First delivery - ADEI

Alex Rubio i Josep Bernad

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Contents

1 Presentation

We are going to work with dataset bank-additional-full.csv with all examples (41188) and 20 inputs, ordered by date (from May 2008 to November 2010), very close to the data analyzed in [Moro et al., 2014].

Deliverables are concerned with Multivariant Data Analysis and model building for response variables: Y-Duration of the call and binary factor Y (Binary Target) if the product (bank term deposit) would be ('yes') or not ('no') subscribed.

2 Bank client data

2.1 Description

Input variables:

1. age (numeric)
2. job : type of job (categorical: 'admin.','blue-collar','entrepreneur','housemaid','management','retired','self-employed','services','student','technician','unemployed','unknown')
3. marital : marital status (categorical: 'divorced','married','single','unknown'; note: 'divorced' means divorced or widowed)
4. education (categorical:'basic.4y','basic.6y','basic.9y','high.school','illiterate','professional.course','university.degree','unkno
5. default: has credit in default? (categorical: 'no','yes','unknown')
6. housing: has housing loan? (categorical: 'no','yes','unknown')

7. loan: has personal loan? (categorical: ‘no’,‘yes’,‘unknown’)# related with the last contact of the current campaign:
8. contact: contact communication type (categorical:‘cellular’,‘telephone’)
9. month: last contact month of year (categorical: ‘jan’, ‘feb’, ‘mar’,. . . , ‘nov’, ‘dec’)
10. day_of_week: last contact day of the week (categorical:‘mon’,‘tue’,‘wed’,‘thu’,‘fri’)
11. duration: last contact duration, in seconds (numeric). Important note: this attribute highly affects the output target (e.g., if duration=0 then y=‘no’). Yet, the duration is not known before a call is performed. Also, after the end of the call y is obviously known. Thus, this input should only be included for benchmark purposes and should be discarded if the intention is to have a realistic predictive model.
12. campaign: number of contacts performed during this campaign and for this client (numeric, includes last contact)
13. pdays: number of days that passed by after the client was last contacted from a previous campaign (numeric; 999 means client was not previously contacted)
14. previous: number of contacts performed before this campaign and for this client (numeric)
15. poutcome: outcome of the previous marketing campaign (categorical: ‘failure’,‘nonexistent’,‘success’)# social and economic context attributes
16. emp.var.rate: employment variation rate - quarterly indicator (numeric)
17. cons.price.idx: consumer price index - monthly indicator (numeric)
18. cons.conf.idx: consumer confidence index - monthly indicator (numeric)
19. euribor3m: euribor 3 month rate - daily indicator (numeric)
20. nr.employed: number of employees - quarterly indicator (numeric)
21. y - has the client subscribed a term deposit? (binary: ‘yes’,‘no’)

3 Loading packages

4 Loading data

```
#rm(list=ls())
# Load Required Packages: to be increased over the course

# Josep
#setwd("~/Developer/r-studio/laboratory-adei/data-directory")
#load("~/Developer/r-studio/laboratory-adei/data-directory/5000_samples.RData")

# Alex
setwd("D:/Google Drive/Uni/ADEI/data-directory")
load(path.expand("D:/Google Drive/Uni/ADEI/data-directory/5000_samples.RData"))

summary(df)
```

```
##       age                  job           marital
##  Min.   :17.00   admin.     :1288   divorced: 546
##  1st Qu.:32.00   blue-collar:1156   married :3029
##  Median :38.00   technician : 831   single  :1416
##  Mean   :39.97   services   : 471   unknown :   9
##  3rd Qu.:47.00   management : 345
##  Max.   :92.00   retired    : 187
##                  (Other)    : 722
##                education       default        housing          loan
##  university.degree  :1431   no     :3939   no     :2226   no     :4138
##  high.school        :1169   unknown:1061   unknown: 112   unknown: 112
##  basic.9y           : 758   yes    :   0   yes    :2662   yes    : 750
##  professional.course: 668
```

```
##  basic.4y           : 493
##  basic.6y           : 272
##  (Other)            : 209
##       contact          month      day_of_week    duration
##  cellular :3182   may    :1679   fri: 948    Min.   :   4.0
##  telephone:1818   jul    : 907   mon:1017    1st Qu.: 104.0
##                   aug    : 699   thu:1031    Median : 181.0
##                   jun    : 660   tue:1005    Mean   : 263.7
##                   nov    : 502   wed: 999    3rd Qu.: 328.0
##                   apr    : 323               Max.   :3078.0
##                   (Other): 230
##     campaign          pdays          previous             poutcome
##  Min.   : 1.000   Min.   :  0.0   Min.   :0.0000   failure    : 493
##  1st Qu.: 1.000   1st Qu.:999.0   1st Qu.:0.0000   nonexistent:4315
##  Median : 2.000   Median :999.0   Median :0.0000   success    : 192
##  Mean   : 2.647   Mean   :957.9   Mean   :0.1772
##  3rd Qu.: 3.000   3rd Qu.:999.0   3rd Qu.:0.0000
##  Max.   :42.000   Max.   :999.0   Max.   :5.0000
##
##   emp.var.rate     cons.price.idx  cons.conf.idx      euribor3m
##  Min.   :-3.4000   Min.   :92.20   Min.   :-50.80   Min.   :0.634
##  1st Qu.:-1.8000   1st Qu.:93.08   1st Qu.:-42.70   1st Qu.:1.344
##  Median : 1.1000   Median :93.88   Median :-41.80   Median :4.857
##  Mean   : 0.1029   Mean   :93.58   Mean   :-40.59   Mean   :3.641
##  3rd Qu.: 1.4000   3rd Qu.:93.99   3rd Qu.:-36.40   3rd Qu.:4.961
##  Max.   : 1.4000   Max.   :94.77   Max.   :-26.90   Max.   :5.045
##
##   nr.employed     y
##  Min.   :4964   no :4416
##  1st Qu.:5099   yes: 584
##  Median :5191
##  Mean   :5168
##  3rd Qu.:5228
##  Max.   :5228
##
```

5 Univariate Descriptive Analysis

Creem factors per cada variable posant abans NA a aquells valos erronis o faltants.

5.1 Transform missing and wrong data to NAs

```
#Default
sel<-which(df$default=="unknown");length(sel)
```

```
## [1] 1061
```

```
df$default[sel] <- NA
df$default <- factor(df$default)
summary(df$default)
```

```
##   no NA's
## 3939 1061
```

```r
#marital
sel<-which(df$marital=="unknown");length(sel)
```

```
## [1] 9
```

```r
df$marital[sel] <- NA
df$marital <- factor(df$marital)
summary(df$marital)
```

```
## divorced  married   single     NA's
##      546     3029     1416        9
```

```r
#Housing
sel<-which(df$housing=="unknown");length(sel)
```

```
## [1] 112
```

```r
df$housing[sel] <- NA
df$housing <- factor(df$housing)
summary(df$housing)
```

```
##   no  yes NA's
## 2226 2662  112
```

```r
#Loan
sel<-which(df$loan=="unknown");length(sel)
```

```
## [1] 112
```

```r
df$loan[sel] <- NA
df$loan <- factor(df$loan)
summary(df$loan)
```

```
##   no  yes NA's
## 4138  750  112
```

```r
#Job
sel<-which(df$job=="unknown");length(sel)
```

```
## [1] 43
```

```r
df$job[sel] <- NA
df$job <- factor(df$job)
summary(df$job)
```

```
##        admin.   blue-collar  entrepreneur     housemaid    management
##          1288          1156           181           132           345
##       retired self-employed      services       student    technician
##           187           152           471           100           831
##    unemployed          NA's
##           114            43
```

```r
S
```

```
## function (object, brief, ...)
## {
##     UseMethod("S")
## }
## <bytecode: 0x00000000196fe4d8>
## <environment: namespace:car>
```

```r
#Education
sel<-which(df$education=="unknown");length(sel)
```

```
## [1] 207
```

```r
df$education[sel] <- NA
df$education <- factor(df$education)
summary(df$education)
```

```
##            basic.4y            basic.6y            basic.9y
##                 493                 272                 758
##         high.school          illiterate professional.course
##                1169                   2                 668
##   university.degree                NA's
##                1431                 207
```

```r
#Pdays
sel<-which(df$pdays==999);length(sel)
```

```
## [1] 4793
```

```r
df$pdays[sel] <- NA
summary(df$pdays)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##   0.000   3.000   6.000   5.792   7.000  18.000    4793
```

```r
#Poutcome
sel<-which(df$poutcome=="nonexistent");length(sel)
```

```
## [1] 4315
```

```r
df$poutcome[sel] <- NA
df$poutcome <- factor(df$poutcome)
summary(df$poutcome)
```

```
## failure success    NA's
##     493     192    4315
```

5.2 Create new factors corresponding to qualitative concepts.

5.2.1 Month

```r
#Modify factor levels label
df$f.month <- factor(df$month, labels=paste("Month", sep="-", levels(df$month)))
table(df$f.month)
```

```
##
## Month-apr Month-aug Month-dec Month-jul Month-jun Month-mar Month-may
##       323       699        19       907       660        66      1679
## Month-nov Month-oct Month-sep
##       502        79        66
```

```r
# Define new factor categories: 1-Spring | 2-Summer | 3-Resta
df$f.season <- 3

# 1 level - spring
sel<-which(df$f.month %in% c("Month-mar","Month-apr","Month-may"))
df$f.season[sel] <-1
```

```r
# 2 level - Summer
sel<-which(df$f.month %in% c("Month-jun","Month-jul","Month-aug"))
df$f.season[sel] <-2

table(df$f.season);summary(df$f.season)
```

```
##
##    1    2    3
## 2068 2266  666
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    1.00    1.00    2.00    1.72    2.00    3.00
```

```r
df$f.season<-factor(df$f.season,levels=1:3,labels=c("Spring","Summer","Aut-Win"))
summary(df$f.season)
```

```
##  Spring  Summer Aut-Win
##    2068    2266     666
```

5.2.2 Job

```r
#Modify factor levels label
df$f.job <- factor(df$job, labels=paste("Job", sep="-", levels(df$job)))

table(df$f.job)
```

```
##
##        Job-admin.   Job-blue-collar  Job-entrepreneur     Job-housemaid
##              1288              1156               181               132
##    Job-management       Job-retired Job-self-employed      Job-services
##               345               187               152               471
##       Job-student    Job-technician    Job-unemployed
##               100               831               114
```

```r
# Define new factor categories: 1-selfemployed | 2-worker | 3-other
df$f.jobsituation<-3

# 1 level - self-employed
sel<-which(df$f.job %in% c("Job-entrepreneur","Job-housemaid","Job-self-employed"))
df$f.jobsituation[sel] <- 1

# 2 level - worker
sel<-which(df$f.job %in% c("Job-admin","Job-blue-collar","Job-management","Job-services","Job-technician
df$f.jobsituation[sel] <- 2

table(df$f.jobsituation);summary(df$f.jobsituation)
```

```
##
##    1    2    3
##  465 2803 1732
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.000   2.000   2.000   2.253   3.000   3.000
```

```r
df$f.jobsituation<-factor(df$f.jobsituation,levels=1:3,labels=c("Self-employed","Worker","Other"))
summary(df$f.jobsituation)
```

```
## Self-employed        Worker         Other
##           465          2803          1732
```

5.2.3 Pdays

```
table(df$pdays)
```

```
##
##  0  1  2  3  4  5  6  7  8  9 10 11 12 13 15 16 17 18
##  1  5 12 62 17  5 48 13  5  9  7  2  4  8  3  1  4  1
```

```
# Define new factor categories: 1-contacted | 2-not contacted
df$f.prev_contacted<-2

# 1 level - contacted
sel<-which(df$pdays %in% c(1:20))
df$f.prev_contacted[sel] <- 1

# 2 level - not contacted
sel<-which(df$pdays %in% c(21:1000))
df$f.prev_contacted[sel] <- 2

table(df$f.prev_contacted);summary(df$f.prev_contacted)
```

```
##
##    1    2
##  206 4794
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.000   2.000   2.000   1.959   2.000   2.000
```

```
df$f.prev_contacted<-factor(df$f.prev_contacted,levels=1:2,labels=c("Contacted","No-contacted"))
summary(df$pdays)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##   0.000   3.000   6.000   5.792   7.000  18.000    4793
```

5.2.4 Education

```
#Modify factor levels label
df$education <- factor(df$education, labels=paste("Edu", sep="-", levels(df$education)))

table(df$education)
```

```
##
##            Edu-basic.4y            Edu-basic.6y            Edu-basic.9y
##                     493                     272                     758
##         Edu-high.school         Edu-illiterate Edu-professional.course
##                    1169                       2                     668
##   Edu-university.degree
##                    1431
```

```
# Define new factor categories: 1-mandatory | 2-nonmandatory | 3-other
df$f.education<-3

# 1 level - mandatory
sel<-which(df$education %in% c("Edu-basic.4y","Edu-basic.6y", "Edu-basic.9y", "Edu-high.school"))
```

```
df$f.education[sel] <- 1

# 2 level - nonmandatory
sel<-which(df$education %in% c("Edu-professional.course","Edu-university.degree"))
df$f.education[sel] <- 2

table(df$f.education);summary(df$f.education)
```

```
##
##    1    2    3
## 2692 2099  209
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.000   1.000   1.000   1.503   2.000   3.000
```

```
df$f.education<-factor(df$f.education,levels=1:3,labels=c("Mandatory","Non-Mandatory","Other"))
summary(df$f.education)
```

```
##     Mandatory Non-Mandatory         Other
##          2692          2099           209
```

5.2.5 Extra Factorization

```
#Housing

df$f.housing<-factor(df$housing,labels=paste("f",sep=".",levels(df$housing)))
table(df$f.housing);summary(df$f.housing);
```

```
##
##  f.no f.yes
##  2226  2662
```

```
##  f.no f.yes  NA's
##  2226  2662   112
```

```
#Marital

df$f.marital<-factor(df$marital,labels=paste("f",sep=".",levels(df$marital)))
table(df$f.marital);summary(df$f.marital);
```

```
##
## f.divorced  f.married   f.single
##        546       3029       1416
```

```
## f.divorced  f.married   f.single       NA's
##        546       3029       1416          9
```

```
#Default
df$f.default<-factor(df$default, labels=paste("f",sep=".",levels(df$default)))
df$f.default <- factor(df$f.default , levels = c(levels(df$f.default), "f.si"))
table(df$f.default);
```

```
##
## f.no f.si
## 3939    0
```

```
#Loan
df$f.loan<-factor(df$loan,labels=paste("f",sep=".",levels(df$loan)))
```

```
table(df$f.loan);summary(df$f.loan)
```

```
##
##  f.no f.yes
##  4138   750
```

```
##  f.no f.yes  NA's
##  4138   750   112
```

```
#Contact
df$f.contact<-factor(df$contact,labels=paste("f",sep=".",levels(df$contact)))
table(df$f.contact);summary(df$f.contact)
```

```
##
##  f.cellular f.telephone
##        3182        1818
```

```
##  f.cellular f.telephone
##        3182        1818
```

```
#Day of Week
df$f.day<-factor(df$day_of_week,labels=paste("f.day",sep=".",levels(df$day)))
table(df$f.day);summary(df$f.day)
```

```
##
## f.day.fri f.day.mon f.day.thu f.day.tue f.day.wed
##       948      1017      1031      1005       999
```

```
## f.day.fri f.day.mon f.day.thu f.day.tue f.day.wed
##       948      1017      1031      1005       999
```

5.3 Create new factors corresponding to quantitative concepts.

5.3.1 Age discreatization

```
summary(df$age)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   17.00   32.00   38.00   39.97   47.00   92.00
```

```
qulist<-quantile(df$age,seq(0,1,0.25),na.rm=TRUE)

varaux<-factor(cut(df$age,breaks=qulist,include.lowest=T))
table(varaux)
```

```
## varaux
## [17,32] (32,38] (38,47] (47,92]
##    1353    1248    1202    1197
```

```
tapply(df$age,varaux,median)
```

```
## [17,32] (32,38] (38,47] (47,92]
##      29      35      43      53
```

```
varaux<-factor(cut(df$age,breaks=c(17,30,40,50,95),include.lowest=T))
table(varaux)
```

```
## varaux
## [17,30] (30,40] (40,50] (50,95]
##     887    2003    1252     858
```

```r
tapply(df$age,varaux,median)
```

```
## [17,30] (30,40] (40,50] (50,95]
##      28      35      45      55
```

```r
df$f.age<-factor(cut(df$age,breaks=c(17,30,40,50,95),include.lowest=T))

summary(df$f.age)
```

```
## [17,30] (30,40] (40,50] (50,95]
##     887    2003    1252     858
```

```r
levels(df$f.age)<-paste0("f.age-",levels(df$f.age))
```

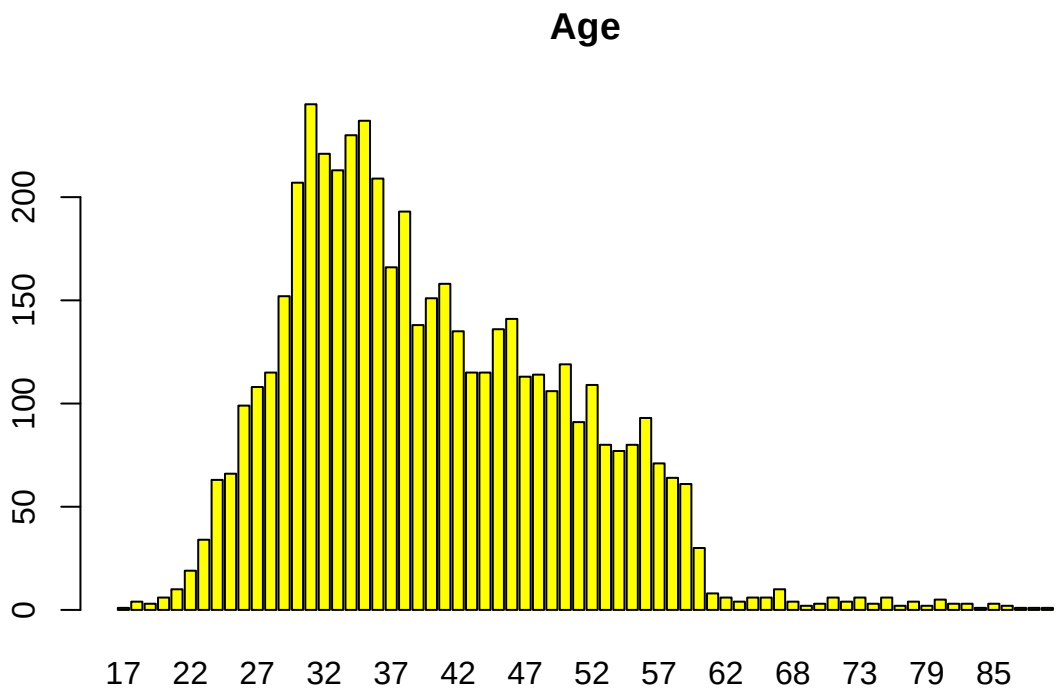
6 Exploratory Data Analysis

6.1 Age

```r
summary(df$age)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   17.00   32.00   38.00   39.97   47.00   92.00
```

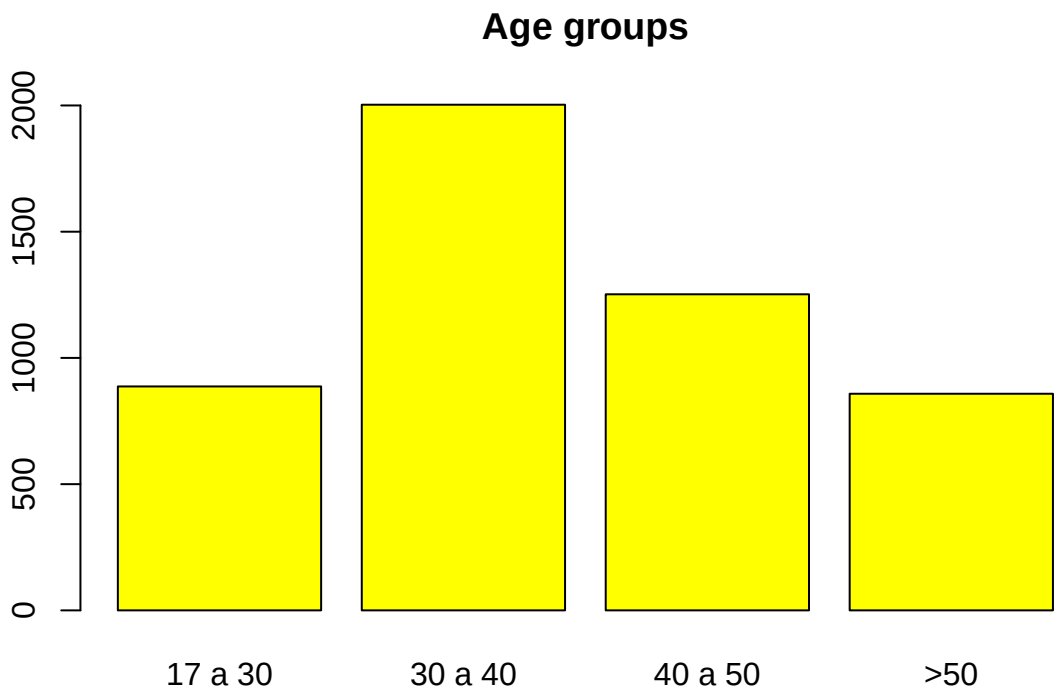
```r
barplot(table(df$age), main= "Age",col="yellow")
```




```r
summary(df$f.age)
```

```
## f.age-[17,30] f.age-(30,40] f.age-(40,50] f.age-(50,95]
##           887          2003          1252           858
```

```
barplot(table(df$f.age), main="Age groups",names.arg=c("17 a 30","30 a 40","40 a 50",">50"),col="yellow
```

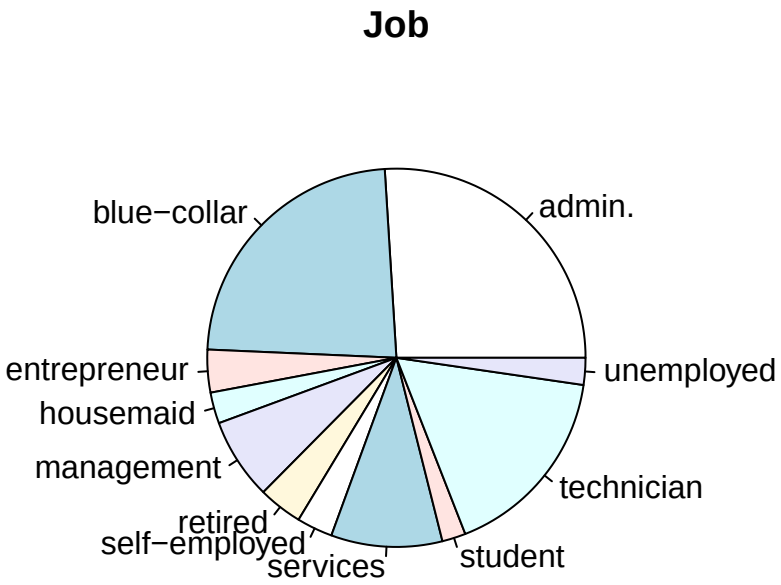


6.2 Job

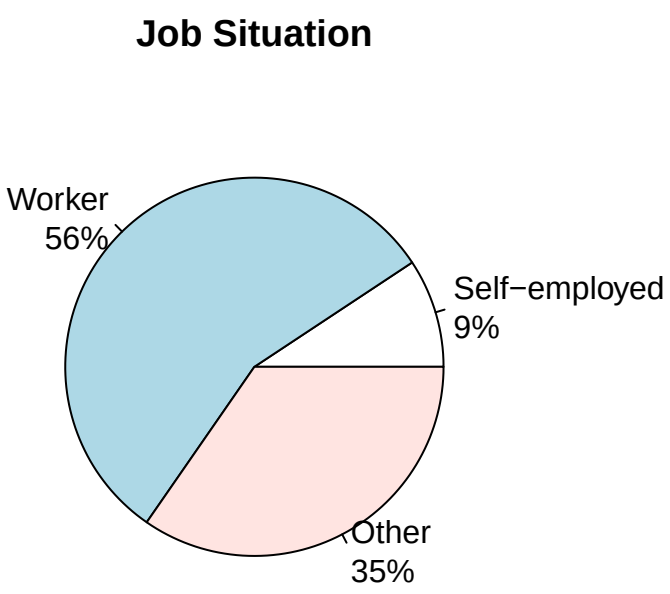
```
table(df$job)
```

```
##
##        admin.   blue-collar  entrepreneur     housemaid    management
##          1288          1156           181           132           345
##       retired self-employed      services       student    technician
##           187           152           471           100           831
##    unemployed
##           114
```

```
pie(table(df$job), main= "Job")
```




```
aux <- table(df$f.jobsituation)
pct <- round(aux/sum(aux)*100)
lbls <- paste(names(aux), "\n", pct, sep="")
lbls <- paste(lbls,"%",sep="") # add % to labels
pie(aux,labels = lbls, main="Job Situation")
```

