.746578
## y=y_no                           24.772245
## marital=married                  15.624362
## job=services                     15.306910
## poutcome=nonexistent             12.133687
## education=high.school            11.058706
## previous=No                      10.094021
## housing=housing_no                7.227463
## age=Adult                         4.069213
## month=jun                         3.488325
## day_of_week=tue                   3.429360
## loan=loan_no                      2.640131
## month=oct                        -2.103415
## day_of_week=wed                  -2.142261
## loan=loan_yes                    -2.640131
## marital=divorced                 -3.083240
## age=Jove                         -3.416500
## day_of_week=thu                  -3.839581
## month=jul                        -5.000584
## age=Gran                         -5.117704
## job=self-employed                -6.475379
## housing=housing_yes              -7.227463
## poutcome=failure                 -8.288695
## poutcome=success                 -9.846880
## previous=Yes                    -10.094021
## month=mar                       -10.781114
## month=nov                       -11.246622
## month=aug                       -12.284049
## job=management                  -12.800795
## marital=single                  -15.066123
## job=admin.                      -17.940188
## month=apr                       -18.969884
## y=y_yes                         -24.772245
## education=professional.course   -27.151061
## contact=cellular                -28.345623
## job=technician                  -29.446951
```

```
## education=university.degree         -Inf
##
## $`2`
##                                 Cla/Mod     Mod/Cla     Global      p.value
## education=professional.course 92.971246  67.6744186 12.6720648 0.000000e+00
## job=technician                88.651535  77.2093023 15.1619433 0.000000e+00
## month=aug                     34.328358  10.6976744  5.4251012 6.104470e-12
## previous=No                   17.720997 100.0000000 98.2388664 5.046124e-08
## age=Jove-Adult                18.989959  74.7674419 68.5425101 1.140506e-05
## poutcome=nonexistent          17.850247  96.7441860 94.3522267 4.129123e-04
## day_of_week=tue               19.565217  27.2093023 24.2105263 2.520745e-02
## age=Gran                       3.333333   0.1162791  0.6072874 2.645836e-02
## age=Adult                     15.339233  24.1860465 27.4493927 1.741316e-02
## job=self-employed              9.221902   3.7209302  7.0242915 8.581173e-06
## age=Jove                       4.761905   0.9302326  3.4008097 6.527235e-07
## month=apr                      8.883827   4.5348837  8.8866397 1.253005e-07
## poutcome=success               0.000000   0.0000000  1.6801619 1.100549e-07
## previous=Yes                   0.000000   0.0000000  1.7611336 5.046124e-08
## job=unemployed                 7.495069   4.4186047 10.2631579 1.343328e-11
## job=services                   5.714286   3.4883721 10.6275304 7.876437e-17
## job=management                 3.466667   1.5116279  7.5910931 7.748804e-18
## education=university.degree    9.541151  15.2325581 27.7935223 2.408001e-21
## education=high.school          6.827644   9.5348837 24.3117409 2.928148e-33
## job=blue-collar                4.147105   6.1627907 25.8704453 3.846798e-59
## job=admin.                     2.588438   3.4883721 23.4615385 6.370328e-69
## education=basic                3.739931   7.5581395 35.1821862 6.391386e-94
##                                  v.test
## education=professional.course       Inf
## job=technician                      Inf
## month=aug                      6.877190
## previous=No                    5.449678
## age=Jove-Adult                 4.388661
## poutcome=nonexistent           3.531691
## day_of_week=tue                2.238209
## age=Gran                      -2.219417
## age=Adult                     -2.377866
## job=self-employed             -4.450147
## age=Jove                      -4.974927
## month=apr                     -5.285590
## poutcome=success              -5.309287
## previous=Yes                  -5.449678
## job=unemployed                -6.763892
## job=services                  -8.333082
## job=management                -8.603253
## education=university.degree   -9.485683
## education=high.school        -12.015997
```