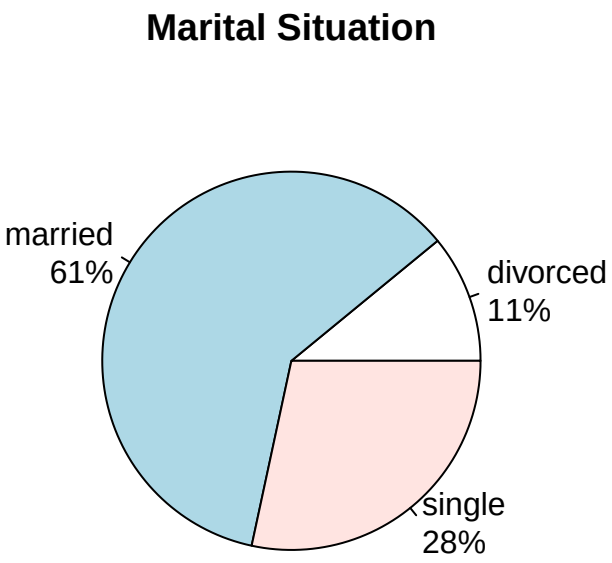


6.3 Marital

```
table(df$marital)
```

```
##
## divorced  married   single
##      546     3029     1416
```

```
aux <- table(df$marital)
pct <- round(aux/sum(aux)*100)
lbls <- paste(names(aux), "\n", pct, sep="")
lbls <- paste(lbls,"%",sep="") # add % to labels
pie(aux,labels = lbls, main="Marital Situation")
```

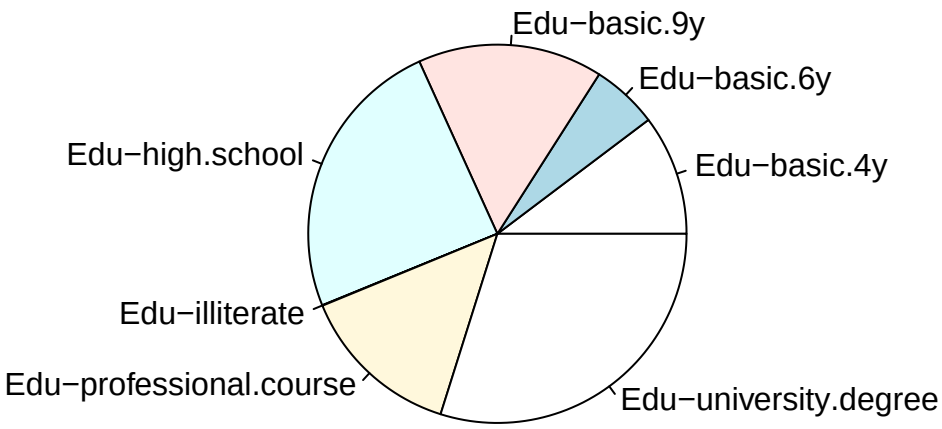


##Education

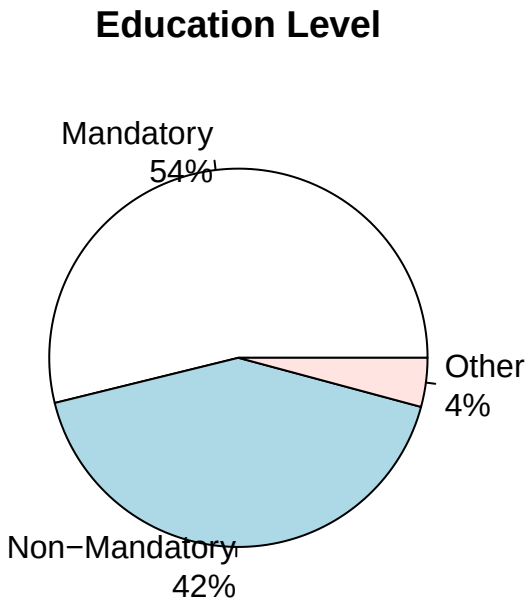
```
table(df$education)
```

```
##
##            Edu-basic.4y            Edu-basic.6y            Edu-basic.9y
##                     493                     272                     758
##         Edu-high.school         Edu-illiterate Edu-professional.course
##                    1169                       2                     668
##   Edu-university.degree
##                    1431
```

```
pie(table(df$education), main= "Education")
```




```
aux <- table(df$f.education)
pct <- round(aux/sum(aux)*100)
lbls <- paste(names(aux), "\n", pct, sep="")
lbls <- paste(lbls,"%",sep="") # ad % to labels
pie(aux,labels = lbls, main="Education Level")
```



6.4 Default-Housing-Loan

```
table(df$default)
```

```
##
##   no
## 3939
```

```
table(df$housing)
```

```
##
##   no  yes
## 2226 2662
```

```
table(df$loan)
```

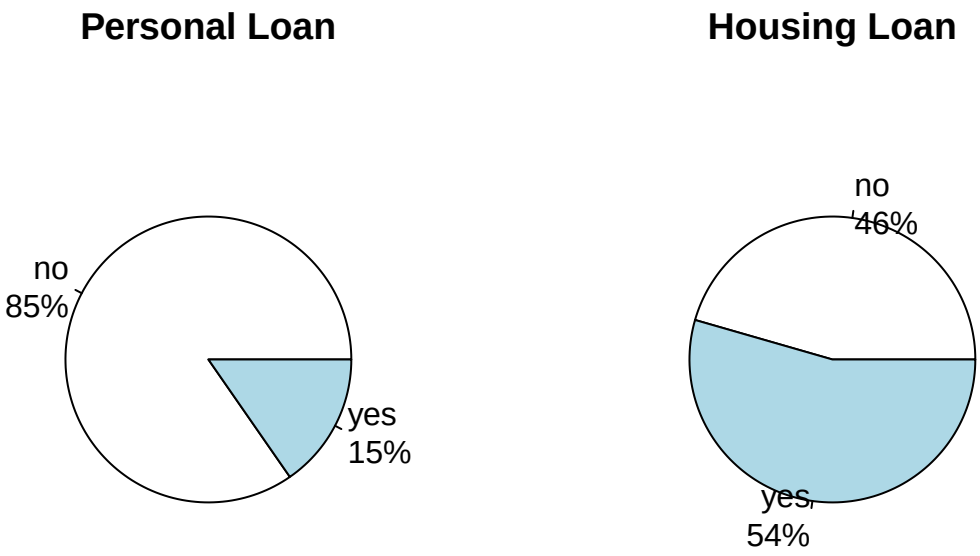
```
##
##   no  yes
## 4138  750
```

```
attach(mtcars)
```

```
## The following object is masked from package:ggplot2:
##
##     mpg
```

```
par(mfrow=c(1,2))
aux <- table(df$loan)
pct <- round(aux/sum(aux)*100)
```

```r
lbls <- paste(names(aux), "\n", pct, sep="")
lbls <- paste(lbls,"%",sep="") # ad % to labels
pie(aux,labels = lbls, main="Personal Loan")
aux <- table(df$housing)
pct <- round(aux/sum(aux)*100)
lbls <- paste(names(aux), "\n", pct, sep="")
lbls <- paste(lbls,"%",sep="") # ad % to labels
pie(aux,labels = lbls, main="Housing Loan")
```




```r
# Retornar l'attach a l'estat predeterminat
attach(mtcars)
```

```
## The following objects are masked from mtcars (pos = 3):
##
##     am, carb, cyl, disp, drat, gear, hp, mpg, qsec, vs, wt
##
## The following object is masked from package:ggplot2:
##
##     mpg
```

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

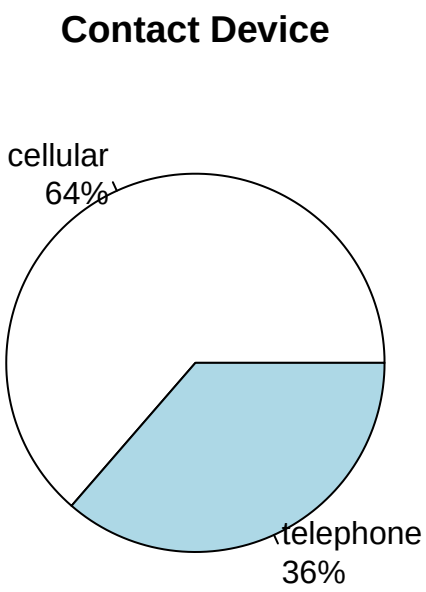
Com es pot veure no hem el gràfic de deutes, ja que el 100% d'individus que han contestat a l'enquesta no en tenien.

6.5 Contact Device

```
table(df$contact)
```

```
##
##  cellular telephone
##      3182      1818
```

```
aux <- table(df$contact)
pct <- round(aux/sum(aux)*100)
lbls <- paste(names(aux), "\n", pct, sep="")
lbls <- paste(lbls,"%",sep="") # ad % to labels
pie(aux,labels = lbls, main="Contact Device")
```



6.6 Date - Month and season

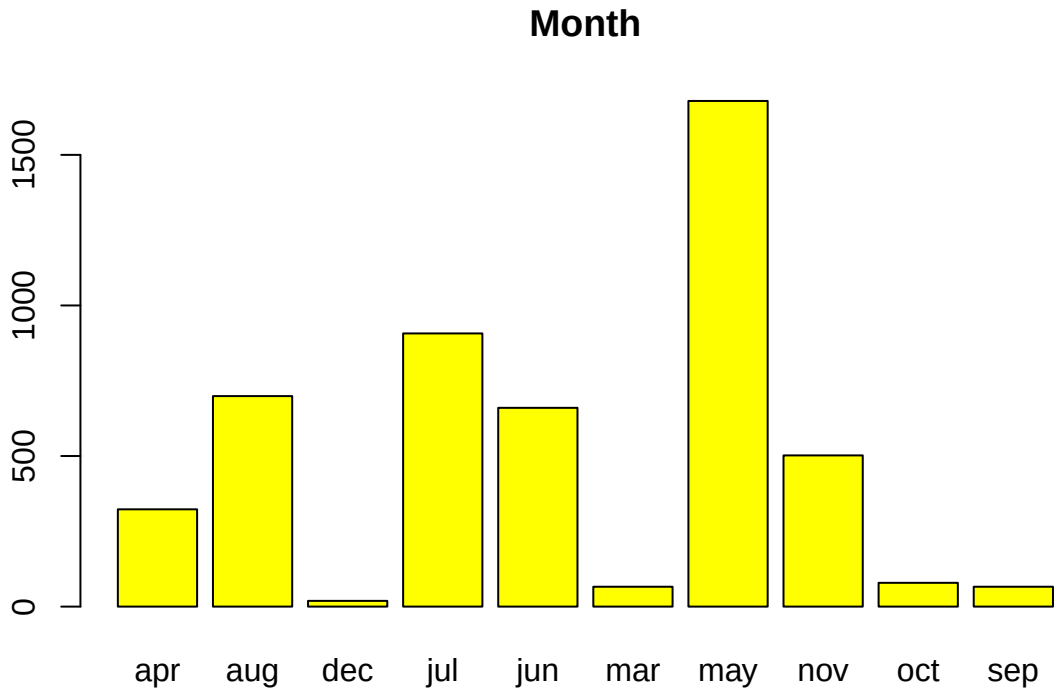
```
table(df$month)
```

```
##
##  apr  aug  dec  jul  jun  mar  may  nov  oct  sep
##  323  699   19  907  660   66 1679  502   79   66
```

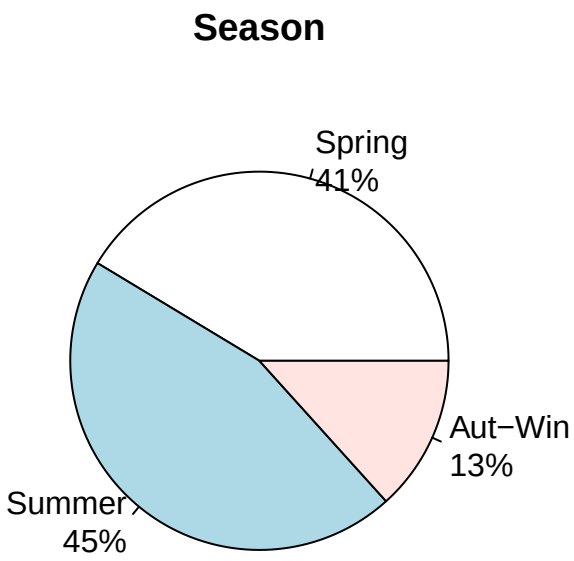
```
table(df$f.season)
```

```
##
##  Spring  Summer Aut-Win
##    2068    2266     666
```

```r
barplot(table(df$month), main= "Month", col="yellow")
```




```r
aux <- table(df$f.season)
pct <- round(aux/sum(aux)*100)
lbls <- paste(names(aux), "\n", pct, sep="")
lbls <- paste(lbls,"%",sep="") # ad % to labels
pie(aux,labels = lbls,
   main="Season")
```

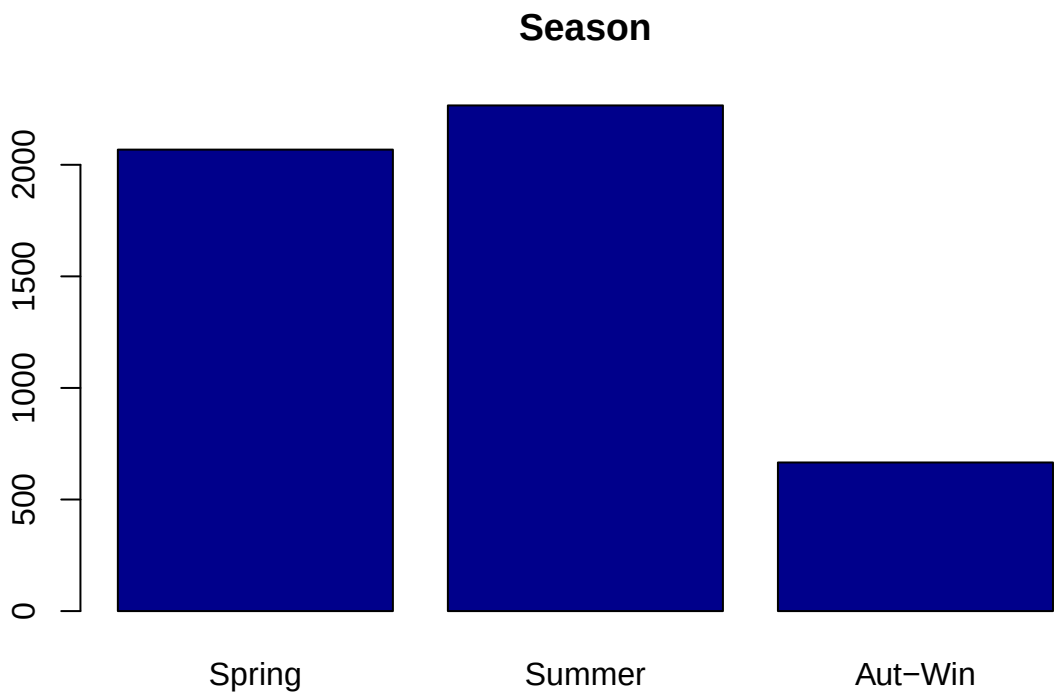


6.7 Date - Day of the week

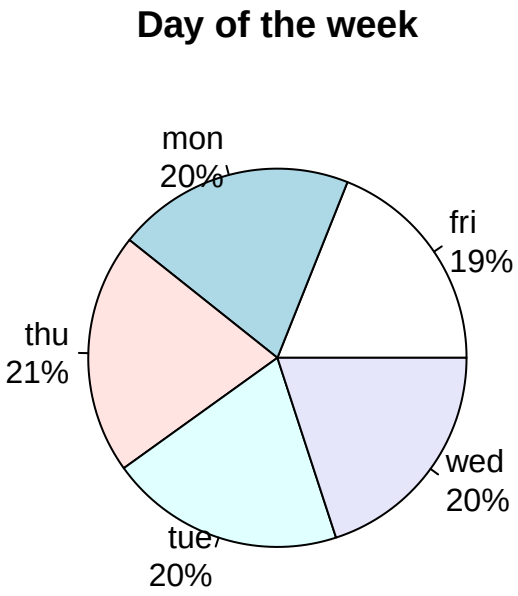
```
table(df$day_of_week)
```

```
##
##  fri  mon  thu  tue  wed
##  948 1017 1031 1005  999
```

```
barplot(table(df$f.season), main= "Season", col="darkblue")
```




```
aux <- table(df$day_of_week)
pct <- round(aux/sum(aux)*100)
lbls <- paste(names(aux), "\n", pct, sep="")
lbls <- paste(lbls,"%",sep="") # ad % to labels
pie(aux,labels = lbls,
   main="Day of the week")
```

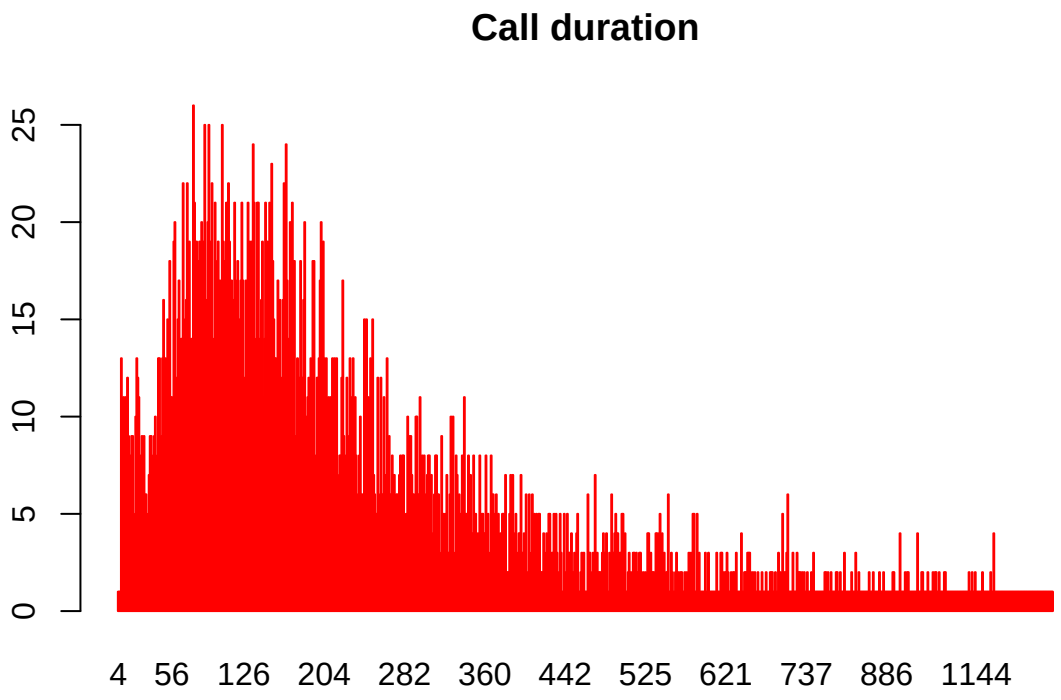


6.8 Duration

```
summary(df$duration)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##     4.0   104.0   181.0   263.7   328.0  3078.0
```

```
barplot(table(df$duration),col="yellow",border="red", main="Call duration")
```

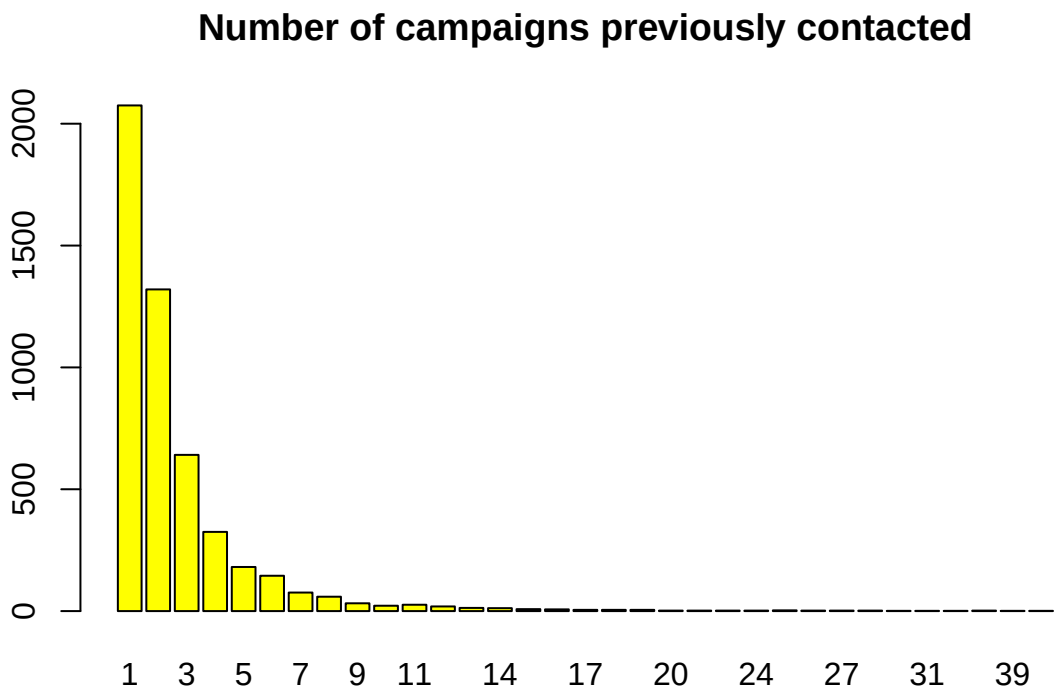


6.9 Campaign

```
summary(df$campaign)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.000   1.000   2.000   2.647   3.000  42.000
```

```
barplot(table(df$campaign),col="yellow", main="Number of campaigns previously contacted")
```

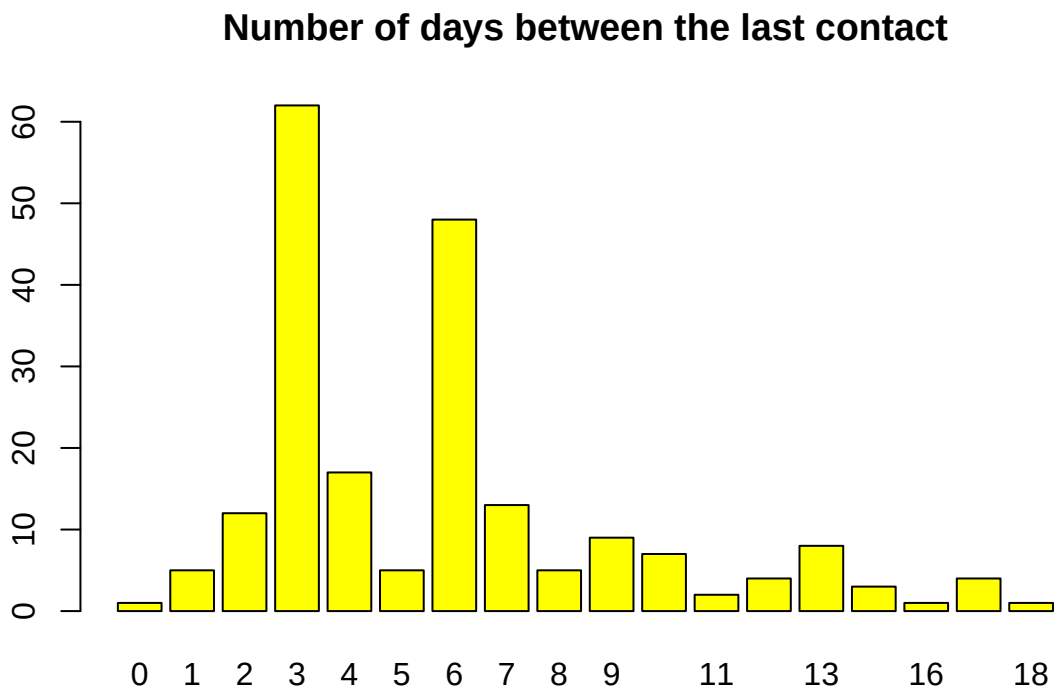


6.10 PDays

```
summary(df$pdays)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##   0.000   3.000   6.000   5.792   7.000  18.000    4793
```

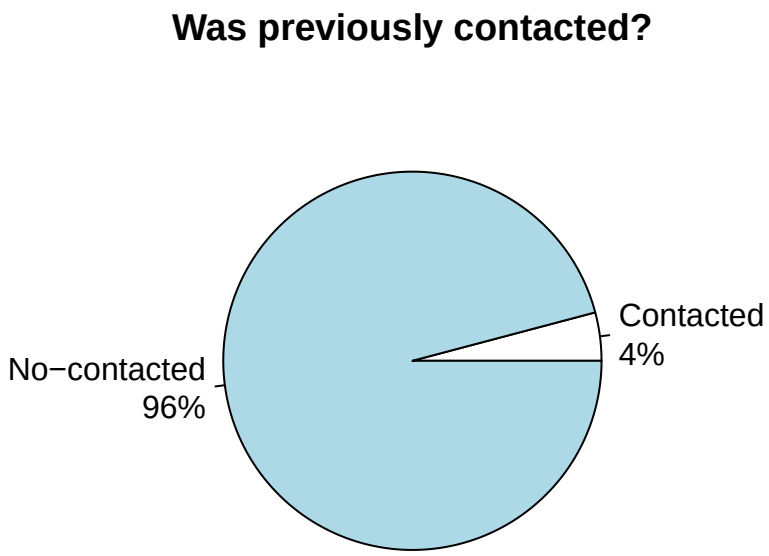
```
barplot(table(df$pdays),col="yellow", main="Number of days between the last contact")
```




```
table(df$f.prev_contacted)
```

```
##
##    Contacted No-contacted
##          206         4794
```

```
aux <- table(df$f.prev_contacted)
pct <- round(aux/sum(aux)*100)
lbls <- paste(names(aux), "\n", pct, sep="")
lbls <- paste(lbls,"%",sep="") # ad % to labels
pie(aux,labels = lbls,
   main="Was previously contacted?")
```



6.11 Prevously

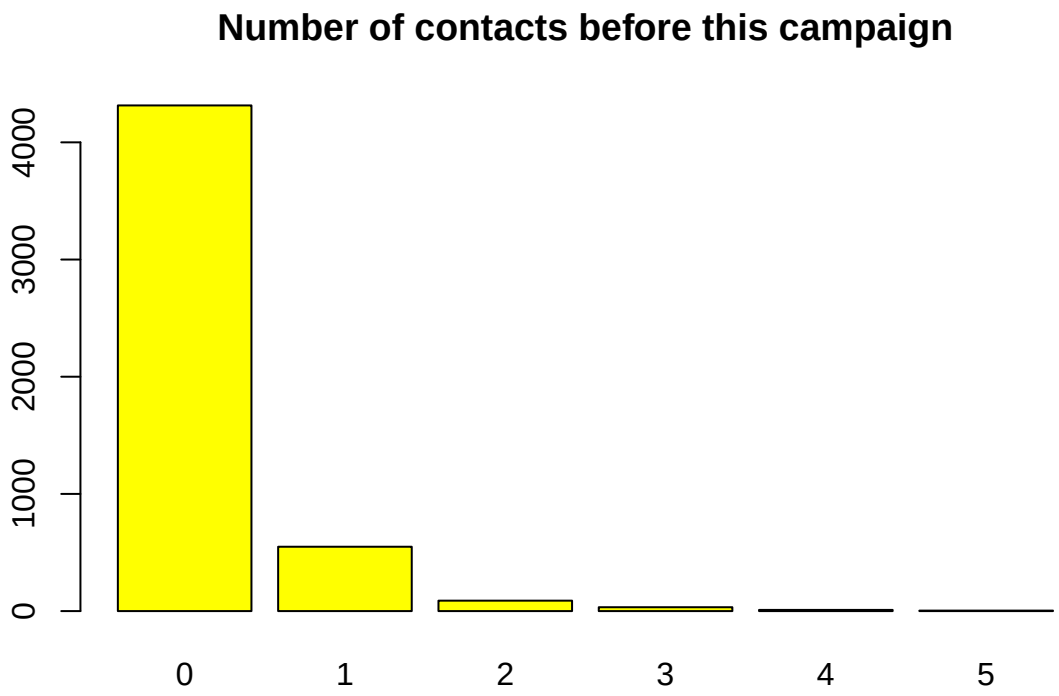
```
summary(df$previous)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.0000  0.0000  0.0000  0.1772  0.0000  5.0000
```

```
table(df$previous)
```

```
##
##    0    1    2    3    4    5
## 4315  549   89   33   10    4
```

```
barplot(table(df$previous),col="yellow", main="Number of contacts before this campaign")
```

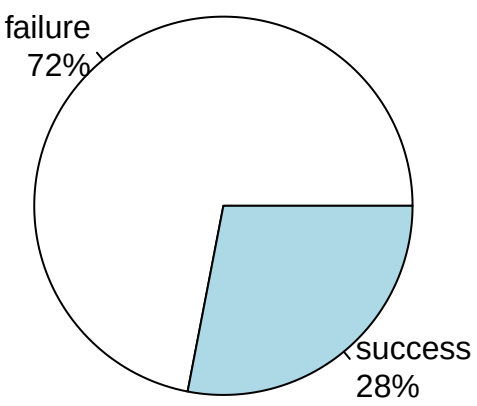


6.12 POutcome

```
table(df$poutcome)
```

```
##
## failure success
##     493     192
```

```
aux <- table(df$poutcome)
pct <- round(aux/sum(aux)*100)
lbls <- paste(names(aux), "\n", pct, sep="")
lbls <- paste(lbls,"%",sep="") # ad % to labels
pie(aux,labels = lbls,
   main="Outome of the previous marketing campaign")
```

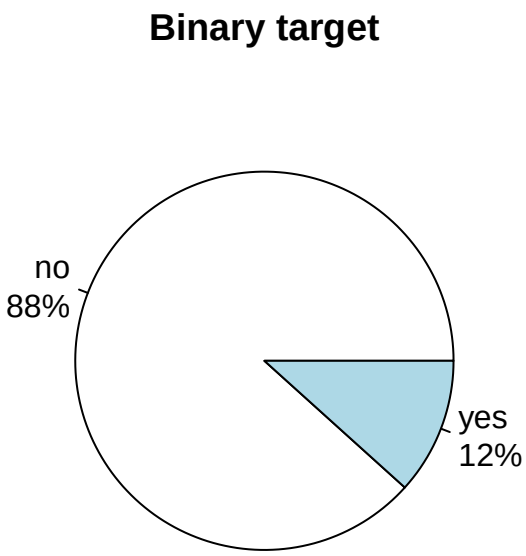


6.13 Y

```
table(df$y)
```

```
##
##   no  yes
## 4416  584
```

```
aux <- table(df$y)
pct <- round(aux/sum(aux)*100)
lbls <- paste(names(aux), "\n", pct, sep="")
lbls <- paste(lbls,"%",sep="") # ad % to labels
pie(aux,labels = lbls,
   main="Binary target")
```



7 Data Quality Report

7.1 Missing Values

```
vmiss<-rep(0,nrow(df))

nInitialVariables<- 21
nmiss<-rep(0,nInitialVariables)

initialVariables <- 0:21
names(nmiss) <- names(df[initialVariables])
names(df[initialVariables])
```

```
##  [1] "age"            "job"            "marital"        "education"
##  [5] "default"        "housing"        "loan"           "contact"
##  [9] "month"          "day_of_week"    "duration"       "campaign"
## [13] "pdays"          "previous"       "poutcome"       "emp.var.rate"
## [17] "cons.price.idx" "cons.conf.idx"  "euribor3m"      "nr.employed"
## [21] "y"
```

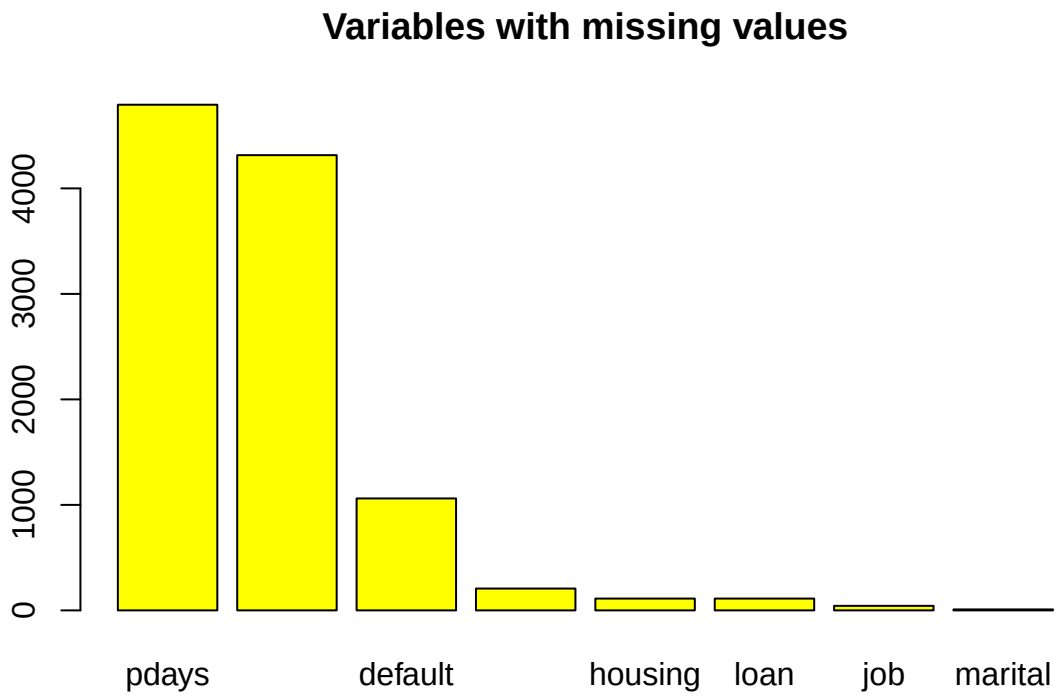
```
for(j in 1:21) {
  nmiss[j]<-nmiss[j]+sum(is.na(df[,j]))
}

nmiss_aux <- nmiss[ nmiss != 0 ]
nmiss_aux <- sort(nmiss_aux, decreasing = TRUE)
```

```r
table(nmiss_aux)
```

```
## nmiss_aux
##    9   43  112  207 1061 4315 4793
##    1    1    2    1    1    1    1
```

```r
barplot(nmiss_aux, col="yellow", main="Variables with missing values");
```



Al barplot sols apareixen les variables amb dades mancants.

7.2 Errors

```r
verrs<-rep(0, nrow(df))

nInitialVariables<- 21
nerrs<-rep(0, nInitialVariables)

initialVariables <- 0:21
names(nerrs) <- names(df[initialVariables])
names(df[initialVariables])
```

```
##  [1] "age"            "job"            "marital"        "education"
##  [5] "default"        "housing"        "loan"           "contact"
##  [9] "month"          "day_of_week"    "duration"       "campaign"
## [13] "pdays"          "previous"       "poutcome"       "emp.var.rate"
## [17] "cons.price.idx" "cons.conf.idx"  "euribor3m"      "nr.employed"
## [21] "y"
```

7.2.1 Job

```
v<-c("admin.", "blue-collar", "entrepreneur", "housemaid", "management", "retired", "self-employed","se
llista<-which(!is.element(df[2], v));
verrs[llista]<-verrs[llista]+1
nerrs[2]<-nerrs[2]+sum(!is.element(df[,2], v))
```

7.2.2 Marital

```
v<-c("divorced", "married", "single", NA)
llista<-which(!is.element(df[3], v));
verrs[llista]<-verrs[llista]+1
nerrs[3]<-nerrs[3]+sum(!is.element(df[,3], v))
```

7.2.3 Education

```
v<-c("Edu-basic.4y", "Edu-basic.6y", "Edu-basic.9y", "Edu-high.school", "Edu-illiterate", "Edu-professi
llista<-which(!is.element(df[4], v));
verrs[llista]<-verrs[llista]+1
nerrs[4]<-nerrs[4]+sum(!is.element(df[,4], v))
```

7.2.4 Default

```
v<-c("no", "yes", NA)
llista<-which(!is.element(df[5], v));
verrs[llista]<-verrs[llista]+1
nerrs[5]<-nerrs[5]+sum(!is.element(df[,5], v))
```

7.2.5 Housing

```
v<-c("no", "yes", NA)
llista<-which(!is.element(df[6], v));
verrs[llista]<-verrs[llista]+1
nerrs[6]<-nerrs[6]+sum(!is.element(df[,6], v))
```

7.2.6 Loan

```
v<-c("no", "yes", NA)
llista<-which(!is.element(df[7], v));
verrs[llista]<-verrs[llista]+1
nerrs[7]<-nerrs[7]+sum(!is.element(df[,7], v))
```

7.2.7 Contact

```
v<-c("cellular", "telephone", NA)
llista<-which(!is.element(df[8], v));
verrs[llista]<-verrs[llista]+1
nerrs[8]<-nerrs[8]+sum(!is.element(df[,8], v))
```

7.2.8 Month

```
v<-c("apr", "aug", "dec", "jul", "jun", "mar", "may", "nov", "oct", "sep", "jan", "feb", NA)
llista<-which(!is.element(df[9], v));
verrs[llista]<-verrs[llista]+1
nerrs[9]<-nerrs[9]+sum(!is.element(df[,9], v))
```

7.2.9 Day of week

```
v<-c("mon", "tue", "wed", "thu", "fri", NA)
llista<-which(!is.element(df[10], v));
verrs[llista]<-verrs[llista]+1
nerrs[10]<-nerrs[10]+sum(!is.element(df[,10], v))
```

7.2.10 Poutcome

```
v<-c("failure", "success", NA)
llista<-which(!is.element(df[,15], v));
verrs[llista]<-verrs[llista]+1
nerrs[15]<-nerrs[15]+sum(!is.element(df[,15], v))
```

7.2.11 Y

```
v<-c("yes", "no", NA)
llista<-which(!is.element(df[21], v));
verrs[llista]<-verrs[llista]+1
nerrs[21]<-nerrs[21]+sum(!is.element(df[,21], v))
```

Així els errors queden:

```
nerrs
```

```
##            age            job        marital      education        default
##              0              0              0              0              0
##        housing           loan        contact          month    day_of_week
##              0              0              0              0              0
##       duration       campaign          pdays       previous       poutcome
##              0              0              0              0              0
##   emp.var.rate cons.price.idx  cons.conf.idx      euribor3m    nr.employed
##              0              0              0              0              0
##              y
##              0
```

7.3 Outliers

```
vout<-rep(0,nrow(df))

nInitialVariables<- 21
nout<-rep(0,nInitialVariables)

initialVariables <- 0:21
names(nout) <- names(df[initialVariables])
names(df[initialVariables])
```

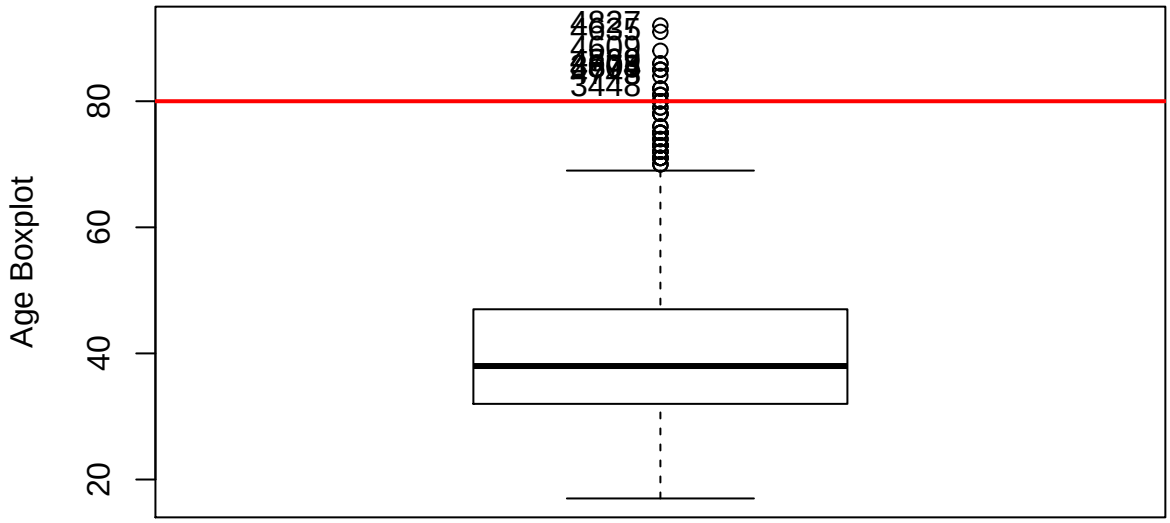
```
##  [1] "age"            "job"            "marital"        "education"
##  [5] "default"        "housing"        "loan"           "contact"
##  [9] "month"          "day_of_week"    "duration"       "campaign"
## [13] "pdays"          "previous"       "poutcome"       "emp.var.rate"
## [17] "cons.price.idx" "cons.conf.idx"  "euribor3m"      "nr.employed"
## [21] "y"
```

7.3.1 Age

```
Boxplot(df$age, ylab = "Age Boxplot")
```

```
##  [1] 4827 4635 4609 4732 4869 3675 4803 4804 4743 3448
```

```
sout <- 80
abline(h=sout,col="red",lwd=2)
```




```
outliers<-which(df$age>sout);length(outliers);
```

```
## [1] 15
```

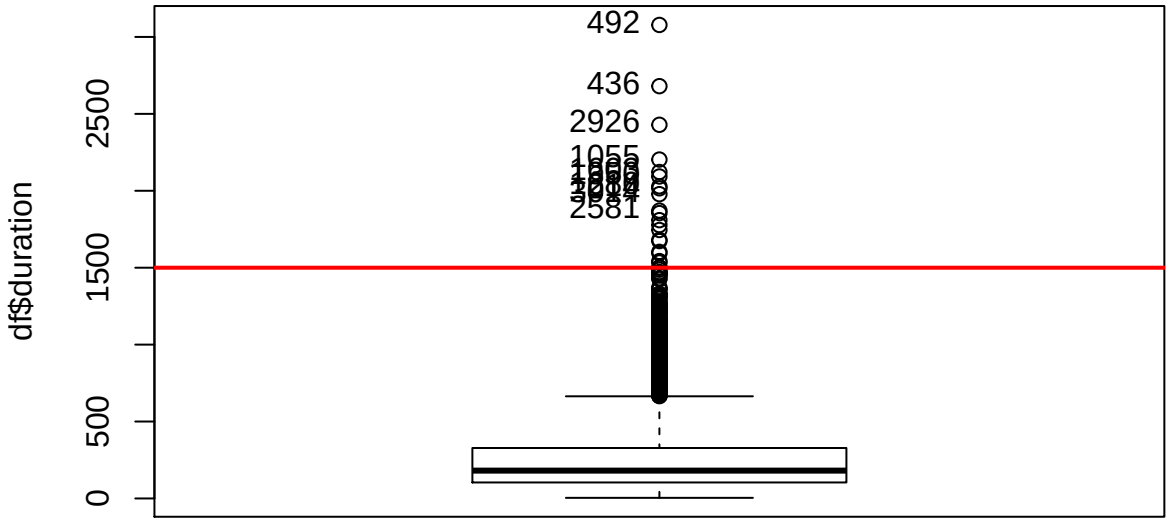
```
df$age[outliers] <- NA;
if(length(outliers)>0){
vout[outliers]<-vout[outliers]+1
nout["age"]<-length(outliers)}
```

7.3.2 duration

```
Boxplot(df$duration)
```

```
##  [1]  492  436 2926 1055 1603 1350 1680  214 3014 2581
```

```
sout <- 1500
abline(h=sout,col="red",lwd=2)
```




```
outliers<-which(df$duration>sout);length(outliers);
```

```
## [1] 21
```

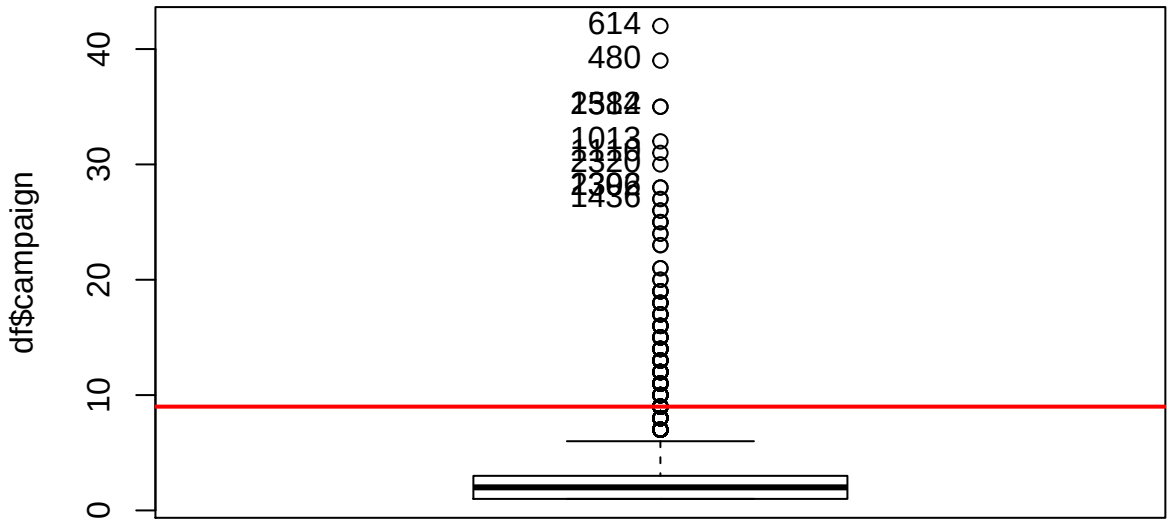
```
if(length(outliers)>0){
vout[outliers]<-vout[outliers]+1
nout["duration"]<-length(outliers)}
```

7.3.3 campaign

```
Boxplot(df$campaign)
```

```
##  [1]  614  480 1584 2312 1013 1110 2320 1392 2306 1436
```

```
sout <- 9
abline(h=sout,col="red",lwd=2)
```



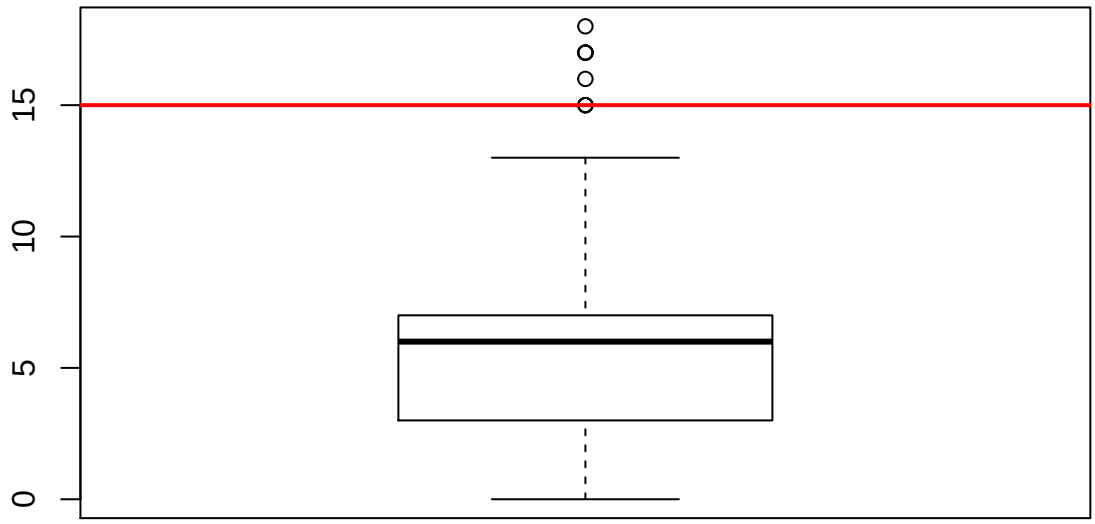

```
outliers<-which(df$campaign>sout);length(outliers);
```

```
## [1] 146
```

```
df$campaign[outliers] <- NA;
if(length(outliers)>0){
vout[outliers]<-vout[outliers]+1
nout["campaign"]<-length(outliers)}
```