```
## job=blue-collar               -16.216639
## job=admin.                    -17.546104
## education=basic               -20.559018
##
## $`3`
##                                 Cla/Mod     Mod/Cla     Global       p.value
## education=university.degree   86.598689 68.13753582 27.7935223  0.000000e+00
## job=admin.                    72.131148 47.90830946 23.4615385 7.295011e-192
## contact=cellular              58.836689 60.28653295 36.1943320 2.586108e-148
## y=y_yes                       51.803140 69.97134670 47.7125506 9.515429e-121
## month=apr                     76.765376 19.31232092  8.8866397  2.709105e-77
## job=management                79.733333 17.13467049  7.5910931  3.553602e-75
## marital=single                52.089783 38.56733524 26.1538462  2.184403e-47
## month=nov                     76.470588  8.19484241  3.7854251  1.407523e-31
## job=self-employed             60.518732 12.03438395  7.0242915  4.199892e-23
## poutcome=failure              66.326531  7.44985673  3.9676113  2.600404e-19
## month=mar                     73.728814  4.98567335  2.3886640  1.020654e-17
## previous=No                   35.936534 99.94269341 98.2388664  1.144210e-15
## age=Jove                      61.309524  5.90257880  3.4008097  3.635738e-12
## age=Gran                      93.333333  1.60458453  0.6072874  3.811565e-11
## month=aug                     54.104478  8.30945559  5.4251012  1.159896e-10
## month=jul                     50.127226 11.28939828  7.9554656  3.779458e-10
## housing=housing_yes           39.414595 56.33237822 50.4858300  1.221197e-09
## day_of_week=thu               40.488301 22.80802292 19.8987854  1.721074e-04
## marital=divorced              42.447419 12.72206304 10.5870445  3.672714e-04
## job=unemployed                42.406312 12.32091691 10.2631579  4.992983e-04
## day_of_week=wed               39.443155 19.48424069 17.4493927  5.647987e-03
## month=oct                     51.219512  1.20343840  0.8299595  3.806523e-02
## age=Adult                     32.669617 25.38681948 27.4493927  1.608590e-02
## month=jun                     25.543478  2.69340974  3.7246964  3.955253e-03
## education=high.school         31.806828 21.89111748 24.3117409  3.241826e-03
## poutcome=nonexistent          34.649217 92.55014327 94.3522267  6.875285e-05
## day_of_week=tue               29.933110 20.51575931 24.2105263  6.301578e-06
## housing=housing_no            31.152903 43.66762178 49.5141700  1.221197e-09
## previous=Yes                   1.149425  0.05730659  1.7611336  1.144210e-15
## poutcome=success               0.000000  0.00000000  1.6801619  1.336576e-16
## job=services                  16.190476  4.87106017 10.6275304  1.268130e-24
## marital=married               27.200000 48.71060172 63.2591093  1.050906e-54
## job=technician                 6.542056  2.80802292 15.1619433  3.344219e-88
## education=professional.course  3.194888  1.14613181 12.6720648  9.838051e-96
## y=y_no                        20.286489 30.02865330 52.2874494 9.515429e-121
## month=may                     23.209429 44.01146132 66.9838057 8.495490e-140
## contact=telephone             21.986041 39.71346705 63.8056680 2.586108e-148
## job=blue-collar                3.990610  2.92263610 25.8704453 3.266085e-204
## education=basic                8.745685  8.71060172 35.1821862 1.448069e-207
##                                  v.test
```

```
## education=university.degree          Inf
## job=admin.                      29.546446
## contact=cellular                25.936442
## y=y_yes                         23.365829
## month=apr                       18.609144
## job=management                  18.345995
## marital=single                  14.459480
## month=nov                       11.691575
## job=self-employed                9.899112
## poutcome=failure                 8.984446
## month=mar                        8.571591
## previous=No                      8.010309
## age=Jove                         6.950663
## age=Gran                         6.611223
## month=aug                        6.444490
## month=jul                        6.262874
## housing=housing_yes              6.077436
## day_of_week=thu                  3.756789
## marital=divorced                 3.562549
## job=unemployed                   3.481133
## day_of_week=wed                  2.767547
## month=oct                        2.074152
## age=Adult                       -2.406961
## month=jun                       -2.881709
## education=high.school           -2.943826
## poutcome=nonexistent            -3.980561
## day_of_week=tue                 -4.516010
## housing=housing_no              -6.077436
## previous=Yes                    -8.010309
## poutcome=success                -8.270269
## job=services                   -10.243317
## marital=married                -15.576540
## job=technician                 -19.909834
## education=professional.course -20.760576
## y=y_no                         -23.365829
## month=may                      -25.170195
## contact=telephone              -25.936442
## job=blue-collar                -30.492603
## education=basic                -30.744506
##
## $`4`
##                        Cla/Mod    Mod/Cla    Global       p.value    v.test
## previous=Yes        98.8505747 100.000000  1.761134 9.693892e-186  29.065884
## poutcome=success   100.0000000  96.511628  1.680162 2.126492e-177  28.398230
## contact=cellular     4.4742729  93.023256 36.194332  5.878562e-29  11.167541
## y=y_yes              3.6487060 100.000000 47.712551  1.008897e-28  11.119452
```