7.3.4 pdays

```
boxplot(df$pdays);
sout <- 15;
abline(h=sout,col="red",lwd=2);
```




```
outliers<-which(df$pdays> sout); length(outliers);
```

```
## [1] 6
```

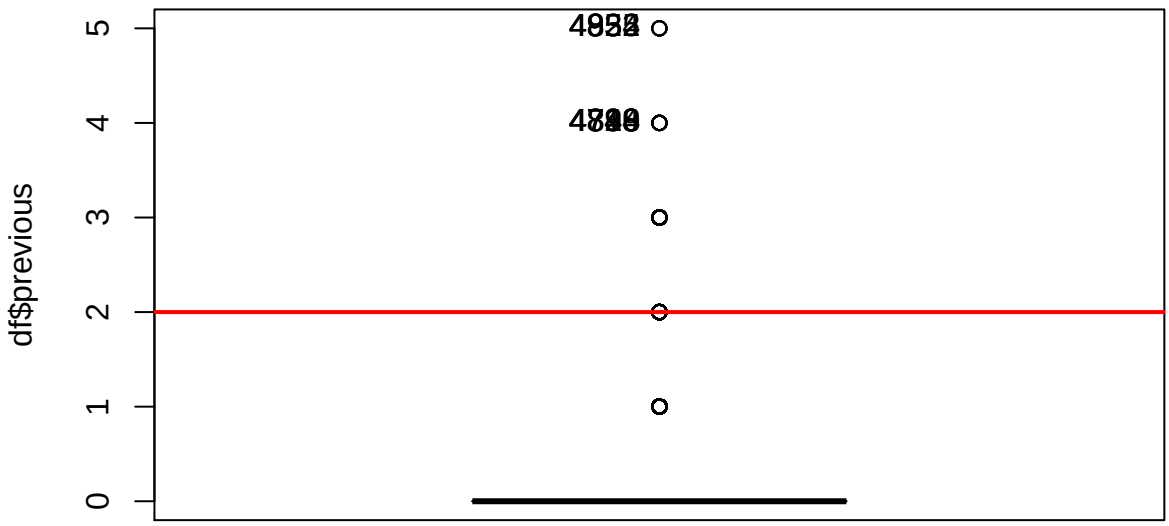
```
df$pdays[outliers] <- NA;
if(length(outliers)>0){
vout[outliers]<-vout[outliers]+1
nout["pdays"]<-length(outliers)}
```

7.3.5 previous

```
Boxplot(df$previous)
```

```
##  [1] 4822 4835 4952 4954 4719 4783 4790 4828 4844 4848
```

```
sout <- 2
abline(h=sout,col="red",lwd=2)
```




```
outliers<-which(df$previous> sout);
df$previous[outliers] <- NA;
length(outliers);
```

```
## [1] 47
```

```
if(length(outliers)>0){
vout[outliers]<-vout[outliers]+1
nout["previous"]<-length(outliers)}
```

Així els outliers queden:

```
nout
```

```
##            age            job        marital      education        default
##             15              0              0              0              0
##        housing           loan        contact          month    day_of_week
##              0              0              0              0              0
##       duration       campaign          pdays       previous       poutcome
##             21            146              6             47              0
##   emp.var.rate cons.price.idx  cons.conf.idx      euribor3m    nr.employed
##              0              0              0              0              0
##              y
##              0
```

8 Rank Variables

```
miss <- sort(nmiss, decreasing =  TRUE)
miss
```

```
##          pdays       poutcome        default      education        housing
##           4793           4315           1061            207            112
##           loan            job        marital            age        contact
##            112             43              9              0              0
##          month    day_of_week       duration       campaign       previous
##              0              0              0              0              0
##   emp.var.rate cons.price.idx  cons.conf.idx      euribor3m    nr.employed
##              0              0              0              0              0
##              y
##              0
```

```
err <- sort(nerrs, decreasing =  TRUE)
err
```

```
##            age            job        marital      education        default
##              0              0              0              0              0
##        housing           loan        contact          month    day_of_week
##              0              0              0              0              0
##       duration       campaign          pdays       previous       poutcome
##              0              0              0              0              0
##   emp.var.rate cons.price.idx  cons.conf.idx      euribor3m    nr.employed
##              0              0              0              0              0
##              y
##              0
```

```
miss <- sort(nmiss, decreasing =  TRUE)
miss
```

```
##          pdays       poutcome        default      education        housing
##           4793           4315           1061            207            112
##           loan            job        marital            age        contact
##            112             43              9              0              0
##          month    day_of_week       duration       campaign       previous
##              0              0              0              0              0
##   emp.var.rate cons.price.idx  cons.conf.idx      euribor3m    nr.employed
##              0              0              0              0              0
##              y
##              0
```

```
out <- sort(nout, decreasing =  TRUE)
out
```

```
##       campaign       previous       duration            age          pdays
##            146             47             21             15              6
##            job        marital      education        default        housing
##              0              0              0              0              0
##           loan        contact          month    day_of_week       poutcome
##              0              0              0              0              0
##   emp.var.rate cons.price.idx  cons.conf.idx      euribor3m    nr.employed
##              0              0              0              0              0
##              y
##              0
```

```
ranking <- nmiss + nerrs + nout;
ranking <- sort(ranking, decreasing = TRUE);
ranking
```

```
##          pdays       poutcome        default      education       campaign
##           4799           4315           1061            207            146
##        housing           loan       previous            job       duration
##            112            112             47             43             21
##            age        marital        contact          month    day_of_week
##             15              9              0              0              0
##   emp.var.rate cons.price.idx  cons.conf.idx      euribor3m    nr.employed
##              0              0              0              0              0
##              y
##              0
```

8.1 Individual

```
vmis<-rep(0, nrow(df))
nmis<-rep(0, ncol(df))
for(i in 1:nrow(df)) {
vmis[i]<-vmis[i]+sum(is.na(df[i,]))
}
### Create variable adding the total number missing values, outliers and errors
df$outliers<-vout
df$errors<-verrs
df$missings<-vmis
```

9 Correlation

```
##Outliers
condes(df, num.var = 35)
```

```
## $quanti
##                 correlation      p.value
## cons.price.idx  0.09277707 4.935483e-11
## duration        0.09217400 6.578690e-11
## missings        0.08750383 5.725813e-10
## cons.conf.idx   0.04206987 2.926427e-03
## campaign       -0.03485868 1.515141e-02
## nr.employed    -0.06723109 1.953740e-06
##
## $quali
##                             R2      p.value
## f.prev_contacted 0.0227976441 6.937572e-27
## month            0.0177019926 2.370453e-15
## f.month          0.0177019926 2.370453e-15
## poutcome         0.0126995605 1.354103e-14
## y                0.0058927611 5.488243e-08
## job              0.0078449930 4.672357e-05
## f.job            0.0078449930 4.672357e-05
## f.jobsituation   0.0036459260 1.088007e-04
## f.season         0.0026809265 1.221971e-03
```

```
## education        0.0035745603 1.249920e-02
## contact          0.0007892906 4.698187e-02
## f.contact        0.0007892906 4.698187e-02
## loan             0.0012042854 4.925618e-02
## f.loan           0.0012042854 4.925618e-02
##
## $category
##                     Estimate      p.value
## Contacted        0.081812419 6.937572e-27
## success          0.072116782 5.134633e-14
## Month-sep        0.132112071 3.375808e-10
## sep              0.132112071 3.375808e-10
## yes              0.025739217 5.488243e-08
## Other            0.014226777 4.381288e-05
## Job-retired      0.049221530 1.038034e-04
## retired          0.049221530 1.038034e-04
## Month-oct        0.059231366 1.236697e-04
## oct              0.059231366 1.236697e-04
## Job-student      0.062269658 6.151821e-04
## student          0.062269658 6.151821e-04
## Summer           0.009445982 1.934820e-03
## Edu-basic.4y     0.027994349 1.707508e-02
## f.no             0.016447061 1.881531e-02
## no               0.016447061 1.881531e-02
## f.single         0.020057898 3.525089e-02
## single           0.020057898 3.525089e-02
## f.married        0.004782537 3.900623e-02
## married          0.004782537 3.900623e-02
## f.age-(50,95]    0.011668659 4.206059e-02
## f.telephone      0.006289677 4.698187e-02
## telephone        0.006289677 4.698187e-02
## f.cellular      -0.006289677 4.698187e-02
## cellular        -0.006289677 4.698187e-02
## failure         -0.022404431 3.040848e-02
## Edu-basic.6y    -0.022588815 2.423028e-02
## Job-services    -0.032252635 2.269021e-02
## services        -0.032252635 2.269021e-02
## Month-jul       -0.017164598 1.433353e-02
## jul             -0.017164598 1.433353e-02
## Month-jun       -0.013342474 1.180245e-02
## jun             -0.013342474 1.180245e-02
## Job-blue-collar -0.024858369 1.096798e-02
## blue-collar     -0.024858369 1.096798e-02
## Edu-basic.9y    -0.013266682 7.404904e-03
## Month-nov       -0.064072886 6.542548e-04
## nov             -0.064072886 6.542548e-04
## Month-may       -0.048442732 3.132088e-04
## may             -0.048442732 3.132088e-04
## Spring          -0.014074703 2.863111e-04
## Worker          -0.013828160 4.717187e-05
## no              -0.025739217 5.488243e-08
## NA              -0.049712351 1.179041e-09
## No-contacted    -0.081812419 6.937572e-27
```

```r
##Errors
##condes(df, num.var = 36)
##Missings
condes(df, num.var = 37)
```

```
## $quanti
##                correlation       p.value
## emp.var.rate    0.32059379 6.915468e-120
## euribor3m       0.31925495 7.539951e-119
## nr.employed     0.31676931 6.159986e-117
## cons.price.idx  0.25210903  2.394819e-73
## age             0.13225565  6.805599e-21
## outliers        0.08750383  5.725813e-10
## cons.conf.idx   0.04099752  3.738104e-03
## campaign        0.03483158  1.523054e-02
## previous       -0.42315303 2.030358e-214
##
## $quali
##                           R2       p.value
## default          0.535780204  0.000000e+00
## f.default        0.535780204  0.000000e+00
## loan             0.241643238 7.313059e-301
## f.loan           0.241643238 7.313059e-301
## housing          0.241517653 1.106051e-300
## f.housing        0.241517653 1.106051e-300
## poutcome         0.204236107 1.286462e-248
## f.prev_contacted 0.113007932 2.380717e-132
## education        0.080884953  6.578439e-87
## job              0.072449068  9.771474e-74
## f.job            0.072449068  9.771474e-74
## f.education      0.061370385  1.891864e-69
## contact          0.046652810  7.324880e-54
## f.contact        0.046652810  7.324880e-54
## month            0.049126070  4.716899e-49
## f.month          0.049126070  4.716899e-49
## y                0.029025116  7.096717e-34
## f.season         0.028568002  3.547259e-32
## f.age            0.022838134  7.424390e-25
## marital          0.022022645  5.860022e-24
## f.marital        0.022022645  5.860022e-24
## f.jobsituation   0.007767691  3.455343e-09
##
## $category
##                            Estimate       p.value
## NA                     1.087223059  0.000000e+00
## NA                     1.087223059  0.000000e+00
## NA                     2.698104360 2.243802e-302
## NA                     2.688966220 2.243802e-302
## NA                     2.698104360 2.243802e-302
## NA                     2.688966220 2.243802e-302
## NA                     1.158397313 1.944798e-227
## No-contacted           1.027183048 2.380717e-132
## NA                     1.151292413  5.804433e-57
## Other                  0.903536808  4.449317e-56
```

```
## f.telephone            0.272689164  7.324880e-54
## telephone              0.272689164  7.324880e-54
## NA                     2.521893692  1.678143e-49
## NA                     2.521893692  1.678143e-49
## no                     0.322138053  7.096717e-34
## Job-blue-collar        0.098621784  1.020782e-18
## blue-collar            0.098621784  1.020782e-18
## Summer                 0.274890250  5.082947e-18
## Edu-basic.4y           0.249890173  1.760364e-14
## NA                     2.130389105  5.531075e-12
## NA                     2.130389105  5.531075e-12
## f.age-(40,50]          0.184697514  9.683462e-11
## Month-jun              0.626592566  1.109488e-10
## jun                    0.626592566  1.109488e-10
## f.age-(50,95]          0.197797300  5.304722e-08
## Worker                 0.084409151  8.550677e-08
## Edu-basic.6y           0.209956096  5.955419e-07
## Month-jul              0.515360065  2.256065e-06
## jul                    0.515360065  2.256065e-06
## Job-housemaid          0.177813354  6.666548e-04
## housemaid              0.177813354  6.666548e-04
## Month-may              0.413964198  3.280969e-03
## may                    0.413964198  3.280969e-03
## Job-management        -0.307496264  3.868777e-02
## management            -0.307496264  3.868777e-02
## Job-technician        -0.266257317  2.039955e-02
## technician            -0.266257317  2.039955e-02
## Month-dec             -0.308176174  1.922055e-02
## dec                   -0.308176174  1.922055e-02
## f.yes                 -1.368490878  2.567887e-03
## yes                   -1.368490878  2.567887e-03
## f.age-(30,40]         -0.087930286  1.231375e-04
## Edu-high.school       -0.270472752  7.333131e-05
## Mandatory             -0.310407397  1.913837e-05
## f.no                  -1.341862621  4.952234e-06
## no                    -1.341862621  4.952234e-06
## Job-student           -0.747641192  2.037418e-06
## student               -0.747641192  2.037418e-06
## Month-apr             -0.014058527  4.532814e-08
## apr                   -0.014058527  4.532814e-08
## f.yes                 -1.347103599  7.963467e-09
## yes                   -1.347103599  7.963467e-09
## Month-oct             -0.439422010  7.506767e-09
## oct                   -0.439422010  7.506767e-09
## Month-mar             -0.521892282  5.489624e-09
## mar                   -0.521892282  5.489624e-09
## Other                 -0.143651719  4.699821e-10
## Month-sep             -0.643104404  2.884680e-11
## sep                   -0.643104404  2.884680e-11
## Month-nov             -0.008008424  7.921110e-12
## nov                   -0.008008424  7.921110e-12
## f.married             -0.550730444  3.578250e-13
## married               -0.550730444  3.578250e-13
## f.single              -0.855957411  5.880094e-14
```

```
## single                -0.855957411  5.880094e-14
## f.age-[17,30]         -0.294564528  6.798179e-15
## Job-admin.            -0.404908272  4.641734e-15
## admin.                -0.404908272  4.641734e-15
## Edu-university.degree -0.426412445  4.461532e-25
## Non-Mandatory         -0.593129411  1.085083e-26
## f.no                  -1.329613482  2.633646e-27
## no                    -1.329613482  2.633646e-27
## Aut-Win               -0.361408450  1.598668e-27
## yes                   -0.322138053  7.096717e-34
## f.cellular            -0.272689164  7.324880e-54
## cellular              -0.272689164  7.324880e-54
## failure               -0.104236689  2.835968e-95
## success               -1.054160624 5.664133e-127
## Contacted             -1.027183048 2.380717e-132
## f.no                  -1.087223059  0.000000e+00
## no                    -1.087223059  0.000000e+00
```

```
aggregate(df$missings, by=list(df$f.age), FUN=mean)
```

```
##         Group.1        x
## 1 f.age-[17,30] 2.153326
## 2 f.age-(30,40] 2.359960
## 3 f.age-(40,50] 2.632588
## 4 f.age-(50,95] 2.645688
```

```
aggregate(df$outliers, by=list(df$f.age), FUN=mean)
```

```
##         Group.1          x
## 1 f.age-[17,30] 0.04847802
## 2 f.age-(30,40] 0.04193709
## 3 f.age-(40,50] 0.04472843
## 4 f.age-(50,95] 0.06060606
```

```
aggregate(df$missings, by=list(df$f.jobsituation), FUN=mean)
```

```
##         Group.1        x
## 1 Self-employed 2.496774
## 2        Worker 2.521941
## 3         Other 2.293880
```

```
aggregate(df$outliers, by=list(df$f.jobsituation), FUN=mean)
```

```
##         Group.1          x
## 1 Self-employed 0.04946237
## 2        Worker 0.03603282
## 3         Other 0.06408776
```

```
aggregate(df$missings, by=list(df$f.education), FUN=mean)
```

```
##         Group.1        x
## 1     Mandatory 2.508544
## 2 Non-Mandatory 2.225822
## 3         Other 3.722488
```

```
aggregate(df$outliers, by=list(df$f.education), FUN=mean)
```

```
##         Group.1          x
```

```
## 1     Mandatory 0.04309064
## 2 Non-Mandatory 0.05050024
## 3         Other 0.06220096
```

```
aggregate(df$missings, by=list(df$f.marital), FUN=mean)
```

```
##      Group.1        x
## 1 f.divorced 2.368132
## 2  f.married 2.541103
## 3   f.single 2.235876
```

```
aggregate(df$outliers, by=list(df$f.marital), FUN=mean)
```

```
##      Group.1          x
## 1 f.divorced 0.04945055
## 2  f.married 0.04192803
## 3   f.single 0.05720339
```

10 Imputation

10.1 Numeric Variables

```
#Outliers -> missings

#Delete duration outliers
outliers<-which(df$duration>1500);length(outliers);
```

```
## [1] 21
```

```
df <- df[-outliers, ]

var_num <-names(df)[c(1, 12:14)] ## age,campaign,pdays,previous
length(var_num)
```

```
## [1] 4
```

```
summary(df[,var_num])
```

```
##       age           campaign         pdays           previous
##  Min.   :17.00   Min.   :1.000   Min.   : 0.000   Min.   :0.000
##  1st Qu.:32.00   1st Qu.:1.000   1st Qu.: 3.000   1st Qu.:0.000
##  Median :38.00   Median :2.000   Median : 5.000   Median :0.000
##  Mean   :39.83   Mean   :2.269   Mean   : 5.458   Mean   :0.147
##  3rd Qu.:47.00   3rd Qu.:3.000   3rd Qu.: 7.000   3rd Qu.:0.000
##  Max.   :80.00   Max.   :9.000   Max.   :15.000   Max.   :2.000
##  NA's   :15      NA's   :145     NA's   :4778     NA's   :47
```

```
res <- imputePCA(df[,var_num],ncp=2)
summary(res$completeObs)
```

```
##       age           campaign         pdays           previous
##  Min.   :17.00   Min.   :1.000   Min.   : 0.000   Min.   :-0.007828
##  1st Qu.:32.00   1st Qu.:1.000   1st Qu.: 5.338   1st Qu.: 0.000000
##  Median :38.00   Median :2.000   Median : 5.394   Median : 0.000000
##  Mean   :39.83   Mean   :2.271   Mean   : 5.389   Mean   : 0.146942
##  3rd Qu.:47.00   3rd Qu.:3.000   3rd Qu.: 5.433   3rd Qu.: 0.000000
##  Max.   :80.00   Max.   :9.000   Max.   :15.000   Max.   : 2.000000
```

```
#S'han imputat valors negatius a previous, els posem a 0

sel <- which(res$completeObs[,"previous"] < 0)
res$completeObs[sel,"previous"] <- 0

df$age <- res$completeObs[,"age"]
df$campaign <- res$completeObs[,"campaign"]
df$pdays <- res$completeObs[,"pdays"]
df$previous <- res$completeObs[,"previous"]
```

10.2 Factors

```
factors <-names(df)[c(24,28, 29 ,31)]; # f.job, f.housing, f.marital, f.loan
summary(df[,factors])
```

```
##              f.job      f.housing         f.marital      f.loan
##  Job-admin.     :1283   f.no :2220   f.divorced: 545   f.no :4120
##  Job-blue-collar:1154   f.yes:2647   f.married :3018   f.yes: 747
##  Job-technician : 829   NA's : 112   f.single  :1407   NA's : 112
##  Job-services   : 469                NA's      :   9
##  Job-management : 343
##  (Other)        : 860
##  NA's           :  41
```

```
resfact <- imputeMCA(df[,factors],ncp=3);
summary(resfact$completeObs)
```

```
##              f.job      f.housing         f.marital      f.loan
##  Job-admin.     :1303   f.no :2223   f.divorced: 545   f.no :4232
##  Job-blue-collar:1175   f.yes:2756   f.married :3027   f.yes: 747
##  Job-technician : 829                f.single  :1407
##  Job-services   : 469
##  Job-management : 343
##  Job-retired    : 186
##  (Other)        : 674
```

```
df$f.housing <- resfact$completeObs[,"f.housing"]
df$f.marital <- resfact$completeObs[,"f.marital"]
df$f.loan <- resfact$completeObs[,"f.loan"]
df$f.job <- resfact$completeObs[,"f.job"]
```

```
#Imputem manualment poutcome ja que pensem que els que no han respós a la pregunta molt probablement ta

sel <- which(is.na(df$poutcome))

df$poutcome <- factor(df$poutcome, labels=paste("Pout", sep="-", levels(df$poutcome)))

table(df$poutcome)
```

```
##
## Pout-failure Pout-success
##          491          192
```

```
df$f.poutcome<-2
```

```r
# 1 level - failure
sel<-which(df$poutcome %in% c("Pout-failure"))
df$f.poutcome[sel] <- 1
sel<- which(is.na(df$poutcome))
df$f.poutcome[sel] <- 1
table(df$f.poutcome)
```

```
##
##    1    2
## 4787  192
```

```r
# 2 level - success
sel<-which(df$poutcome %in% c("Pout-success"))
df$f.poutcome[sel] <- 2
summary(df$f.education)
```

```
##     Mandatory Non-Mandatory         Other
##          2685          2086           208
```

```r
df$f.poutcome<-factor(df$f.poutcome,levels=1:2,labels=c("f.Pout-failure","f.Pout-success"))
summary(df$f.poutcome)
```

```
## f.Pout-failure f.Pout-success
##           4787            192
```

```r
#Imputem manualment default ja que pensem que els que no han respós a la pregunta no poden ser imputats

sel <- which(is.na(df$default))
df$f.default[sel] <- "f.no"
table(df$f.default)
```

```
##
## f.no f.si
## 4979    0
```

11 Profiling

```r
condes(df[c(1:29, 31:34,38)],11)
```

```
## $quanti
##             correlation      p.value
## pdays        0.02993732 0.0346537787
## nr.employed -0.03189122 0.0244288564
## campaign    -0.04723473 0.0008560601
##
## $quali
##                            R2       p.value
## y                 0.160738690 1.169792e-191
## month             0.006371350  2.170869e-04
## f.month           0.006371350  2.170869e-04
## day_of_week       0.002933693  5.566255e-03
## f.day             0.002933693  5.566255e-03
## f.prev_contacted  0.001373939  8.903355e-03
## f.poutcome        0.001278653  1.162430e-02
## contact           0.001010183  2.491598e-02
```

```
## f.contact        0.001010183  2.491598e-02
## f.housing        0.001007355  2.511947e-02
## poutcome         0.001405185  3.024097e-02
##
## $category
##                      Estimate       p.value
## yes                148.5619189 1.169792e-191
## f.day.wed           23.8425938  3.704865e-04
## wed                 23.8425938  3.704865e-04
## Contacted           21.9755934  8.903355e-03
## Month-dec          122.9070700  9.727753e-03
## dec                122.9070700  9.727753e-03
## Job-self-employed   45.0705179  1.128480e-02
## self-employed       42.4765578  1.128480e-02
## f.Pout-success      21.9270496  1.162430e-02
## Pout-success        31.6018377  1.162430e-02
## Month-jul            0.4019466  1.503004e-02
## jul                  0.4019466  1.503004e-02
## no                  10.6116297  2.191781e-02
## f.cellular           7.8044172  2.491598e-02
## cellular             7.8044172  2.491598e-02
## f.no                 7.5382090  2.511947e-02
## Mandatory           11.4647925  2.667720e-02
## f.day.mon          -13.0962186  4.765549e-02
## mon                -13.0962186  4.765549e-02
## yes                 -4.7751417  2.952173e-02
## Summer              -9.4533836  2.921958e-02
## f.yes               -7.5382090  2.511947e-02
## f.telephone         -7.8044172  2.491598e-02
## telephone           -7.8044172  2.491598e-02
## Job-housemaid      -48.9550116  2.360381e-02
## housemaid          -51.5489717  2.360381e-02
## f.Pout-failure     -21.9270496  1.162430e-02
## No-contacted       -21.9755934  8.903355e-03
## Month-aug          -40.1682151  4.976285e-03
## aug                -40.1682151  4.976285e-03
## Month-jun          -43.5063607  1.930997e-03
## jun                -43.5063607  1.930997e-03
## no                -148.5619189 1.169792e-191
```

```
catdes(df, num.var = 21)
```

```
##
## Link between the cluster variable and the categorical variables (chi-square test)
## =================================================================================
##                          p.value df
## f.default          0.000000e+00  1
## f.prev_contacted 1.746438e-113  1
## poutcome         1.256455e-110  2
## f.poutcome       6.599570e-109  1
## month             2.092803e-78  9
## f.month           2.092803e-78  9
## f.job             2.831986e-27 10
## job               6.520196e-27 11
## contact           7.944988e-25  1
```

```
## f.contact         7.944988e-25  1
## default           1.313876e-11  1
## f.jobsituation    3.313476e-08  2
## f.age             4.789647e-08  3
## f.season          5.088671e-08  2
## f.marital         1.549949e-05  2
## marital           3.916274e-05  3
## education         8.492460e-05  7
## f.education       7.801545e-03  2
##
## Description of each cluster by the categories
## =============================================
## $no
##                                  Cla/Mod    Mod/Cla     Global
## f.prev_contacted=No-contacted   90.65577 98.1624319 95.8626230
## f.poutcome=f.Pout-failure       90.53687 98.3212341 96.1438040
## poutcome=NA                     91.13128 88.8157895 86.2823860
## f.contact=f.telephone           94.68733 38.8157895 36.2924282
## contact=telephone               94.68733 38.8157895 36.2924282
## f.month=Month-may               93.12612 35.3448276 33.6011247
## month=may                       93.12612 35.3448276 33.6011247
## default=NA                      94.41816 22.6406534 21.2291625
## job=blue-collar                 94.02080 24.6143376 23.1773448
## f.job=Job-blue-collar           93.95745 25.0453721 23.5991163
## f.jobsituation=Worker           90.30411 57.2595281 56.1357702
## f.marital=f.married             89.85795 61.7059891 60.7953404
## marital=married                 89.82770 61.5018149 60.6145812
## f.age=f.age-(30,40]             90.27569 40.8575318 40.0682868
## education=Edu-basic.9y          91.80978 15.7667877 15.2038562
## f.age=f.age-(40,50]             90.93098 25.7032668 25.0251054
## f.education=Mandatory           89.68343 54.6279492 53.9264913
## f.month=Month-nov               91.58317 10.3675136 10.0220928
## month=nov                       91.58317 10.3675136 10.0220928
## f.season=Summer                 89.63226 45.8938294 45.3303876
## f.month=Month-jun               90.85366 13.5208711 13.1753364
## month=jun                       90.85366 13.5208711 13.1753364
## f.jobsituation=Self-employed    91.32321  9.5508167  9.2588873
## f.job=Job-management            85.13120  6.6243194  6.8889335
## job=management                  85.13120  6.6243194  6.8889335
## poutcome=Pout-failure           85.33605  9.5054446  9.8614180
## f.month=Month-dec               63.15789  0.2722323  0.3816027
## month=dec                       63.15789  0.2722323  0.3816027
## f.age=f.age-(50,95]             85.12881 16.4927405 17.1520386
## education=Edu-university.degree 86.07595 27.7676951 28.5599518
## f.age=f.age-[17,30]             84.50226 16.9464610 17.7545692
## f.job=Job-retired               76.88172  3.2441016  3.7356899
## job=retired                     76.88172  3.2441016  3.7356899
## f.marital=f.single              85.14570 27.1778584 28.2586865
## marital=single                  85.14570 27.1778584 28.2586865
## f.month=Month-apr               78.57143  5.7395644  6.4671621
## month=apr                       78.57143  5.7395644  6.4671621
## f.season=Aut-Win                81.84569 12.2731397 13.2757582
## f.jobsituation=Other            84.91004 33.1896552 34.6053424
## default=no                      86.94544 77.3593466 78.7708375
```

```
## f.job=Job-student                59.59596  1.3384755  1.9883511
## job=student                      59.59596  1.3384755  1.9883511
## f.month=Month-sep                50.00000  0.7486388  1.3255674
## f.month=Month-mar                50.00000  0.7486388  1.3255674
## month=sep                        50.00000  0.7486388  1.3255674
## month=mar                        50.00000  0.7486388  1.3255674
## f.month=Month-oct                50.64935  0.8847550  1.5464953
## month=oct                        50.64935  0.8847550  1.5464953
## f.contact=f.cellular             85.02522 61.1842105 63.7075718
## contact=cellular                 85.02522 61.1842105 63.7075718
## f.poutcome=f.Pout-success        38.54167  1.6787659  3.8561960
## poutcome=Pout-success            38.54167  1.6787659  3.8561960
## f.prev_contacted=Contacted       39.32039  1.8375681  4.1373770
##                                       p.value     v.test
## f.prev_contacted=No-contacted   1.227915e-68  17.508783
## f.poutcome=f.Pout-failure       1.666964e-65  17.093224
## poutcome=NA                     5.763783e-38  12.880929
## f.contact=f.telephone           2.440539e-27  10.831526
## contact=telephone               2.440539e-27  10.831526
## f.month=Month-may               6.034473e-14   7.507332
## month=may                       6.034473e-14   7.507332
## default=NA                      4.251760e-13   7.247295
## job=blue-collar                 1.334762e-12   7.090658
## f.job=Job-blue-collar           1.422485e-12   7.081844
## f.jobsituation=Worker           9.925677e-06   4.418786
## f.marital=f.married             2.858318e-04   3.627813
## marital=married                 4.111959e-04   3.532792
## f.age=f.age-(30,40]             1.478138e-03   3.178942
## education=Edu-basic.9y          1.493774e-03   3.175890
## f.age=f.age-(40,50]             1.761035e-03   3.127827
## f.education=Mandatory           5.915694e-03   2.752418
## f.month=Month-nov               2.035659e-02   2.319710
## month=nov                       2.035659e-02   2.319710
## f.season=Summer                 2.628277e-02   2.222008
## f.month=Month-jun               4.135002e-02   2.040003
## month=jun                       4.135002e-02   2.040003
## f.jobsituation=Self-employed    4.326162e-02   2.021175
## f.job=Job-management            4.686185e-02  -1.987547
## job=management                  4.686185e-02  -1.987547
## poutcome=Pout-failure           2.293362e-02  -2.274539
## f.month=Month-dec               4.353220e-03  -2.851363
## month=dec                       4.353220e-03  -2.851363
## f.age=f.age-(50,95]             8.677261e-04  -3.330235
## education=Edu-university.degree 7.167173e-04  -3.383103
## f.age=f.age-[17,30]             6.154673e-05  -4.006801
## f.job=Job-retired               4.756560e-06  -4.575248
## job=retired                     4.756560e-06  -4.575248
## f.marital=f.single              4.173805e-06  -4.602534
## marital=single                  4.173805e-06  -4.602534
## f.month=Month-apr               1.145794e-07  -5.301939
## month=apr                       1.145794e-07  -5.301939
## f.season=Aut-Win                4.630214e-08  -5.464956
## f.jobsituation=Other            9.853123e-09  -5.733238
## default=no                      4.251760e-13  -7.247295
```

```
## f.job=Job-student               9.483114e-14  -7.447909
## job=student                     9.483114e-14  -7.447909
## f.month=Month-sep               8.048922e-15  -7.766807
## f.month=Month-mar               8.048922e-15  -7.766807
## month=sep                       8.048922e-15  -7.766807
## month=mar                       8.048922e-15  -7.766807
## f.month=Month-oct               1.184930e-16  -8.284614
## month=oct                       1.184930e-16  -8.284614
## f.contact=f.cellular            2.440539e-27 -10.831526
## contact=cellular                2.440539e-27 -10.831526
## f.poutcome=f.Pout-success       1.666964e-65 -17.093224
## poutcome=Pout-success           1.666964e-65 -17.093224
## f.prev_contacted=Contacted      1.227915e-68 -17.508783
##
## $yes
##                                   Cla/Mod   Mod/Cla     Global
## f.prev_contacted=Contacted      60.679612 21.891419  4.1373770
## f.poutcome=f.Pout-success       61.458333 20.665499  3.8561960
## poutcome=Pout-success           61.458333 20.665499  3.8561960
## f.contact=f.cellular            14.974779 83.187391 63.7075718
## contact=cellular                14.974779 83.187391 63.7075718
## f.month=Month-oct               49.350649  6.654991  1.5464953
## month=oct                       49.350649  6.654991  1.5464953
## f.month=Month-sep               50.000000  5.779335  1.3255674
## f.month=Month-mar               50.000000  5.779335  1.3255674
## month=sep                       50.000000  5.779335  1.3255674
## month=mar                       50.000000  5.779335  1.3255674
## f.job=Job-student               40.404040  7.005254  1.9883511
## job=student                     40.404040  7.005254  1.9883511
## default=no                      13.054564 89.667250 78.7708375
## f.jobsituation=Other            15.089959 45.534151 34.6053424
## f.season=Aut-Win                18.154312 21.015762 13.2757582
## f.month=Month-apr               21.428571 12.084063  6.4671621
## month=apr                       21.428571 12.084063  6.4671621
## f.marital=f.single              14.854300 36.602452 28.2586865
## marital=single                  14.854300 36.602452 28.2586865
## f.job=Job-retired               23.118280  7.530648  3.7356899
## job=retired                     23.118280  7.530648  3.7356899
## f.age=f.age-[17,30]             15.497738 23.992995 17.7545692
## education=Edu-university.degree 13.924051 34.676007 28.5599518
## f.age=f.age-(50,95]             14.871194 22.241681 17.1520386
## f.month=Month-dec               36.842105  1.225919  0.3816027
## month=dec                       36.842105  1.225919  0.3816027
## poutcome=Pout-failure           14.663951 12.609457  9.8614180
## f.job=Job-management            14.868805  8.931699  6.8889335
## job=management                  14.868805  8.931699  6.8889335
## f.jobsituation=Self-employed     8.676790  7.005254  9.2588873
## f.month=Month-jun                9.146341 10.507881 13.1753364
## month=jun                        9.146341 10.507881 13.1753364
## f.season=Summer                 10.367745 40.980736 45.3303876
## f.month=Month-nov                8.416834  7.355517 10.0220928
## month=nov                        8.416834  7.355517 10.0220928
## f.education=Mandatory           10.316574 48.511384 53.9264913
## f.age=f.age-(40,50]              9.069021 19.789842 25.0251054
```

```
## education=Edu-basic.9y           8.190225 10.858144 15.2038562
## f.age=f.age-(30,40]              9.724311 33.975482 40.0682868
## marital=married                 10.172300 53.765324 60.6145812
## f.marital=f.married             10.142055 53.765324 60.7953404
## f.jobsituation=Worker            9.695886 47.460595 56.1357702
## f.job=Job-blue-collar            6.042553 12.434326 23.5991163
## job=blue-collar                  5.979203 12.084063 23.1773448
## default=NA                       5.581835 10.332750 21.2291625
## f.month=Month-may                6.873879 20.140105 33.6011247
## month=may                        6.873879 20.140105 33.6011247
## f.contact=f.telephone            5.312673 16.812609 36.2924282
## contact=telephone                5.312673 16.812609 36.2924282
## poutcome=NA                      8.868715 66.725044 86.2823860
## f.poutcome=f.Pout-failure        9.463129 79.334501 96.1438040
## f.prev_contacted=No-contacted    9.344228 78.108581 95.8626230
##                                      p.value     v.test
## f.prev_contacted=Contacted      1.227915e-68  17.508783
## f.poutcome=f.Pout-success       1.666964e-65  17.093224
## poutcome=Pout-success           1.666964e-65  17.093224
## f.contact=f.cellular            2.440539e-27  10.831526
## contact=cellular                2.440539e-27  10.831526
## f.month=Month-oct               1.184930e-16   8.284614
## month=oct                       1.184930e-16   8.284614
## f.month=Month-sep               8.048922e-15   7.766807
## f.month=Month-mar               8.048922e-15   7.766807
## month=sep                       8.048922e-15   7.766807
## month=mar                       8.048922e-15   7.766807
## f.job=Job-student               9.483114e-14   7.447909
## job=student                     9.483114e-14   7.447909
## default=no                      4.251760e-13   7.247295
## f.jobsituation=Other            9.853123e-09   5.733238
## f.season=Aut-Win                4.630214e-08   5.464956
## f.month=Month-apr               1.145794e-07   5.301939
## month=apr                       1.145794e-07   5.301939
## f.marital=f.single              4.173805e-06   4.602534
## marital=single                  4.173805e-06   4.602534
## f.job=Job-retired               4.756560e-06   4.575248
## job=retired                     4.756560e-06   4.575248
## f.age=f.age-[17,30]             6.154673e-05   4.006801
## education=Edu-university.degree 7.167173e-04   3.383103
## f.age=f.age-(50,95]             8.677261e-04   3.330235
## f.month=Month-dec               4.353220e-03   2.851363
## month=dec                       4.353220e-03   2.851363
## poutcome=Pout-failure           2.293362e-02   2.274539
## f.job=Job-management            4.686185e-02   1.987547
## job=management                  4.686185e-02   1.987547
## f.jobsituation=Self-employed    4.326162e-02  -2.021175
## f.month=Month-jun               4.135002e-02  -2.040003
## month=jun                       4.135002e-02  -2.040003
## f.season=Summer                 2.628277e-02  -2.222008
## f.month=Month-nov               2.035659e-02  -2.319710
## month=nov                       2.035659e-02  -2.319710
## f.education=Mandatory           5.915694e-03  -2.752418
## f.age=f.age-(40,50]             1.761035e-03  -3.127827
```

```
## education=Edu-basic.9y          1.493774e-03  -3.175890
## f.age=f.age-(30,40]             1.478138e-03  -3.178942
## marital=married                 4.111959e-04  -3.532792
## f.marital=f.married             2.858318e-04  -3.627813
## f.jobsituation=Worker           9.925677e-06  -4.418786
## f.job=Job-blue-collar           1.422485e-12  -7.081844
## job=blue-collar                 1.334762e-12  -7.090658
## default=NA                      4.251760e-13  -7.247295
## f.month=Month-may               6.034473e-14  -7.507332
## month=may                       6.034473e-14  -7.507332
## f.contact=f.telephone           2.440539e-27 -10.831526
## contact=telephone               2.440539e-27 -10.831526
## poutcome=NA                     5.763783e-38 -12.880929
## f.poutcome=f.Pout-failure       1.666964e-65 -17.093224
## f.prev_contacted=No-contacted   1.227915e-68 -17.508783
##
##
## Link between the cluster variable and the quantitative variables
## ================================================================
##                       Eta2       P-value
## duration       0.160738690 1.169792e-191
## nr.employed    0.120745600 2.760101e-141
## euribor3m      0.087576045 3.394474e-101
## emp.var.rate   0.081696867  3.070308e-94
## previous       0.042285141  1.108497e-48
## missings       0.030232449  4.294241e-35
## cons.price.idx 0.017977169  2.070129e-21
## cons.conf.idx  0.008055104  2.236211e-10
## campaign       0.005633367  1.143924e-07
## outliers       0.002285655  7.393671e-04
##
## Description of each cluster by quantitative variables
## =====================================================
## $no
##                     v.test Mean in category  Overall mean sd in category
## nr.employed     24.516762    5177.09015426 5168.16794537     63.4164811
## euribor3m       20.879501       3.82261162    3.63896766      1.6252539
## emp.var.rate    20.166482       0.26197822    0.10236995      1.4608943
## missings        12.267727       2.51610708    2.44004820      1.1967189
## cons.price.idx   9.459934      93.61071461   93.58315164      0.5520673
## campaign         5.295555       2.31459362    2.27063047      1.6629733
## outliers        -3.373128       0.03924682    0.04277967      0.1976554
## cons.conf.idx   -6.332323     -40.74344374  -40.59754971      4.2611089
## previous       -14.508461       0.11734053    0.14694311      0.3499570
## duration       -28.287050     222.56442831  256.63908415    194.8113004
##                  Overall sd       p.value
## nr.employed     71.3410455 9.788565e-133
## euribor3m        1.7241963  8.224659e-97
## emp.var.rate     1.5515130  1.928802e-90
## missings         1.2153909  1.349895e-34
## cons.price.idx   0.5711736  3.081386e-21
## campaign         1.6274493  1.186556e-07
## outliers         0.2053159  7.431944e-04
## cons.conf.idx    4.5165276  2.414979e-10
```

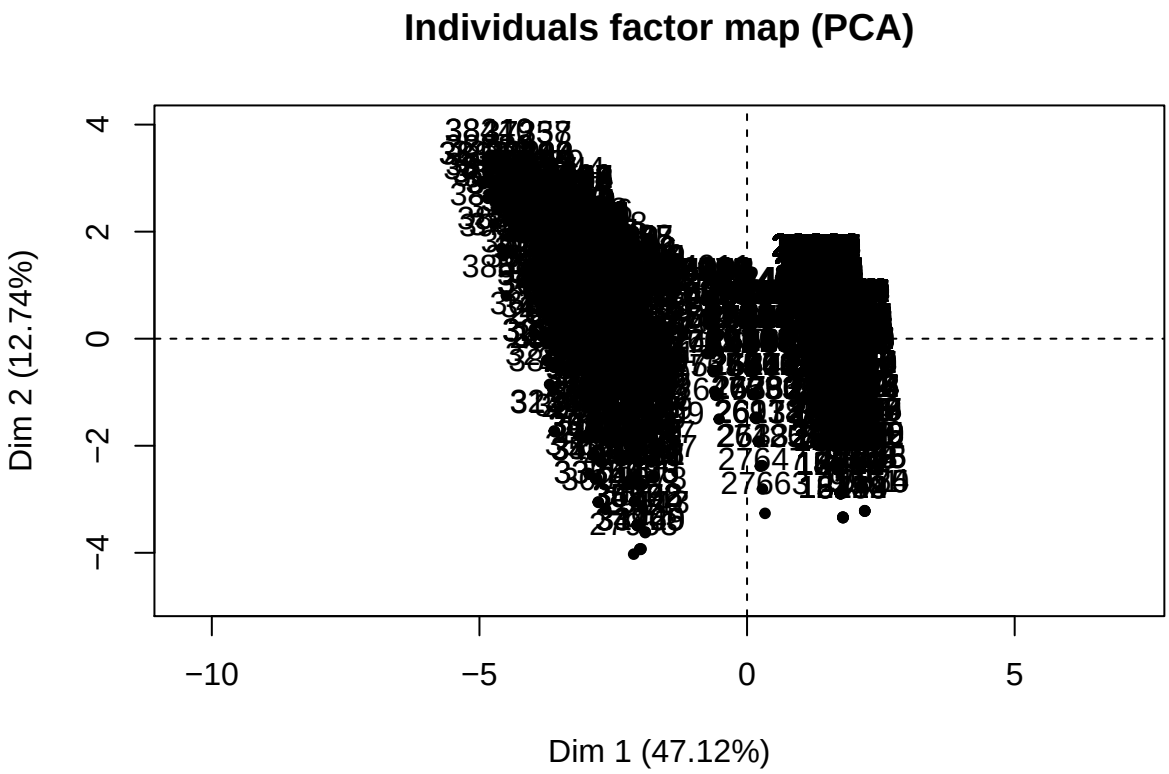
```
## previous         0.3999801  1.070970e-47
## duration       236.1424174 4.987506e-176
##
## $yes
##                    v.test Mean in category  Overall mean sd in category
## duration        28.287050     519.68826620  256.63908415    339.2762889
## previous        14.508461       0.37546879    0.14694311      0.6249775
## cons.conf.idx    6.332323     -39.47127846  -40.59754971      6.0227719
## outliers         3.373128       0.07005254    0.04277967      0.2552355
## campaign        -5.295555       1.93124423    2.27063047      1.2712707
## cons.price.idx  -9.459934      93.37037128   93.58315164      0.6639079
## missings       -12.267727       1.85288967    2.44004820      1.1981032
## emp.var.rate   -20.166482      -1.12977233    0.10236995      1.6732331
## euribor3m      -20.879501       2.22127496    3.63896766      1.8058259
## nr.employed    -24.516762    5099.29036778 5168.16794537     89.3017729
##                 Overall sd       p.value
## duration       236.1424174 4.987506e-176
## previous         0.3999801  1.070970e-47
## cons.conf.idx    4.5165276  2.414979e-10
## outliers         0.2053159  7.431944e-04
## campaign         1.6274493  1.186556e-07
## cons.price.idx   0.5711736  3.081386e-21
## missings         1.2153909  1.349895e-34
## emp.var.rate     1.5515130  1.928802e-90
## euribor3m        1.7241963  8.224659e-97
## nr.employed     71.3410455 9.788565e-133
```

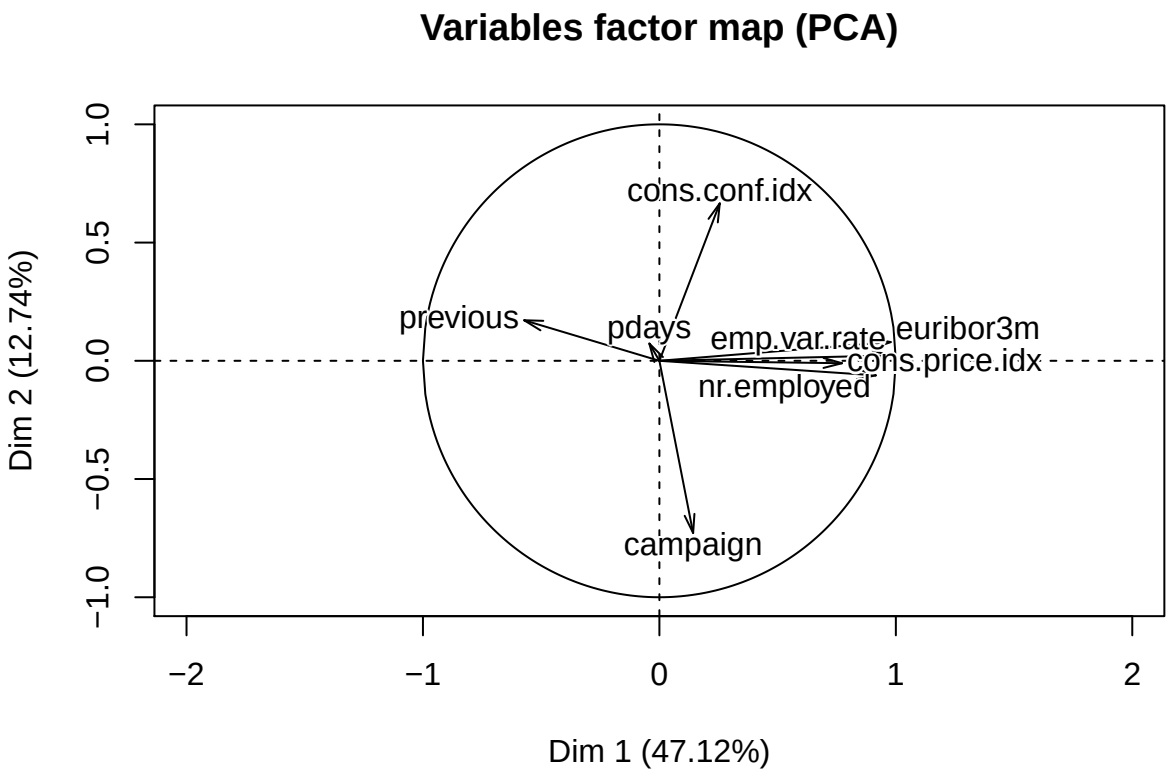
12 Deliverable II: PCA, CA and Clustering