```
## month=apr              7.9726651  40.697674  8.886640  1.072676e-15   8.018244
## day_of_week=thu        3.7639878  43.023256 19.898785  9.257787e-07   4.906793
## job=technician         2.8037383  24.418605 15.161943  2.337339e-02   2.267276
## month=jun              0.0000000   0.000000  3.724696  3.712800e-02  -2.084354
## month=may              1.3901481  53.488372 66.983806  9.052054e-03  -2.610082
## month=aug              0.0000000   0.000000  5.425101  7.908101e-03  -2.655968
## month=jul              0.0000000   0.000000  7.955466  7.511337e-04  -3.370201
## day_of_week=tue        0.6688963   9.302326 24.210526  4.297599e-04  -3.521100
## y=y_no                 0.0000000   0.000000 52.287449  1.008897e-28 -11.119452
## contact=telephone      0.1903553   6.976744 63.805668  5.878562e-29 -11.167541
## poutcome=nonexistent   0.0000000   0.000000 94.352227 4.020961e-114 -22.704752
## previous=No            0.0000000   0.000000 98.238866 9.693892e-186 -29.065884
```

- Cluster 1
  - job
    1. blue.collar (51,45%)
    2. services (17,87%)
    3. admin (11.92%) (de forma negativa)
  - education
    1. basic (66,56%)
    2. high.school (31,7%)
  - month
    1. may (85,33%)

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

- Cluster 2
  - job
    1. technician (77.21%)
  - education
    1. professional.course (67.67%): Veiem una clara relació entre aquests nivells d'estudis i la categoria technician de la variable job: la majoria de fp estan destinades a feines tècniques.
    2. university.degree (15.23%) (de forma negativa)
  - month
    1. aug (10,69%)
    2. apr (4,53%) (de forma negativa)

En aquest cluster la variable té molt poc pes.

- Cluster 3
  - job
    1. admin (47,91%)
    2. management (17,13%)
    3. self-employed (12,03%)

    Aquestes tres categories estan bastant relacionades amb el tipus de feina que són, ja que feines administratives, de control i d'autònom són similars.
  - education
    1. university.degree (68.14%): Aquesta categoria esta bastant relacionada amb els nivells de job descrits anteriorment, ja que són posicions de feina altes i aquí es descriu el nivell més alt d'estudis registrat.
    2. high.school (21.89%) (de forma negativa)
  - month
    1. may (44,01%) (de forma negativa)
    2. apr (19,31%)
    3. jul (11,29%)
    4. aug (8,31%)
- Cluster 4
  - month
    1. may (53,49%) (de forma negativa)
    2. apr (40,70%)

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

- Cut quality

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

Parangons and class-specific individuals

En aquest apartat podem observar els individus més cercans i més allunyats dels centroides de cada cluster.

A la taula següent podem veure, per cada cluster, els 5 individus més cercans als centroides amb les respectives distàncies:

```
res.hcpc_mca$desc.ind$para
```

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

A la taula següent podem veure, per cada cluster, els 5 individus més distants als centroides amb les respectives distàncies:

```
res.hcpc_mca$desc.ind$dist
```

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

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

```
##         y duration        age         job marital education     housing
## 217  y_no      251 Jove-Adult blue-collar  single     basic housing_yes
## 218  y_no      408 Jove-Adult blue-collar  single     basic housing_yes
## 2140 y_no      163 Jove-Adult blue-collar  single     basic housing_yes
## 162  y_no      163 Jove-Adult blue-collar  single     basic housing_yes
## 70   y_no      177 Jove-Adult blue-collar  single     basic housing_yes
##          loan   contact month day_of_week previous    poutcome clust
## 217   loan_no telephone   may         mon       No nonexistent     1
## 218  loan_yes telephone   may         mon       No nonexistent     1
## 2140 loan_yes telephone   may         mon       No nonexistent     1
## 162  loan_yes telephone   may         mon       No nonexistent     1
## 70   loan_yes telephone   may         mon       No nonexistent     1
```

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

```
##           y duration  age        job marital   education     housing     loan
## 30005 y_yes      137 Gran unemployed married       basic housing_yes  loan_no
## 1764  y_yes      654 Jove   services  single high.school housing_yes  loan_no
## 1725   y_no       64 Jove   services  single high.school housing_yes  loan_no
## 1730   y_no      377 Jove   services  single high.school  housing_no  loan_no
## 1760   y_no      134 Jove   services  single high.school  housing_no loan_yes
##         contact month day_of_week previous    poutcome clust
## 30005 telephone   apr         tue       No nonexistent     1
## 1764  telephone   may         fri       No nonexistent     1
## 1725  telephone   may         fri       No nonexistent     1
## 1730  telephone   may         fri       No nonexistent     1
## 1760  telephone   may         fri       No nonexistent     1
```

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

```
##           y duration        age           job marital           education
## 19754 y_yes      243 Jove-Adult    technician married         high.school
## 21748 y_yes      836 Jove-Adult      services married professional.course
## 35970 y_yes      377 Jove-Adult    technician married professional.course
## 2006   y_no      111      Adult    technician  single professional.course
## 2385   y_no       94 Jove-Adult self-employed  single professional.course
##           housing     loan   contact month day_of_week previous    poutcome
## 19754  housing_no  loan_no telephone   aug         fri       No nonexistent
```

```
## 21748  housing_no  loan_no  cellular   aug         tue       No nonexistent
## 35970  housing_no  loan_no  cellular   may         mon       No nonexistent
## 2006  housing_yes  loan_no telephone   may         mon       No nonexistent
## 2385  housing_yes loan_yes telephone   may         tue       No nonexistent
##       clust
## 19754     2
## 21748     2
## 35970     2
## 2006      2
## 2385      2
```

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