12.1 PCA analysis

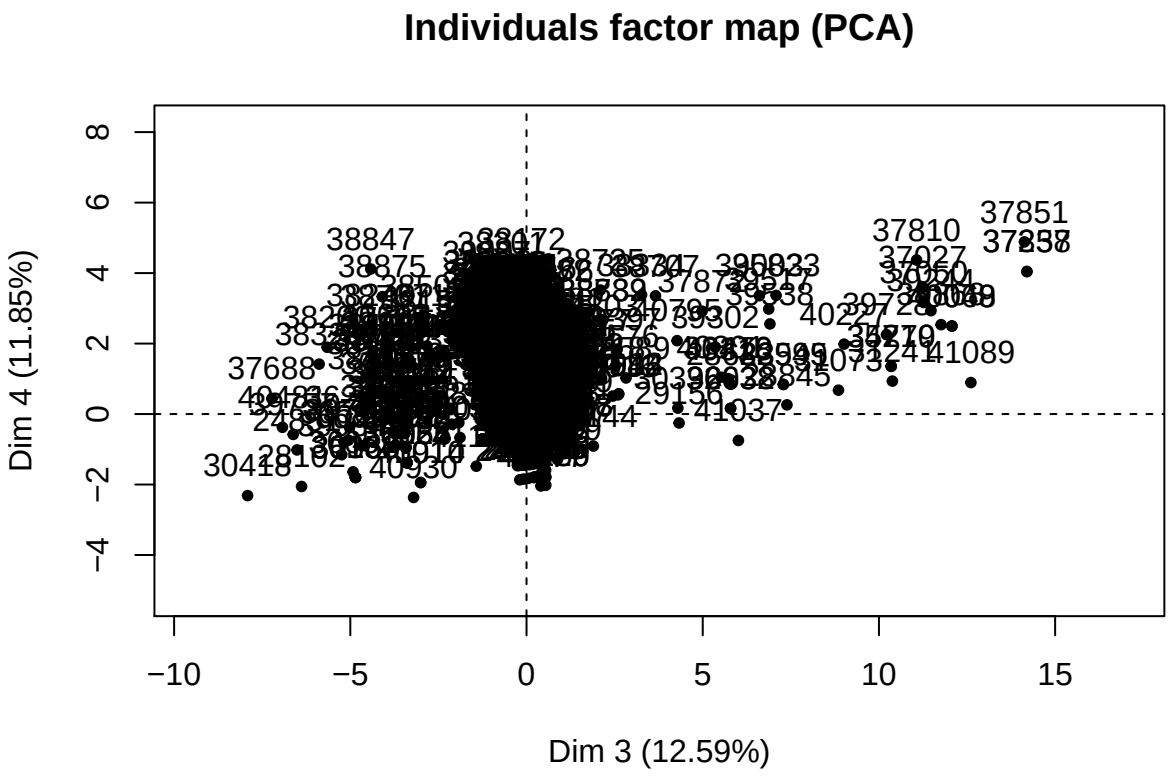
12.1.1 Eigenvalues and dominant axes analysis

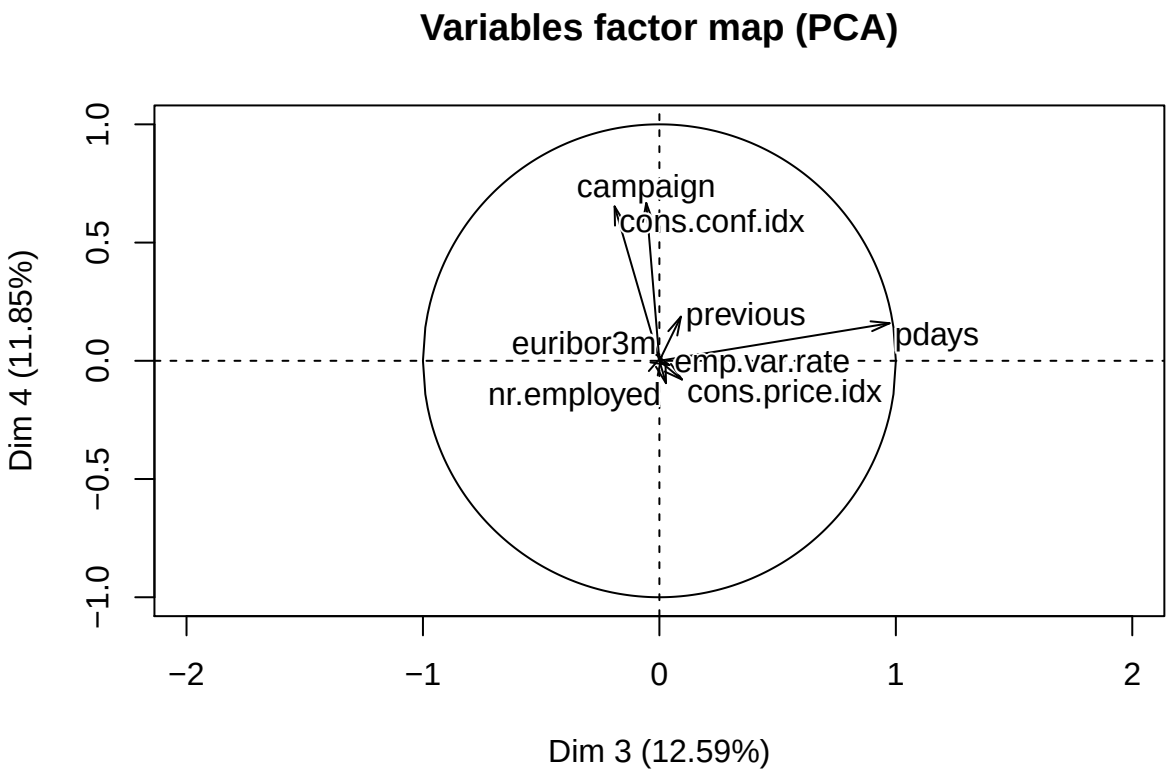
```
#PCA Y analysis (11)
vfact <- names(df[c(23,25:29,31:34)])
vnum <- names(df[c(12:14,16:20)])
res.pca <- PCA(df[,vnum])
```


Individuals factor map (PCA)
Dim 2 (12.74%)
Dim 1 (47.12%)
4
2
0
−2
−4
−10
−5
0
5




```
res.pca <-PCA(df[,vnum], axes=c(3,4))
```


Individuals factor map (PCA)
Dim 4 (11.85%)
Dim 3 (12.59%)
−10
−5
0
5
10
15
−4
−2
0
2
4
6
8
38847
37851
37810
37027
37688
30418
40930
41037
41089

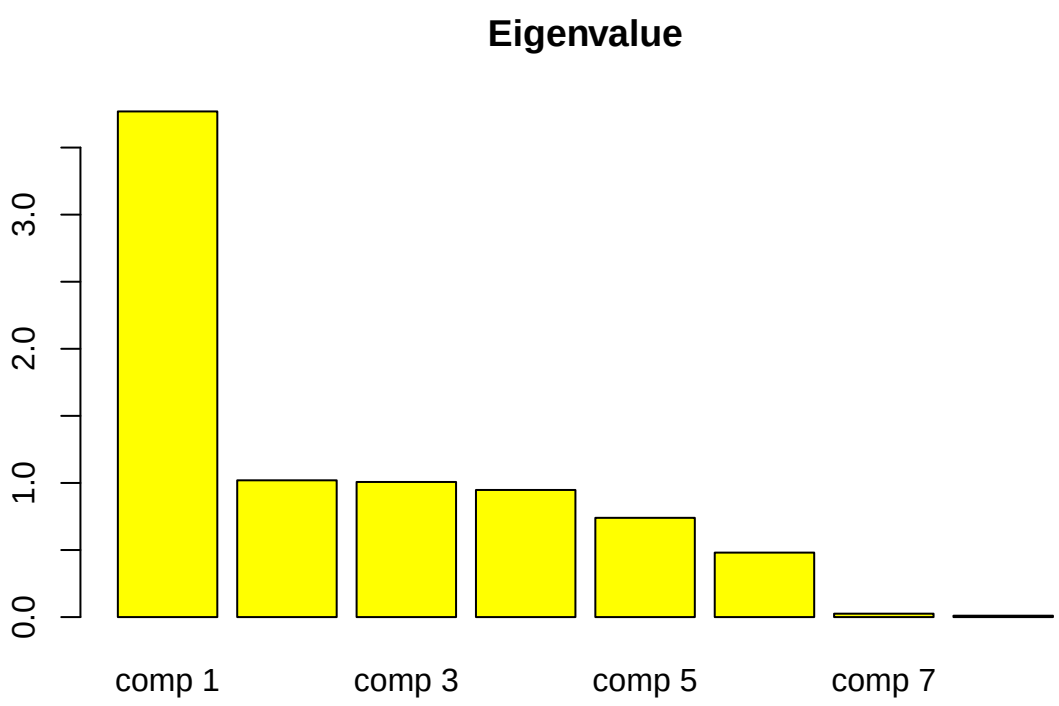



```
summary(res.pca, nb.dec = 2, nbelements = 10)
```

```
##
## Call:
## PCA(X = df[, vnum], axes = c(3, 4))
##
##
## Eigenvalues
##                        Dim.1  Dim.2  Dim.3  Dim.4  Dim.5  Dim.6  Dim.7
## Variance                3.77   1.02   1.01   0.95   0.74   0.48   0.03
## % of var.              47.12  12.74  12.59  11.85   9.25   6.01   0.32
## Cumulative % of var.   47.12  59.86  72.45  84.30  93.55  99.55  99.87
##                        Dim.8
## Variance                0.01
## % of var.               0.13
## Cumulative % of var. 100.00
##
## Individuals (the 10 first)
##                   Dist   Dim.1    ctr  cos2   Dim.2    ctr  cos2   Dim.3
## 4              |  1.77 |  1.29  0.01  0.53 |  1.16  0.03  0.43 | -0.06
## 9              |  1.78 |  1.29  0.01  0.52 |  1.17  0.03  0.43 |  0.09
## 22             |  1.78 |  1.29  0.01  0.53 |  1.15  0.03  0.41 | -0.20
## 47             |  1.78 |  1.29  0.01  0.53 |  1.14  0.03  0.41 | -0.22
## 55             |  1.61 |  1.34  0.01  0.69 |  0.70  0.01  0.19 | -0.24
## 56             |  1.78 |  1.29  0.01  0.53 |  1.15  0.03  0.41 | -0.20
## 62             |  1.78 |  1.29  0.01  0.53 |  1.15  0.03  0.42 | -0.16
```

```
## 71             |  1.77 |  1.29  0.01  0.53 |  1.16  0.03  0.43 | -0.07
## 77             |  1.78 |  1.29  0.01  0.53 |  1.15  0.03  0.41 | -0.20
## 79             |  1.78 |  1.29  0.01  0.53 |  1.15  0.03  0.41 | -0.20
##                 ctr  cos2
## 4              0.00  0.00 |
## 9              0.00  0.00 |
## 22             0.00  0.01 |
## 47             0.00  0.02 |
## 55             0.00  0.02 |
## 56             0.00  0.01 |
## 62             0.00  0.01 |
## 71             0.00  0.00 |
## 77             0.00  0.01 |
## 79             0.00  0.01 |
##
## Variables
##                  Dim.1   ctr  cos2   Dim.2   ctr  cos2   Dim.3   ctr  cos2
## campaign       |  0.14  0.54  0.02 | -0.73 52.04  0.53 | -0.06  0.31  0.00
## pdays          | -0.04  0.05  0.00 |  0.07  0.52  0.01 |  0.97 94.13  0.95
## previous       | -0.57  8.68  0.33 |  0.17  2.88  0.03 |  0.09  0.82  0.01
## emp.var.rate   |  0.98 25.52  0.96 |  0.02  0.05  0.00 |  0.04  0.18  0.00
## cons.price.idx |  0.77 15.83  0.60 | -0.01  0.01  0.00 |  0.10  0.91  0.01
## cons.conf.idx  |  0.26  1.73  0.07 |  0.67 43.50  0.44 | -0.19  3.57  0.04
## euribor3m      |  0.98 25.40  0.96 |  0.08  0.62  0.01 |  0.01  0.01  0.00
## nr.employed    |  0.92 22.25  0.84 | -0.06  0.37  0.00 |  0.03  0.08  0.00
##
## campaign       |
## pdays          |
## previous       |
## emp.var.rate   |
## cons.price.idx |
## cons.conf.idx  |
## euribor3m      |
## nr.employed    |
```

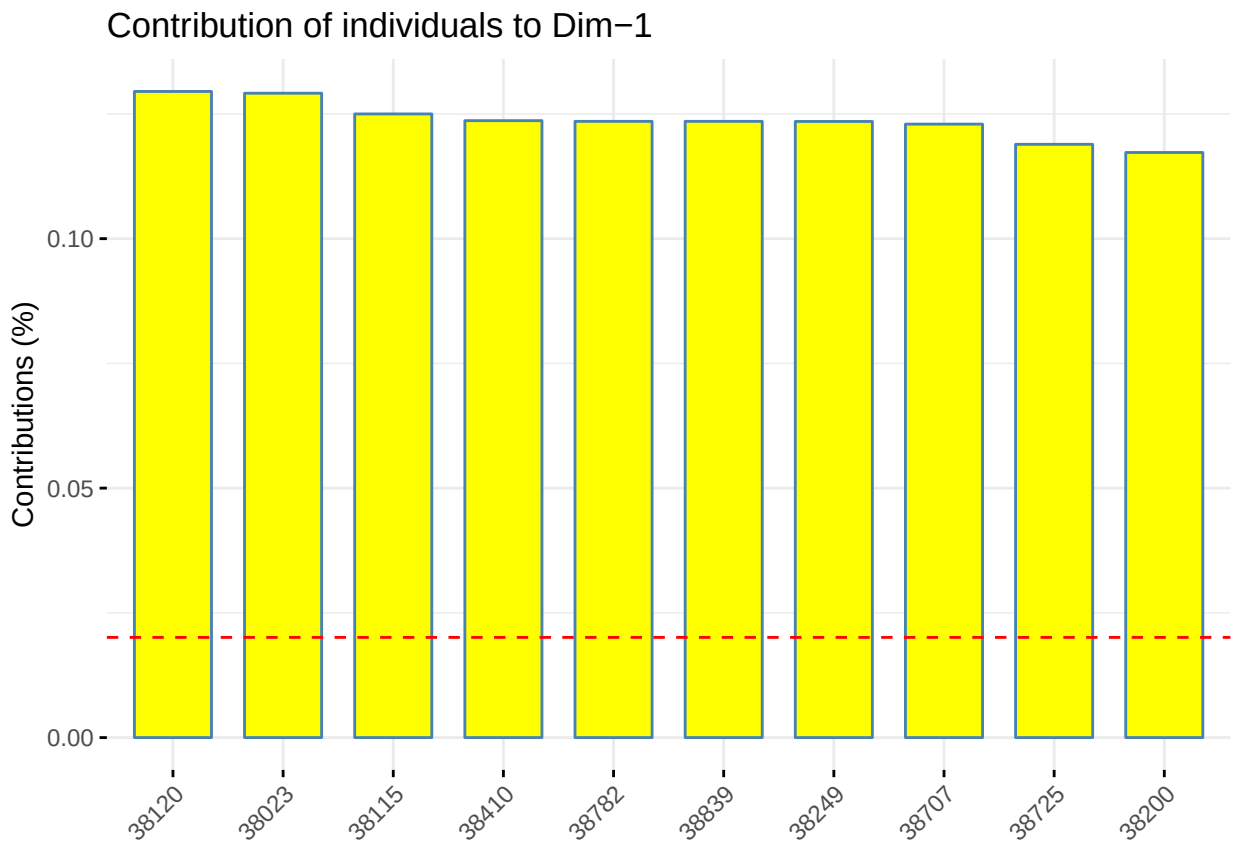
```r
#Segons criteri de Khaiser realitzarem la interpretació de les 3 primeres dimensions, ja que la quarta
barplot(res.pca$eig[,1], col = "yellow", main= "Eigenvalue")
```



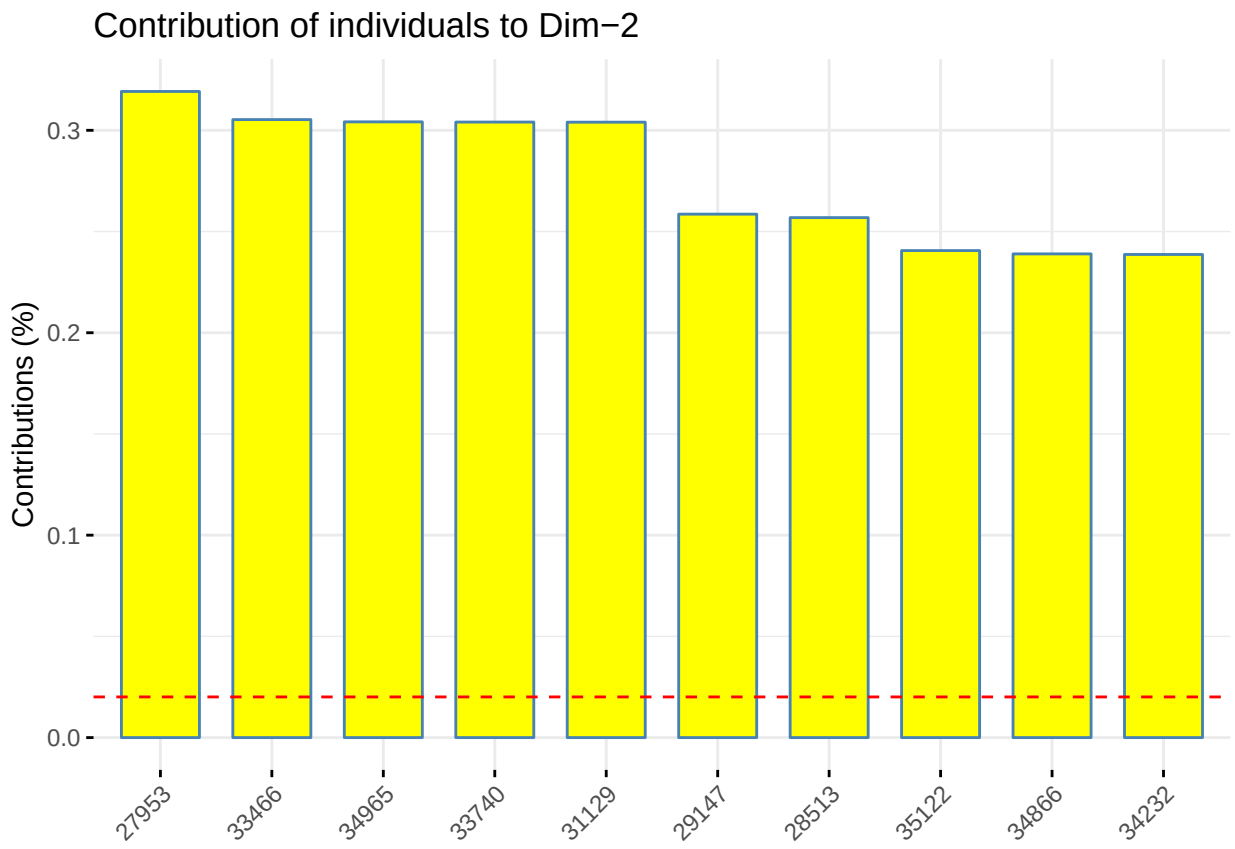

```
#En canvi, interpretariem 6 dimensions per Elbow's rule ja que notem una baixada considerable en a part
```

12.1.2 Individuals point of view

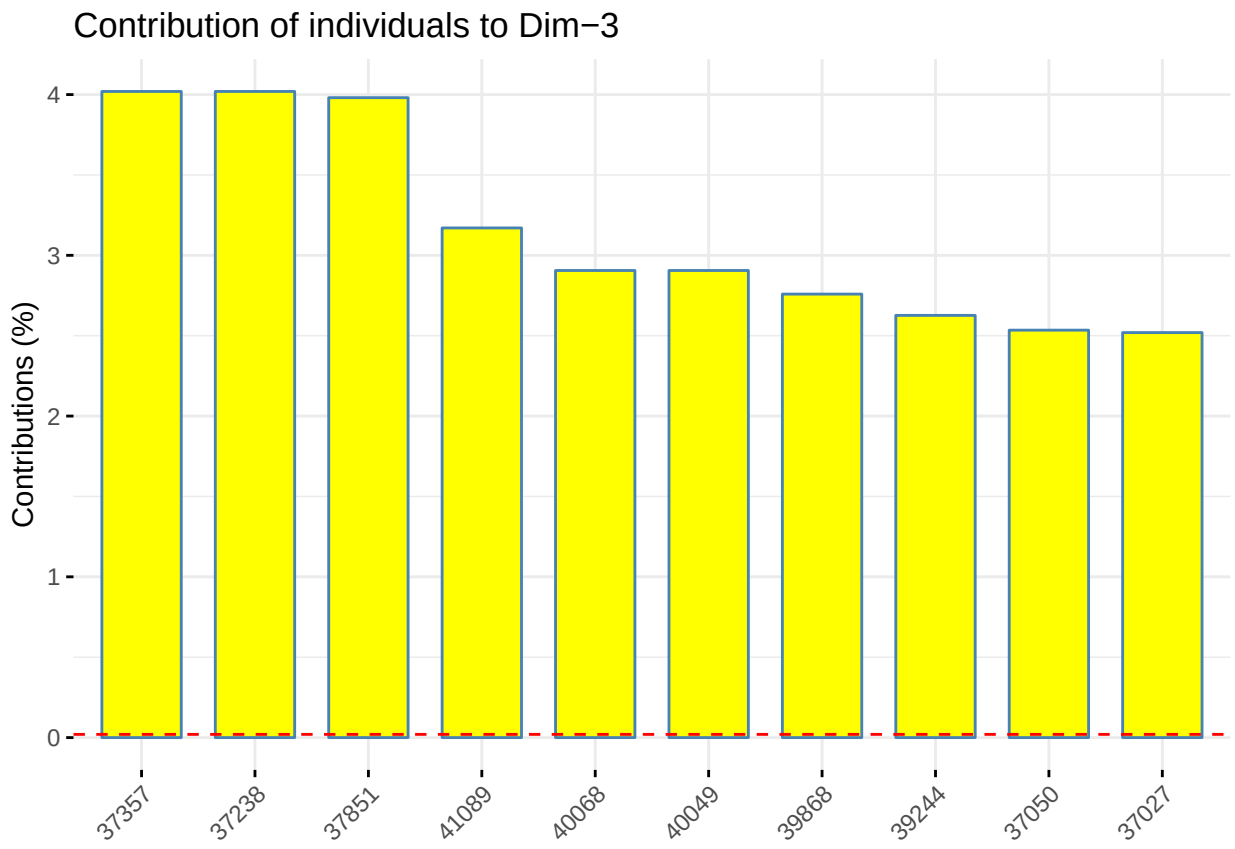
```
#Individus que contribuieixen més a la dimensió 1
fviz_contrib(res.pca, choice = "ind", top = 10, fill = "yellow", axes = 1); # Dimensió 1
```