```
##           y duration        age        job marital           education
## 27767 y_yes      544 Jove-Adult technician  single professional.course
## 19249 y_yes      952 Jove-Adult technician  single professional.course
## 30141 y_yes      381 Jove-Adult technician married professional.course
## 30302 y_yes      269      Adult technician married professional.course
## 27724 y_yes       83       Gran technician married professional.course
##           housing     loan  contact month day_of_week previous    poutcome
## 27767 housing_yes loan_yes cellular   mar         fri       No nonexistent
## 19249 housing_yes loan_yes cellular   aug         wed       No nonexistent
## 30141 housing_yes  loan_no cellular   apr         thu       No     failure
## 30302 housing_yes loan_yes cellular   apr         thu       No     failure
## 27724 housing_yes  loan_no cellular   mar         tue       No nonexistent
##       clust
## 27767     2
## 19249     2
## 30141     2
## 30302     2
## 27724     2
```

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

```
##           y  duration        age        job marital         education
## 17809 y_yes  815.5668 Jove-Adult     admin. married university.degree
## 15936 y_yes 1360.0000 Jove-Adult     admin. married university.degree
## 12566 y_yes  599.0000 Jove-Adult management married       high.school
## 25995 y_yes 1061.0000      Adult     admin. married       high.school
## 14696 y_yes  838.0000 Jove-Adult management married       high.school
##           housing    loan  contact month day_of_week previous    poutcome clust
## 17809  housing_no loan_no cellular   jul         tue       No nonexistent     3
```

```
## 15936  housing_no loan_no cellular   jul         mon       No nonexistent     3
## 12566 housing_yes loan_no cellular   jul         mon       No nonexistent     3
## 25995  housing_no loan_no cellular   nov         wed       No nonexistent     3
## 14696 housing_yes loan_no cellular   jul         tue       No nonexistent     3
```

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

```
##           y duration  age        job marital education     housing     loan
## 30384 y_yes      416 Gran unemployed  single     basic housing_yes  loan_no
## 28541 y_yes      167 Gran unemployed married     basic  housing_no  loan_no
## 29982 y_yes      109 Gran unemployed married     basic  housing_no  loan_no
## 30001 y_yes      356 Gran unemployed married     basic  housing_no  loan_no
## 28615 y_yes      139 Gran unemployed married     basic  housing_no loan_yes
##        contact month day_of_week previous    poutcome clust
## 30384 cellular   apr         thu       No nonexistent     3
## 28541 cellular   apr         wed       No     failure     3
## 29982 cellular   apr         tue       No     failure     3
## 30001 cellular   apr         tue       No     failure     3
## 28615 cellular   apr         wed       No     failure     3
```

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

```
##           y duration        age         job marital   education     housing
## 34649 y_yes      479 Jove-Adult  technician  single       basic housing_yes
## 25854 y_yes      522 Jove-Adult blue-collar  single high.school housing_yes
## 30464 y_yes      417 Jove-Adult  unemployed married high.school  housing_no
## 30502 y_yes      214 Jove-Adult  unemployed married high.school housing_yes
## 33387 y_yes      549 Jove-Adult      admin.  single       basic  housing_no
##           loan  contact month day_of_week previous poutcome clust
## 34649  loan_no cellular   may         thu      Yes  success     4
## 25854  loan_no cellular   nov         wed      Yes  success     4
## 30464  loan_no cellular   may         mon      Yes  success     4
## 30502  loan_no cellular   may         mon      Yes  success     4
## 33387 loan_yes cellular   may         tue      Yes  success     4
```

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

```
##           y duration        age         job marital           education
## 30239 y_yes      687      Adult  technician married professional.course
## 28677 y_yes      583 Jove-Adult blue-collar married               basic
```

```
## 30208 y_yes      218 Jove-Adult  technician  single professional.course
## 30154 y_yes      412 Jove-Adult    services married         high.school
## 30236 y_yes      297      Adult  technician married professional.course
##           housing     loan  contact month day_of_week previous poutcome clust
## 30239 housing_yes  loan_no cellular   apr         thu      Yes  success     4
## 28677  housing_no  loan_no cellular   apr         thu      Yes  success     4
## 30208 housing_yes  loan_no cellular   apr         thu      Yes  success     4
## 30154 housing_yes  loan_no cellular   apr         thu      Yes  success     4
## 30236 housing_yes loan_yes cellular   apr         thu      Yes  success     4
```

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

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

Comparison of clusters

```
tt1<-table(res.hcpc$data.clust$clust,res.hcpc_mca$data.clust$clust); tt1
```

```
##
##        1    2    3    4
##   1  212  141  619   83
##   2  444  266  607    3
##   3 1593  453  519    0
```

```
100*sum(diag(tt1)/sum(tt1))
```

```
## [1] 20.18219
```

```
tt2<-table(kc$cluster, res.hcpc_mca$data.clust$clust); tt2
```

```
##
##        1    2    3    4
##   1  212  141  619   83
```

```
##   2  423  121  145    0
##   3 1157  334  374    0
##   4  139   90  258    3
##   5  318  174  349    0
```

```
100*sum(diag(tt2)/sum(tt2))
```

```
## [1] 14.37247
```

Per fer la comparació agafarem els resultats dels clusters de PCA i de MCA, veurem dimensió per dimensió com varian les dues targets i els compararem.

Target (y)

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

```
## $`1`
##                    v.test Mean in category Overall mean sd in category
## y               38.338282         1.000000    0.4771255     0.00000000
## duration         8.866357       537.192355  451.5148423   329.95927318
## campaign        -4.762643         1.882851    2.0659116     1.23327956
## age_num         -6.479975        38.331754   40.0534413    11.74491465
## cons.conf.idx  -61.197160       -46.999242  -39.5948381     1.14605418
## cons.price.idx -61.496214        92.963010   93.7237951     0.09580868
## nr.employed    -66.750380      5099.173175 5177.9568016     2.37566471
## emp.var.rate   -68.306030        -1.798483    0.4769231     0.04923657
## euribor3m      -69.834889         1.379672    4.1040802     0.13067118
##                 Overall sd      p.value
## y                0.4994765 0.000000e+00
## duration       353.8929338 7.557823e-19
## campaign         1.4076541 1.910738e-06
## age_num          9.7304136 9.173795e-11
## cons.conf.idx    4.4310744 0.000000e+00
## cons.price.idx   0.4530683 0.000000e+00
## nr.employed     43.2247469 0.000000e+00
## emp.var.rate     1.2199729 0.000000e+00
## euribor3m        1.4287293 0.000000e+00
##
## $`2`
##                   v.test Mean in category Overall mean sd in category
## y              43.138393        0.9848485    0.4771255      0.1221554
## duration       42.672278      807.3636565  451.5148423    319.4681962
```

```
## nr.employed    36.933342     5215.5750758 5177.9568016     16.7671936
## euribor3m      21.271137        4.8202045    4.1040802      0.2855248
## emp.var.rate   21.176161        1.0856818    0.4769231      0.5523088
## campaign        8.501825        2.3479160    2.0659116      1.6933763
## cons.price.idx  7.787766       93.8069379   93.7237951      0.3867083
## age_num        -2.701203       39.4340909   40.0534413      9.2679092
## cons.conf.idx  -2.750672      -39.8820455  -39.5948381      2.9500288
##                 Overall sd       p.value
## y                0.4994765  0.000000e+00
## duration       353.8929338  0.000000e+00
## nr.employed     43.2247469 1.348324e-298
## euribor3m        1.4287293 2.101252e-100
## emp.var.rate     1.2199729  1.584309e-99
## campaign         1.4076541  1.866331e-17
## cons.price.idx   0.4530683  6.820447e-15
## age_num          9.7304136  6.908905e-03
## cons.conf.idx    4.4310744  5.947320e-03
##
## $`3`
##                   v.test Mean in category Overall mean sd in category
## cons.conf.idx   52.633125    -3.640156e+01  -39.5948381   7.896445e-02
## cons.price.idx  43.544978     9.399392e+01   93.7237951   3.869258e-03
## euribor3m       38.443129     4.856114e+00    4.1040802   2.362042e-03
## emp.var.rate    37.273199     1.099532e+00    0.4769231   2.368934e-02
## nr.employed     22.041713     5.191002e+03 5177.9568016   9.475734e-02
## age_num          7.707540     4.108031e+01   40.0534413   8.884695e+00
## campaign        -3.623146     1.996080e+00    2.0659116   1.286602e+00
## duration       -45.065648     2.331483e+02  451.5148423   1.674289e+02
## y              -69.652814     7.797271e-04    0.4771255   2.791271e-02
##                 Overall sd       p.value
## cons.conf.idx    4.4310744  0.000000e+00
## cons.price.idx   0.4530683  0.000000e+00
## euribor3m        1.4287293  0.000000e+00
## emp.var.rate     1.2199729 4.461163e-304
## nr.employed     43.2247469 1.147149e-107
## age_num          9.7304136  1.282658e-14
## campaign         1.4076541  2.910411e-04
## duration       353.8929338  0.000000e+00
## y                0.4994765  0.000000e+00
```

```
res.hcpc_mca$desc.var$category
```

```
## $`1`
##                               Cla/Mod      Mod/Cla     Global       p.value
## education=basic             86.133487  66.56291685 35.1821862  0.000000e+00
```