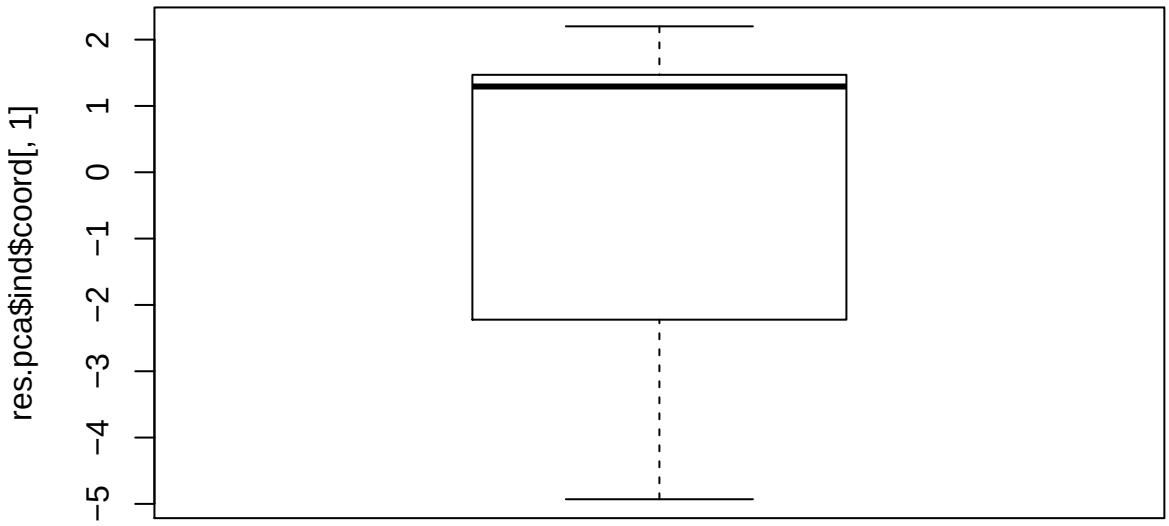

```
#Individus que contribuieixen més a la dimensió 2
fviz_contrib(res.pca, choice = "ind", top = 10, fill = "yellow", axes = 2); # Dimensió 2
```




```
#Individus que contribuieixen més a la dimensió 3
fviz_contrib(res.pca, choice = "ind", top = 10, fill = "yellow", axes = 3); # Dimensió 3
```




```
#Ara observem els individus més extrems del nostre data frame.
indiv_out.d1<-Boxplot(res.pca$ind$coord[,1]); indiv_out.d1; # Dimensió 1
```




```
## NULL
```

```
#En la dimensió 1 no trobem cap extrem
```

```
# Dimensió 2
indiv_out.d2<-Boxplot(res.pca$ind$coord[,2]); indiv_out.d2;
```

```
##  [1] 3394 4068 4246 4099 3786 3535 3464 4264 4231 4152 4662 4641 4547 4535
## [15] 4699 4703 4634 4615 4650 4680
```

```
q1 = quantile(res.pca$ind$coord[,1])[2];q1;
```

```
##       25%
## -2.222655
```

```
q3 = quantile(res.pca$ind$coord[,1])[4];q3;
```

```
##      75%
## 1.469477
```

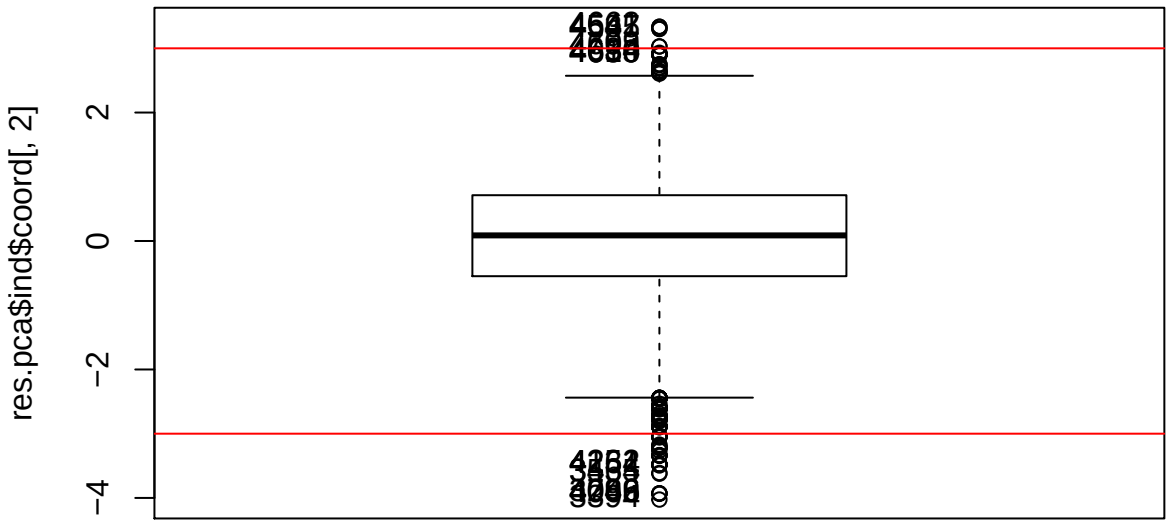
```
mild.threshold.upper = (q3-q1) * 1.5 + q3;mild.threshold.upper;
```

```
##      75%
## 7.007677
```

```
mild.threshold.lower = q1 -(q3-q1) * 1.5;mild.threshold.lower;
```

```
##       25%
## -7.760854
```

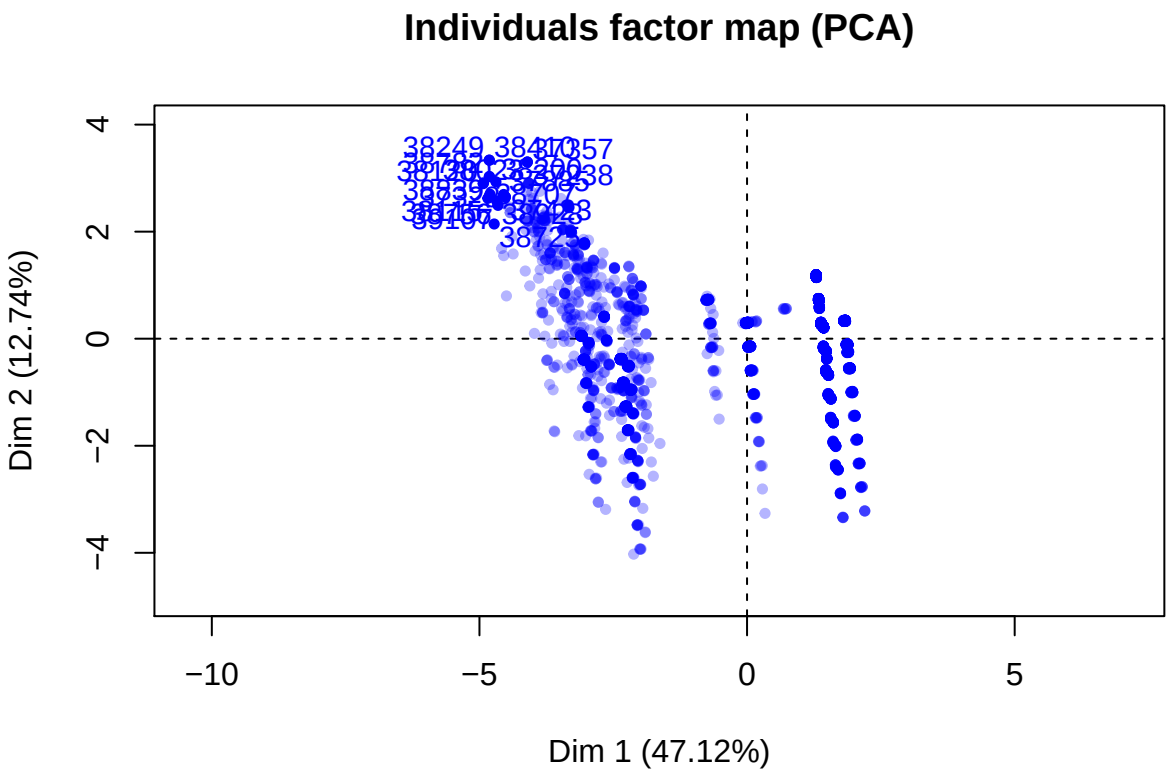
```r
abline(h=c(3, -3), col = "red")
```




```r
indiv_sup.d2 <- which(res.pca$ind$coord[,2] >= 3 | res.pca$ind$coord[,2] <= -3);
aux <- sort(indiv_sup.d2, decreasing= TRUE)
df[aux[1:5], vfact]
```

```
##       f.season f.jobsituation f.prev_contacted   f.education f.housing
## 38839  Aut-Win         Worker        Contacted Non-Mandatory      f.no
## 38782  Aut-Win          Other        Contacted Non-Mandatory      f.no
## 38410  Aut-Win          Other     No-contacted Non-Mandatory      f.no
## 38249  Aut-Win         Worker     No-contacted Non-Mandatory      f.no
## 37357   Summer          Other        Contacted Non-Mandatory      f.no
##        f.marital f.loan  f.contact     f.day         f.age
## 38839   f.single   f.no f.cellular f.day.mon f.age-(30,40]
## 38782   f.single   f.no f.cellular f.day.thu f.age-(30,40]
## 38410   f.single  f.yes f.cellular f.day.wed f.age-(30,40]
## 38249 f.divorced  f.yes f.cellular f.day.tue f.age-(30,40]
## 37357   f.single   f.no f.cellular f.day.tue f.age-[17,30]
```

```r
#En la dimensió 2 podem veure una petita mostra  que les coordenades més extremes ens apareixen en indi
plot.PCA(res.pca,choix=c("ind"),cex=0.95, col.ind="blue",select = "contrib 18")
```




```
#Dimensió 3
indiv_out.d3<-Boxplot(res.pca$ind$coord[,3]); indiv_out.d3;
```

```
##  [1] 3699 4578 4901 4818 3013 3415 4651 4634 4844 4451 4547 4535 4597 4969
## [15] 4856 4853 4828 4745 4512 4510
```

```
q1 = quantile(res.pca$ind$coord[,1])[2];q1;
```

```
##       25%
## -2.222655
```

```
q3 = quantile(res.pca$ind$coord[,1])[4];q3;
```

```
##      75%
## 1.469477
```

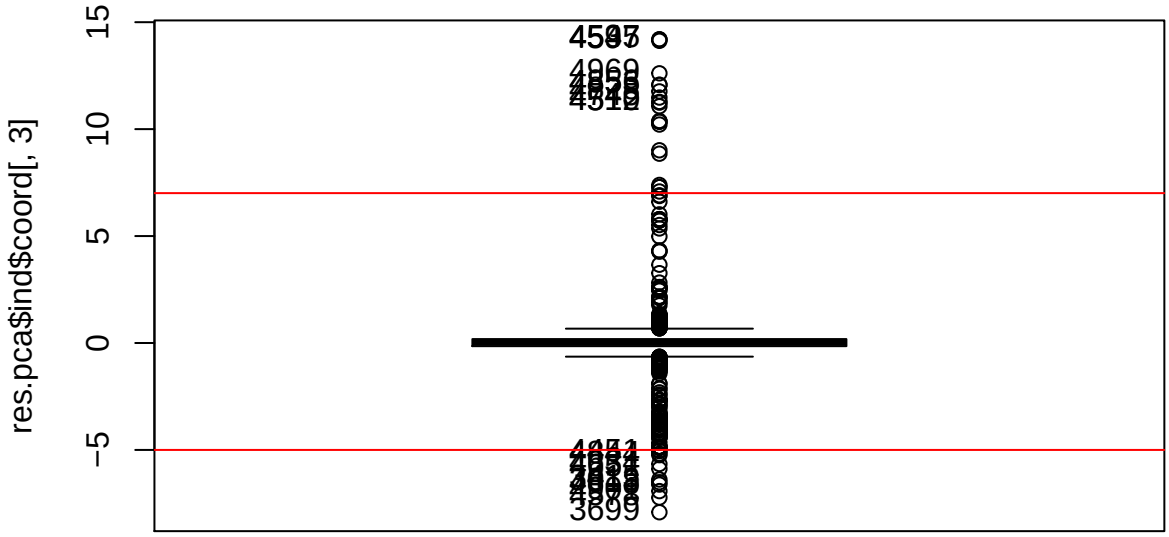
```
mild.threshold.upper = (q3-q1) * 1.5 + q3;mild.threshold.upper;
```

```
##      75%
## 7.007677
```

```
mild.threshold.lower = q1 -(q3-q1) * 1.5;mild.threshold.lower;
```

```
##       25%
## -7.760854
```

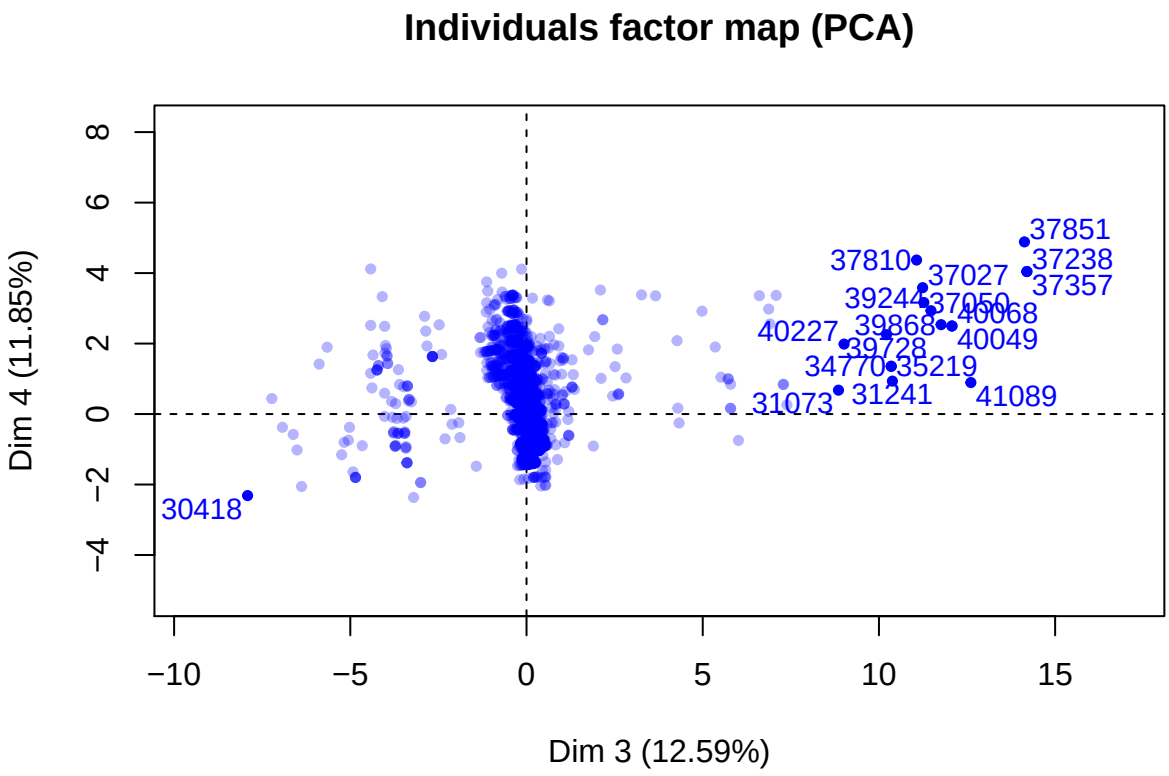
```
abline(h=c(mild.threshold.upper, -5), col = "red")
```




```
indiv_sup.d3 <- which(res.pca$ind$coord[,3] >= mild.threshold.upper | res.pca$ind$coord[,3] <= -5);
aux <- sort(indiv_sup.d3, decreasing= TRUE)
df[aux[1:7], vfact]
```

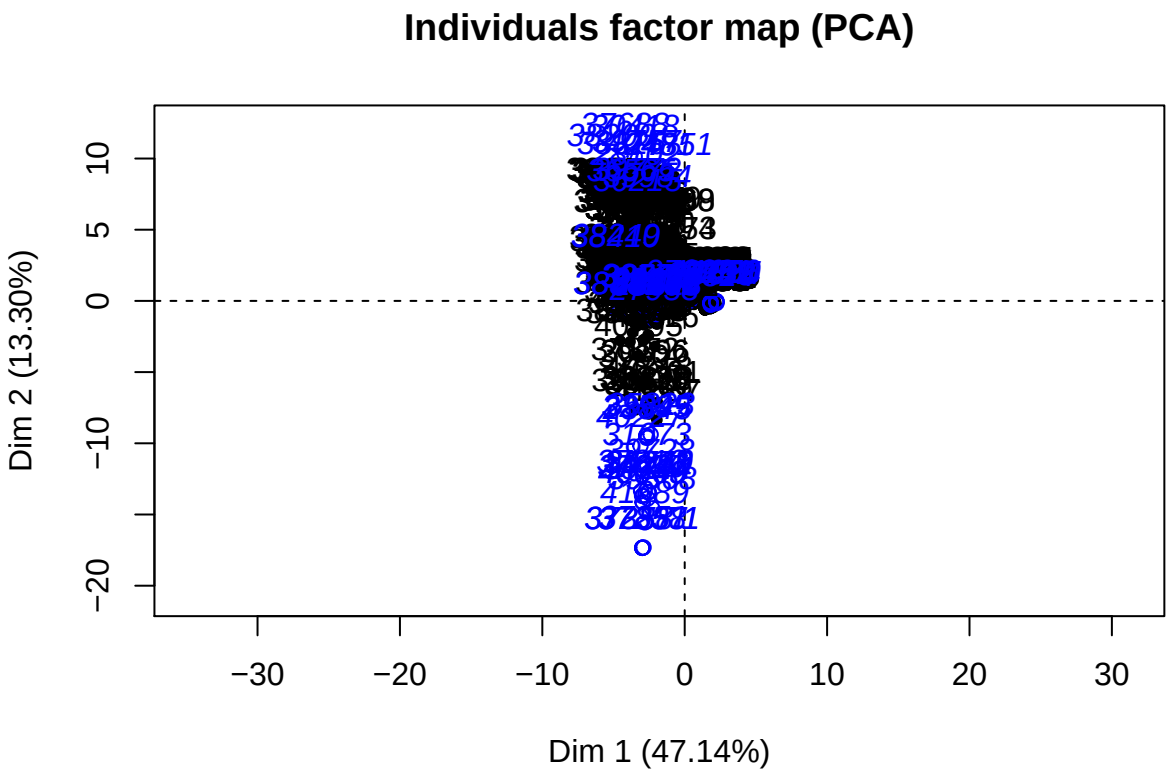
```
##       f.season f.jobsituation f.prev_contacted   f.education f.housing
## 41089  Aut-Win          Other        Contacted     Mandatory     f.yes
## 40481   Summer         Worker        Contacted Non-Mandatory     f.yes
## 40227   Summer         Worker        Contacted     Mandatory     f.yes
## 40068   Summer          Other        Contacted         Other     f.yes
## 40049   Summer          Other        Contacted     Mandatory     f.yes
## 39984   Summer  Self-employed        Contacted     Mandatory      f.no
## 39868   Summer          Other        Contacted     Mandatory     f.yes
##       f.marital f.loan   f.contact     f.day         f.age
## 41089  f.single   f.no f.telephone f.day.tue f.age-[17,30]
## 40481 f.married   f.no  f.cellular f.day.thu f.age-(50,95]
## 40227  f.single   f.no  f.cellular f.day.thu f.age-[17,30]
## 40068  f.single   f.no  f.cellular f.day.thu f.age-[17,30]
## 40049 f.married  f.yes  f.cellular f.day.tue f.age-(40,50]
## 39984 f.married   f.no  f.cellular f.day.tue f.age-(30,40]
## 39868 f.married   f.no  f.cellular f.day.tue f.age-[17,30]
```

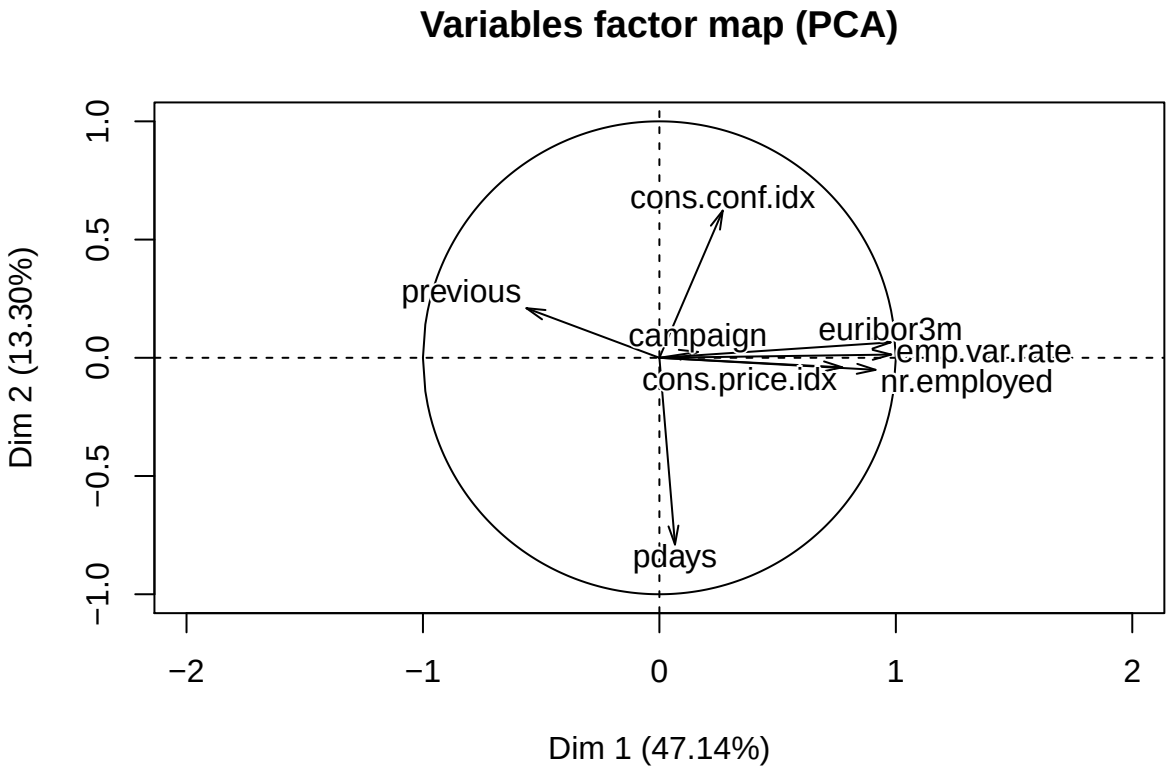
```
#En la dimensió 3 en canvi podem veure que les coordenades més extremes ens apareixen en individus amb
plot.PCA(res.pca,choix=c("ind"),cex=0.95, col.ind="blue",select = "contrib 18", axes = 3:4)
```




```
#Tornem a realitzar el calcul dels PCA ara tenint en compte que els nostres individus considerats outli

newres.pca <- PCA(df[,vnum], ind.sup = c(indiv_sup.d2, indiv_sup.d3))
```