```
## job=blue-collar                90.532081  51.44508671 25.8704453  0.000000e+00
## contact=telephone              60.247462  84.43752779 63.8056680 9.477077e-177
## month=may                      57.993351  85.32681192 66.9838057 3.520823e-146
## y=y_no                         62.098335  71.32058693 52.2874494 1.785644e-135
## marital=married                53.888000  74.87772343 63.2591093  4.968708e-55
## job=services                   76.571429  17.87461094 10.6275304  6.875358e-53
## poutcome=nonexistent           47.500536  98.44375278 94.3522267  7.002413e-34
## education=high.school          59.367194  31.70297910 24.3117409  1.989472e-28
## previous=No                    46.342469 100.00000000 98.2388664  5.871416e-24
## housing=housing_no             50.695012  55.13561583 49.5141700  4.920995e-13
## age=Adult                      50.221239  30.28012450 27.4493927  4.717230e-05
## month=jun                      58.152174   4.75767008  3.7246964  4.860564e-04
## day_of_week=tue                49.832776  26.50066696 24.2105263  6.050054e-04
## loan=loan_no                   46.290170  87.10538017 85.6680162  8.287388e-03
## month=oct                      29.268293   0.53357048  0.8299595  3.542951e-02
## day_of_week=wed                42.227378  16.18497110 17.4493927  3.217246e-02
## loan=loan_yes                  40.960452  12.89461983 14.3319838  8.287388e-03
## marital=divorced               39.196941   9.11516229 10.5870445  2.047602e-03
## age=Jove                       32.738095   2.44553135  3.4008097  6.343174e-04
## day_of_week=thu                40.081384  17.51889729 19.8987854  1.232443e-04
## month=jul                      33.587786   5.86927523  7.9554656  5.715705e-07
## age=Gran                        3.333333   0.04446421  0.6072874  3.092767e-07
## job=self-employed              29.106628   4.49088484  7.0242915  9.457441e-11
## housing=housing_yes            40.457097  44.86438417 50.4858300  4.920995e-13
## poutcome=failure               17.857143   1.55624722  3.9676113  1.144982e-16
## poutcome=success                0.000000   0.00000000  1.6801619  7.070463e-23
## previous=Yes                    0.000000   0.00000000  1.7611336  5.871416e-24
## month=mar                       2.542373   0.13339262  2.3886640  4.227342e-27
## month=nov                       8.556150   0.71142730  3.7854251  2.406330e-29
## month=aug                      11.567164   1.37839040  5.4251012  1.103349e-34
## job=management                 15.466667   2.57892397  7.5910931  1.622807e-37
## marital=single                 27.863777  16.00711427 26.1538462  2.705281e-51
## job=admin.                     23.123382  11.91640729 23.4615385  5.726114e-72
## month=apr                       6.378132   1.24499778  8.8866397  3.025751e-80
## y=y_yes                        27.365295  28.67941307 47.7125506 1.785644e-135
## education=professional.course  1.437700   0.40017786 12.6720648 2.460003e-162
## contact=cellular               19.574944  15.56247221 36.1943320 9.477077e-177
## job=technician                  2.002670   0.66696309 15.1619433 1.377363e-190
## education=university.degree     2.184996   1.33392619 27.7935223  0.000000e+00
##                                   v.test
## education=basic                      Inf
## job=blue-collar                      Inf
## contact=telephone              28.345623
## month=may                      25.746578
## y=y_no                         24.772245
## marital=married                15.624362
```

```
## job=services                   15.306910
## poutcome=nonexistent           12.133687
## education=high.school          11.058706
## previous=No                    10.094021
## housing=housing_no              7.227463
## age=Adult                       4.069213
## month=jun                       3.488325
## day_of_week=tue                 3.429360
## loan=loan_no                    2.640131
## month=oct                      -2.103415
## day_of_week=wed                -2.142261
## loan=loan_yes                  -2.640131
## marital=divorced               -3.083240
## age=Jove                       -3.416500
## day_of_week=thu                -3.839581
## month=jul                      -5.000584
## age=Gran                       -5.117704
## job=self-employed              -6.475379
## housing=housing_yes            -7.227463
## poutcome=failure               -8.288695
## poutcome=success               -9.846880
## previous=Yes                  -10.094021
## month=mar                     -10.781114
## month=nov                     -11.246622
## month=aug                     -12.284049
## job=management                -12.800795
## marital=single                -15.066123
## job=admin.                    -17.940188
## month=apr                     -18.969884
## y=y_yes                       -24.772245
## education=professional.course -27.151061
## contact=cellular              -28.345623
## job=technician                -29.446951
## education=university.degree         -Inf
##
## $`2`
##                                 Cla/Mod     Mod/Cla     Global      p.value
## education=professional.course 92.971246  67.6744186 12.6720648 0.000000e+00
## job=technician                88.651535  77.2093023 15.1619433 0.000000e+00
## month=aug                     34.328358  10.6976744  5.4251012 6.104470e-12
## previous=No                   17.720997 100.0000000 98.2388664 5.046124e-08
## age=Jove-Adult                18.989959  74.7674419 68.5425101 1.140506e-05
## poutcome=nonexistent          17.850247  96.7441860 94.3522267 4.129123e-04
## day_of_week=tue               19.565217  27.2093023 24.2105263 2.520745e-02
## age=Gran                       3.333333   0.1162791  0.6072874 2.645836e-02
## age=Adult                     15.339233  24.1860465 27.4493927 1.741316e-02
```

```
## job=self-employed              9.221902   3.7209302  7.0242915 8.581173e-06
## age=Jove                       4.761905   0.9302326  3.4008097 6.527235e-07
## month=apr                      8.883827   4.5348837  8.8866397 1.253005e-07
## poutcome=success               0.000000   0.0000000  1.6801619 1.100549e-07
## previous=Yes                   0.000000   0.0000000  1.7611336 5.046124e-08
## job=unemployed                 7.495069   4.4186047 10.2631579 1.343328e-11
## job=services                   5.714286   3.4883721 10.6275304 7.876437e-17
## job=management                 3.466667   1.5116279  7.5910931 7.748804e-18
## education=university.degree    9.541151  15.2325581 27.7935223 2.408001e-21
## education=high.school          6.827644   9.5348837 24.3117409 2.928148e-33
## job=blue-collar                4.147105   6.1627907 25.8704453 3.846798e-59
## job=admin.                     2.588438   3.4883721 23.4615385 6.370328e-69
## education=basic                3.739931   7.5581395 35.1821862 6.391386e-94
##                                  v.test
## education=professional.course       Inf
## job=technician                      Inf
## month=aug                      6.877190
## previous=No                    5.449678
## age=Jove-Adult                 4.388661
## poutcome=nonexistent           3.531691
## day_of_week=tue                2.238209
## age=Gran                      -2.219417
## age=Adult                     -2.377866
## job=self-employed             -4.450147
## age=Jove                      -4.974927
## month=apr                     -5.285590
## poutcome=success              -5.309287
## previous=Yes                  -5.449678
## job=unemployed                -6.763892
## job=services                  -8.333082
## job=management                -8.603253
## education=university.degree   -9.485683
## education=high.school        -12.015997
## job=blue-collar              -16.216639
## job=admin.                   -17.546104
## education=basic              -20.559018
##
## $`3`
##                                 Cla/Mod     Mod/Cla     Global       p.value
## education=university.degree   86.598689 68.13753582 27.7935223  0.000000e+00
## job=admin.                    72.131148 47.90830946 23.4615385 7.295011e-192
## contact=cellular              58.836689 60.28653295 36.1943320 2.586108e-148
## y=y_yes                       51.803140 69.97134670 47.7125506 9.515429e-121
## month=apr                     76.765376 19.31232092  8.8866397  2.709105e-77
## job=management                79.733333 17.13467049  7.5910931  3.553602e-75
## marital=single                52.089783 38.56733524 26.1538462  2.184403e-47
```

```
## month=nov                      76.470588  8.19484241  3.7854251  1.407523e-31
## job=self-employed              60.518732 12.03438395  7.0242915  4.199892e-23
## poutcome=failure               66.326531  7.44985673  3.9676113  2.600404e-19
## month=mar                      73.728814  4.98567335  2.3886640  1.020654e-17
## previous=No                    35.936534 99.94269341 98.2388664  1.144210e-15
## age=Jove                       61.309524  5.90257880  3.4008097  3.635738e-12
## age=Gran                       93.333333  1.60458453  0.6072874  3.811565e-11
## month=aug                      54.104478  8.30945559  5.4251012  1.159896e-10
## month=jul                      50.127226 11.28939828  7.9554656  3.779458e-10
## housing=housing_yes            39.414595 56.33237822 50.4858300  1.221197e-09
## day_of_week=thu                40.488301 22.80802292 19.8987854  1.721074e-04
## marital=divorced               42.447419 12.72206304 10.5870445  3.672714e-04
## job=unemployed                 42.406312 12.32091691 10.2631579  4.992983e-04
## day_of_week=wed                39.443155 19.48424069 17.4493927  5.647987e-03
## month=oct                      51.219512  1.20343840  0.8299595  3.806523e-02
## age=Adult                      32.669617 25.38681948 27.4493927  1.608590e-02
## month=jun                      25.543478  2.69340974  3.7246964  3.955253e-03
## education=high.school          31.806828 21.89111748 24.3117409  3.241826e-03
## poutcome=nonexistent           34.649217 92.55014327 94.3522267  6.875285e-05
## day_of_week=tue                29.933110 20.51575931 24.2105263  6.301578e-06
## housing=housing_no             31.152903 43.66762178 49.5141700  1.221197e-09
## previous=Yes                    1.149425  0.05730659  1.7611336  1.144210e-15
## poutcome=success                0.000000  0.00000000  1.6801619  1.336576e-16
## job=services                   16.190476  4.87106017 10.6275304  1.268130e-24
## marital=married                27.200000 48.71060172 63.2591093  1.050906e-54
## job=technician                  6.542056  2.80802292 15.1619433  3.344219e-88
## education=professional.course   3.194888  1.14613181 12.6720648  9.838051e-96
## y=y_no                         20.286489 30.02865330 52.2874494 9.515429e-121
## month=may                      23.209429 44.01146132 66.9838057 8.495490e-140
## contact=telephone              21.986041 39.71346705 63.8056680 2.586108e-148
## job=blue-collar                 3.990610  2.92263610 25.8704453 3.266085e-204
## education=basic                 8.745685  8.71060172 35.1821862 1.448069e-207
##                                    v.test
## education=university.degree           Inf
## job=admin.                      29.546446
## contact=cellular                25.936442
## y=y_yes                         23.365829
## month=apr                       18.609144
## job=management                  18.345995
## marital=single                  14.459480
## month=nov                       11.691575
## job=self-employed                9.899112
## poutcome=failure                 8.984446
## month=mar                        8.571591
## previous=No                      8.010309
## age=Jove                         6.950663
```

```
## age=Gran                         6.611223
## month=aug                        6.444490
## month=jul                        6.262874
## housing=housing_yes              6.077436
## day_of_week=thu                  3.756789
## marital=divorced                 3.562549
## job=unemployed                   3.481133
## day_of_week=wed                  2.767547
## month=oct                        2.074152
## age=Adult                       -2.406961
## month=jun                       -2.881709
## education=high.school           -2.943826
## poutcome=nonexistent            -3.980561
## day_of_week=tue                 -4.516010
## housing=housing_no              -6.077436
## previous=Yes                    -8.010309
## poutcome=success                -8.270269
## job=services                   -10.243317
## marital=married                -15.576540
## job=technician                 -19.909834
## education=professional.course -20.760576
## y=y_no                         -23.365829
## month=may                      -25.170195
## contact=telephone              -25.936442
## job=blue-collar                -30.492603
## education=basic                -30.744506
##
## $`4`
##                          Cla/Mod    Mod/Cla    Global       p.value     v.test
## previous=Yes          98.8505747 100.000000  1.761134 9.693892e-186  29.065884
## poutcome=success     100.0000000  96.511628  1.680162 2.126492e-177  28.398230
## contact=cellular       4.4742729  93.023256 36.194332  5.878562e-29  11.167541
## y=y_yes                3.6487060 100.000000 47.712551  1.008897e-28  11.119452
## month=apr              7.9726651  40.697674  8.886640  1.072676e-15   8.018244
## day_of_week=thu        3.7639878  43.023256 19.898785  9.257787e-07   4.906793
## job=technician         2.8037383  24.418605 15.161943  2.337339e-02   2.267276
## month=jun              0.0000000   0.000000  3.724696  3.712800e-02  -2.084354
## month=may              1.3901481  53.488372 66.983806  9.052054e-03  -2.610082
## month=aug              0.0000000   0.000000  5.425101  7.908101e-03  -2.655968
## month=jul              0.0000000   0.000000  7.955466  7.511337e-04  -3.370201
## day_of_week=tue        0.6688963   9.302326 24.210526  4.297599e-04  -3.521100
## y=y_no                 0.0000000   0.000000 52.287449  1.008897e-28 -11.119452
## contact=telephone      0.1903553   6.976744 63.805668  5.878562e-29 -11.167541
## poutcome=nonexistent   0.0000000   0.000000 94.352227 4.020961e-114 -22.704752
## previous=No            0.0000000   0.000000 98.238866 9.693892e-186 -29.065884
```

- Dimensió 1

Per PCA, aquesta primera target és la més representativa mentres que en MCA, la categoria y__no de la target té un pes important, el 63% d'aquesta categoria es troba en aquesta dimensió.

- Dimensió 2

En aquesta segona dimensió, per PCA també és considerable la target y, mentres que per MCA no ens surt cap categoria de la variable.

- Dimensió 3

En aquesta última dimensió vista en el PCA, la variable y passa a representar-la de forma negativa. En el MCA la categoria y__yes passa a tenir pes, un 51% d'aquesta categoria es troba a la dimensió 3.

- Dimensió 4

Sols per MCA, destacar que totes les categories de la target son y__yes.

Target (duration)

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

```
##                     Eta2      P-value
## duration       0.48037755 0.000000e+00
## emp.var.rate   0.94469043 0.000000e+00
## cons.price.idx 0.79574759 0.000000e+00
## cons.conf.idx  0.86711351 0.000000e+00
## euribor3m      0.98754043 0.000000e+00
## nr.employed    0.95914529 0.000000e+00
## y              0.98239602 0.000000e+00
## campaign       0.01561385 1.345944e-17
## age_num        0.01355134 2.359805e-15
```

```
res.hcpc_mca$desc.var$quanti.var
```

```
##               Eta2      P-value
## duration 0.02505959 5.616258e-27
```

Si comparem els valors Eta2 dels diferents anàlisis, per PCA ens surt un valor superior (0.48) que per MCA (0.025). Això significa que per PCA, la variable ha tingut més pes a l'hora de crear els clusters que en MCA.