Individuals factor map (PCA)
Dim 2 (13.30%)
10
5
0
−10
−20
−30
−20
−10
0
10
20
30
Dim 1 (47.14%)




```
#Podem veure que en utilizar els otuliers indivius com a individus suplmenetaris els eigenvalues canvie

summary(newres.pca, nb.dec = 2, nbelements = 10)
```

```
##
## Call:
## PCA(X = df[, vnum], ind.sup = c(indiv_sup.d2, indiv_sup.d3))
##
##
## Eigenvalues
##                        Dim.1  Dim.2  Dim.3  Dim.4  Dim.5  Dim.6  Dim.7
## Variance                3.77   1.06   0.98   0.91   0.75   0.48   0.03
## % of var.              47.14  13.30  12.29  11.37   9.40   6.04   0.32
## Cumulative % of var.   47.14  60.44  72.73  84.10  93.50  99.55  99.87
##                        Dim.8
## Variance                0.01
## % of var.               0.13
## Cumulative % of var. 100.00
##
## Individuals (the 10 first)
##                    Dist   Dim.1   ctr  cos2   Dim.2   ctr  cos2   Dim.3
## 4               |  1.76 |  1.27  0.01  0.51 |  0.45  0.00  0.06 | -1.02
## 9               |  1.79 |  1.27  0.01  0.51 |  0.26  0.00  0.02 | -1.04
## 22              |  1.78 |  1.26  0.01  0.50 |  0.63  0.01  0.13 | -0.99
## 47              |  1.78 |  1.26  0.01  0.50 |  0.65  0.01  0.13 | -0.99
## 55              |  1.60 |  1.31  0.01  0.67 |  0.65  0.01  0.17 | -0.36
```

```
## 56             |  1.78 |  1.26  0.01  0.50 |  0.63  0.01  0.13 | -0.99
## 62             |  1.77 |  1.26  0.01  0.51 |  0.58  0.01  0.11 | -1.00
## 71             |  1.76 |  1.26  0.01  0.51 |  0.46  0.00  0.07 | -1.02
## 77             |  1.78 |  1.26  0.01  0.50 |  0.63  0.01  0.13 | -0.99
## 79             |  1.78 |  1.26  0.01  0.50 |  0.63  0.01  0.13 | -0.99
##                 ctr  cos2
## 4              0.02  0.33 |
## 9              0.02  0.34 |
## 22             0.02  0.31 |
## 47             0.02  0.31 |
## 55             0.00  0.05 |
## 56             0.02  0.31 |
## 62             0.02  0.32 |
## 71             0.02  0.33 |
## 77             0.02  0.31 |
## 79             0.02  0.31 |
##
## Supplementary individuals (the 10 first)
##                   Dist   Dim.1  cos2   Dim.2  cos2   Dim.3  cos2
## 9951           |  4.84 |  2.23  0.21 | -0.02  0.00 |  4.20  0.76 |
## 10574          |  4.83 |  2.23  0.21 | -0.15  0.00 |  4.18  0.75 |
## 10825          |  4.83 |  2.23  0.21 | -0.07  0.00 |  4.20  0.75 |
## 11050          |  4.84 |  2.23  0.21 | -0.02  0.00 |  4.20  0.76 |
## 12452          |  4.64 |  1.82  0.15 | -0.13  0.00 |  4.26  0.84 |
## 15324          |  4.63 |  1.82  0.15 | -0.27  0.00 |  4.24  0.84 |
## 16243          |  4.64 |  1.82  0.15 | -0.10  0.00 |  4.26  0.84 |
## 18119          |  4.64 |  1.82  0.15 | -0.09  0.00 |  4.26  0.84 |
## 18738          |  4.63 |  1.82  0.15 | -0.22  0.00 |  4.24  0.84 |
## 27663          |  4.45 |  0.35  0.01 |  0.00  0.00 |  4.31  0.94 |
##
## Variables
##                  Dim.1   ctr  cos2   Dim.2   ctr  cos2   Dim.3   ctr  cos2
## campaign       |  0.16  0.70  0.03 |  0.02  0.06  0.00 |  0.97 95.39  0.94
## pdays          |  0.07  0.12  0.00 | -0.79 58.58  0.62 | -0.11  1.13  0.01
## previous       | -0.56  8.39  0.32 |  0.21  4.13  0.04 |  0.02  0.03  0.00
## emp.var.rate   |  0.98 25.49  0.96 |  0.01  0.02  0.00 | -0.02  0.06  0.00
## cons.price.idx |  0.77 15.87  0.60 | -0.04  0.15  0.00 | -0.02  0.05  0.00
## cons.conf.idx  |  0.27  1.90  0.07 |  0.62 36.41  0.39 | -0.17  3.08  0.03
## euribor3m      |  0.98 25.37  0.96 |  0.07  0.40  0.00 | -0.05  0.26  0.00
## nr.employed    |  0.91 22.16  0.84 | -0.05  0.24  0.00 |  0.00  0.00  0.00
##
## campaign       |
## pdays          |
## previous       |
## emp.var.rate   |
## cons.price.idx |
## cons.conf.idx  |
## euribor3m      |
## nr.employed    |
```

12.1.3 Interpreting the axes

```
#Comprovem de manera més exhaustiva quines variables afecten més als diferents eixos.
```

```r
dimdesc(newres.pca, axes = 1:3)
```

```
## $Dim.1
## $Dim.1$quanti
##                 correlation      p.value
## emp.var.rate     0.98049415 0.000000e+00
## euribor3m        0.97805412 0.000000e+00
## nr.employed      0.91405151 0.000000e+00
## cons.price.idx   0.77352829 0.000000e+00
## cons.conf.idx    0.26799918 1.557909e-81
## campaign         0.16290029 1.506009e-30
## pdays            0.06603261 3.641267e-06
## previous        -0.56248739 0.000000e+00
##
##
## $Dim.2
## $Dim.2$quanti
##                 correlation      p.value
## cons.conf.idx    0.62247943 0.000000e+00
## previous         0.20972163 6.242514e-50
## euribor3m        0.06518106 4.853424e-06
## cons.price.idx  -0.04039870 4.636959e-03
## nr.employed     -0.05103148 3.472055e-04
## pdays           -0.78955218 0.000000e+00
##
##
## $Dim.3
## $Dim.3$quanti
##                correlation      p.value
## campaign        0.96854829 0.000000e+00
## euribor3m      -0.05087184 3.623859e-04
## pdays          -0.10532598 1.371656e-13
## cons.conf.idx  -0.17391113 1.207461e-34
```

```r
#Pel que fa a la primera dimensió, les variables socioeconòmiques son les que ens mostren una major coo

#Pel que fa a la segona dimensió,  el més destacable és la relació inversament proporcional que el sego

#En canvi el tercer eix de dimensions està altament relacionat amb el numero de vegades que un clientha
```

12.2 K-Means Classification

```r
set.seed(676489)

summary(res.pca)
```

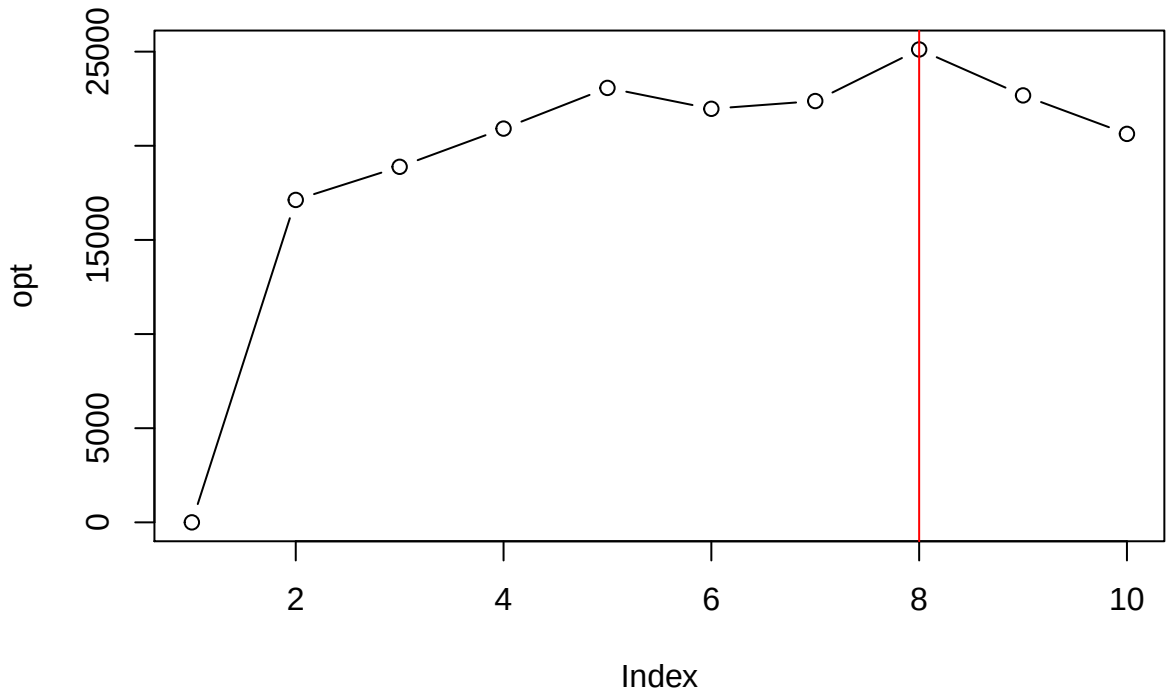
```
##
## Call:
## PCA(X = df[, vnum], axes = c(3, 4))
##
##
## Eigenvalues
##                        Dim.1   Dim.2   Dim.3   Dim.4   Dim.5   Dim.6
## Variance               3.769   1.020   1.007   0.948   0.740   0.481
```

```
## % of var.             47.117  12.744  12.591  11.845   9.248   6.008
## Cumulative % of var.  47.117  59.861  72.452  84.297  93.545  99.553
##                        Dim.7   Dim.8
## Variance               0.025   0.010
## % of var.              0.317   0.129
## Cumulative % of var.  99.871 100.000
##
## Individuals (the 10 first)
##                    Dist    Dim.1    ctr   cos2    Dim.2    ctr   cos2
## 4               |  1.772 |  1.291  0.009  0.531 |  1.156  0.026  0.426 |
## 9               |  1.778 |  1.288  0.009  0.525 |  1.167  0.027  0.431 |
## 22              |  1.779 |  1.295  0.009  0.530 |  1.146  0.026  0.415 |
## 47              |  1.780 |  1.295  0.009  0.529 |  1.144  0.026  0.413 |
## 55              |  1.607 |  1.340  0.010  0.695 |  0.702  0.010  0.191 |
## 56              |  1.779 |  1.295  0.009  0.530 |  1.146  0.026  0.415 |
## 62              |  1.776 |  1.294  0.009  0.531 |  1.148  0.026  0.418 |
## 71              |  1.772 |  1.292  0.009  0.531 |  1.155  0.026  0.425 |
## 77              |  1.779 |  1.295  0.009  0.530 |  1.146  0.026  0.415 |
## 79              |  1.779 |  1.295  0.009  0.530 |  1.146  0.026  0.415 |
##                  Dim.3    ctr   cos2
## 4               -0.062  0.000  0.001 |
## 9                0.088  0.000  0.002 |
## 22              -0.201  0.001  0.013 |
## 47              -0.220  0.001  0.015 |
## 55              -0.243  0.001  0.023 |
## 56              -0.201  0.001  0.013 |
## 62              -0.164  0.001  0.009 |
## 71              -0.071  0.000  0.002 |
## 77              -0.201  0.001  0.013 |
## 79              -0.201  0.001  0.013 |
##
## Variables
##                     Dim.1    ctr   cos2    Dim.2    ctr   cos2    Dim.3
## campaign         |  0.143  0.540  0.020 | -0.728 52.045  0.531 | -0.056
## pdays            | -0.043  0.048  0.002 |  0.073  0.524  0.005 |  0.974
## previous         | -0.572  8.683  0.327 |  0.171  2.882  0.029 |  0.091
## emp.var.rate     |  0.981 25.520  0.962 |  0.022  0.049  0.000 |  0.043
## cons.price.idx   |  0.773 15.833  0.597 | -0.010  0.010  0.000 |  0.096
## cons.conf.idx    |  0.255  1.732  0.065 |  0.666 43.501  0.443 | -0.189
## euribor3m        |  0.978 25.398  0.957 |  0.079  0.615  0.006 |  0.009
## nr.employed      |  0.916 22.246  0.839 | -0.062  0.373  0.004 |  0.028
##                     ctr   cos2
## campaign          0.306  0.003 |
## pdays            94.130  0.948 |
## previous          0.823  0.008 |
## emp.var.rate      0.180  0.002 |
## cons.price.idx    0.910  0.009 |
## cons.conf.idx     3.565  0.036 |
## euribor3m         0.008  0.000 |
## nr.employed       0.078  0.001 |
```

```
opt <- kmeans(res.pca$ind$coord[,1:3], centers = 1)$betweenss
opt[2] <- kmeans(res.pca$ind$coord[,1:3], centers = 2)$betweenss
opt[3] <- kmeans(res.pca$ind$coord[,1:3], centers = 3)$betweenss
```

```r
opt[4] <- kmeans(res.pca$ind$coord[,1:3], centers = 4)$betweenss
opt[5] <- kmeans(res.pca$ind$coord[,1:3], centers = 5)$betweenss
opt[6] <- kmeans(res.pca$ind$coord[,1:3], centers = 6)$betweenss
opt[7] <- kmeans(res.pca$ind$coord[,1:3], centers = 7)$betweenss
opt[8] <- kmeans(res.pca$ind$coord[,1:3], centers = 8)$betweenss
opt[9] <- kmeans(res.pca$ind$coord[,1:3], centers = 9)$betweenss
opt[10] <- kmeans(res.pca$ind$coord[,1:3], centers = 10)$betweenss


plot(opt, type = "b")
abline(v = 8, col = "red")
```



Com podem comprovar en el gràfic de forma visual, trobem un pic en el moment en que el nombre de clusters és optim. En aquest cas n'utilitzarem 7. ###Description of clusters

```r
set.seed(676489)
def <- kmeans(res.pca$ind$coord[,1:3], centers = 8)
df$kmeansclu<-factor(def$cluster)

vclust <- c(vfact, vnum, "kmeansclu")
targ <- which(vclust == "kmeansclu")
catdes(df[,vclust], targ)
```

```
##
## Link between the cluster variable and the categorical variables (chi-square test)
## =================================================================================
##                         p.value df
```

```
## f.season          0.000000e+00 14
## f.prev_contacted  0.000000e+00  7
## f.contact        9.529352e-253  7
## f.age             6.450985e-39 21
## f.jobsituation    2.112793e-23 14
## f.marital         8.985336e-14 14
## f.education       1.878068e-11 14
## f.day             2.731759e-07 28
## f.housing         5.320342e-05  7
##
## Description of each cluster by the categories
## ============================================
## $`1`
##                                  Cla/Mod   Mod/Cla    Global      p.value
## f.prev_contacted=Contacted    16.5048544 100.00000  4.137377 5.822212e-49
## f.jobsituation=Other           1.2768427  64.70588 34.605342 3.998384e-04
## f.contact=f.cellular           0.9457755  88.23529 63.707572 1.599915e-03
## f.marital=f.single             1.1371713  47.05882 28.258686 2.068110e-02
## f.age=f.age-[17,30]            1.2443439  32.35294 17.754569 3.924935e-02
## f.marital=f.married            0.4625041  41.17647 60.795340 2.213685e-02
## f.jobsituation=Worker          0.3935599  32.35294 56.135770 5.746337e-03
## f.contact=f.telephone          0.2213614  11.76471 36.292428 1.599915e-03
## f.prev_contacted=No-contacted  0.0000000   0.00000 95.862623 5.822212e-49
##                                   v.test
## f.prev_contacted=Contacted     14.706890
## f.jobsituation=Other            3.540190
## f.contact=f.cellular            3.155922
## f.marital=f.single              2.313756
## f.age=f.age-[17,30]             2.061563
## f.marital=f.married            -2.288012
## f.jobsituation=Worker          -2.761915
## f.contact=f.telephone          -3.155922
## f.prev_contacted=No-contacted -14.706890
##
## $`2`
##                                  Cla/Mod   Mod/Cla    Global      p.value
## f.prev_contacted=Contacted    58.252427 35.190616  4.137377 2.099940e-92
## f.season=Aut-Win              20.574887 39.882698 13.275758 1.027456e-37
## f.contact=f.cellular           9.709962 90.322581 63.707572 4.143143e-31
## f.jobsituation=Other          11.839814 59.824047 34.605342 7.969224e-23
## f.age=f.age-(50,95]           14.168618 35.483871 17.152039 2.320965e-17
## f.education=Non-Mandatory      8.916587 54.545455 41.895963 1.166636e-06
## f.education=Other             11.538462  7.038123  4.177546 1.130290e-02
## f.marital=f.single             8.102345 33.431085 28.258686 3.021896e-02
## f.marital=f.married            6.243806 55.425220 60.795340 3.655493e-02
## f.day=f.day.fri                5.196182 14.369501 18.939546 2.240708e-02
## f.season=Summer                5.494019 36.363636 45.330388 5.288761e-04
## f.age=f.age-(30,40]            5.062657 29.618768 40.068287 3.457015e-05
## f.age=f.age-(40,50]            3.611557 13.196481 25.025105 3.022398e-08
## f.education=Mandatory          4.878957 38.416422 53.926491 2.781501e-09
## f.season=Spring                3.930131 23.753666 41.393854 1.691600e-12
## f.jobsituation=Worker          4.042934 33.137830 56.135770 9.075160e-19
## f.contact=f.telephone          1.826231  9.677419 36.292428 4.143143e-31
## f.prev_contacted=No-contacted  4.630212 64.809384 95.862623 2.099940e-92
```

```
##                                   v.test
## f.prev_contacted=Contacted     20.388857
## f.season=Aut-Win               12.836239
## f.contact=f.cellular           11.599537
## f.jobsituation=Other            9.834842
## f.age=f.age-(50,95]             8.476487
## f.education=Non-Mandatory       4.861221
## f.education=Other               2.533192
## f.marital=f.single              2.167208
## f.marital=f.married            -2.090700
## f.day=f.day.fri                -2.283396
## f.season=Summer                -3.465688
## f.age=f.age-(30,40]            -4.141062
## f.age=f.age-(40,50]            -5.540134
## f.education=Mandatory          -5.944000
## f.season=Spring                -7.057799
## f.jobsituation=Worker          -8.845952
## f.contact=f.telephone         -11.599537
## f.prev_contacted=No-contacted -20.388857
##
## $`3`
##                               Cla/Mod   Mod/Cla   Global       p.value
## f.season=Spring           50.072780 83.766234 41.39385 7.180797e-275
## f.contact=f.cellular      35.403531 91.152597 63.70757 1.041593e-137
## f.age=f.age-[17,30]       34.049774 24.431818 17.75457  6.099324e-12
## f.marital=f.single        31.485430 35.957792 28.25869  9.741118e-12
## f.housing=f.yes           26.560232 59.415584 55.35248  9.249461e-04
## f.education=Mandatory     26.443203 57.629870 53.92649  2.621338e-03
## f.day=f.day.fri           27.995758 21.428571 18.93955  1.091708e-02
## f.marital=f.divorced      20.000000  8.847403 10.94597  5.691355e-03
## f.education=Non-Mandatory 22.674976 38.392857 41.89596  3.993617e-03
## f.day=f.day.tue           21.257485 17.288961 20.12452  3.835554e-03
## f.housing=f.no            22.492128 40.584416 44.64752  9.249461e-04
## f.age=f.age-(40,50]       20.786517 21.022727 25.02511  1.557078e-04
## f.age=f.age-(50,95]       19.203747 13.311688 17.15204  2.599294e-05
## f.marital=f.married       22.464486 55.194805 60.79534  3.872533e-06
## f.season=Aut-Win           8.925870  4.788961 13.27576  2.195961e-28
## f.contact=f.telephone      6.032097  8.847403 36.29243 1.041593e-137
## f.season=Summer            6.247231 11.444805 45.33039 8.570615e-187
##                              v.test
## f.season=Spring           35.424441
## f.contact=f.cellular      24.978711
## f.age=f.age-[17,30]        6.877310
## f.marital=f.single         6.810277
## f.housing=f.yes            3.312414
## f.education=Mandatory      3.008971
## f.day=f.day.fri            2.545342
## f.marital=f.divorced      -2.765053
## f.education=Non-Mandatory -2.878665
## f.day=f.day.tue           -2.891379
## f.housing=f.no            -3.312414
## f.age=f.age-(40,50]       -3.781785
## f.age=f.age-(50,95]       -4.206001
## f.marital=f.married       -4.618109
```

```
## f.season=Aut-Win          -11.049844
## f.contact=f.telephone     -24.978711
## f.season=Summer           -29.149123
##
## $`4`
##                                Cla/Mod    Mod/Cla    Global       p.value
## f.season=Aut-Win             27.8366112 100.000000 13.275758 7.469427e-173
## f.contact=f.cellular          5.2963430  91.304348 63.707572  2.118037e-18
## f.education=Non-Mandatory     5.0814957  57.608696 41.895963  1.334185e-05
## f.day=f.day.fri               5.4082715  27.717391 18.939546  3.111384e-03
## f.jobsituation=Self-employed  6.2906725  15.760870  9.258887  4.131217e-03
## f.day=f.day.thu               4.8780488  27.173913 20.586463  2.889605e-02
## f.education=Other             0.9615385   1.086957  4.177546  1.776257e-02
## f.age=f.age-[17,30]           2.2624434  10.869565 17.754569  9.262198e-03
## f.day=f.day.tue               2.2954092  12.500000 20.124523  6.118809e-03
## f.day=f.day.mon               2.2682446  12.500000 20.365535  4.814364e-03
## f.education=Mandatory         2.8305400  41.304348 53.926491  4.895913e-04
## f.contact=f.telephone         0.8854455   8.695652 36.292428  2.118037e-18
## f.season=Spring               0.0000000   0.000000 41.393854  1.692208e-44
## f.season=Summer               0.0000000   0.000000 45.330388  3.044426e-50
##                                  v.test
## f.season=Aut-Win              28.027706
## f.contact=f.cellular           8.750822
## f.education=Non-Mandatory      4.354422
## f.day=f.day.fri                2.956514
## f.jobsituation=Self-employed   2.867965
## f.day=f.day.thu                2.184902
## f.education=Other             -2.370531
## f.age=f.age-[17,30]           -2.602222
## f.day=f.day.tue               -2.741346
## f.day=f.day.mon               -2.819199
## f.education=Mandatory         -3.486387
## f.contact=f.telephone         -8.750822
## f.season=Spring              -13.994159
## f.season=Summer              -14.905300
##
## $`5`
##                                   Cla/Mod     Mod/Cla    Global
## f.season=Aut-Win               39.6369138 100.0000000 13.275758
## f.contact=f.cellular            7.4716267  90.4580153 63.707572
## f.prev_contacted=No-contacted   5.4473078  99.2366412 95.862623
## f.housing=f.yes                 6.1683599  64.8854962 55.352480
## f.age=f.age-(30,40]             6.5162907  49.6183206 40.068287
## f.marital=f.divorced            7.1559633  14.8854962 10.945973
## f.education=Other               2.4038462   1.9083969  4.177546
## f.housing=f.no                  4.1385515  35.1145038 44.647520
## f.prev_contacted=Contacted      0.9708738   0.7633588  4.137377
## f.age=f.age-[17,30]             2.9411765   9.9236641 17.754569
## f.contact=f.telephone           1.3835086   9.5419847 36.292428
## f.season=Spring                 0.0000000   0.0000000 41.393854
## f.season=Summer                 0.0000000   0.0000000 45.330388
##                                      p.value     v.test
## f.season=Aut-Win               1.186073e-253  34.018519
## f.contact=f.cellular            3.372737e-24  10.148275
```

```
## f.prev_contacted=No-contacted  1.108220e-03   3.261506
## f.housing=f.yes                1.326847e-03   3.210109
## f.age=f.age-(30,40]            1.339483e-03   3.207383
## f.marital=f.divorced           4.327817e-02   2.021015
## f.education=Other              4.489318e-02  -2.005654
## f.housing=f.no                 1.326847e-03  -3.210109
## f.prev_contacted=Contacted     1.108220e-03  -3.261506
## f.age=f.age-[17,30]            3.059024e-04  -3.610250
## f.contact=f.telephone          3.372737e-24 -10.148275
## f.season=Spring                9.752018e-64 -16.854322
## f.season=Summer                4.859935e-72 -17.949300
##
## $`6`
##                                 Cla/Mod    Mod/Cla    Global      p.value
## f.season=Summer                15.152858  85.929648 45.330388 7.576666e-69
## f.prev_contacted=No-contacted   8.338571 100.000000 95.862623 2.408690e-08
## f.contact=f.telephone          10.680686  48.492462 36.292428 2.141525e-07
## f.day=f.day.tue                10.179641  25.628141 20.124523 5.414381e-03
## f.housing=f.no                  8.951867  50.000000 44.647520 2.564174e-02
## f.housing=f.yes                 7.220610  50.000000 55.352480 2.564174e-02
## f.day=f.day.fri                 5.938494  14.070352 18.939546 7.954203e-03
## f.contact=f.cellular            6.462799  51.507538 63.707572 2.141525e-07
## f.prev_contacted=Contacted      0.000000   0.000000  4.137377 2.408690e-08
## f.season=Aut-Win                1.361573   2.261307 13.275758 1.558582e-15
## f.season=Spring                 2.280446  11.809045 41.393854 3.687233e-41
##                                    v.test
## f.season=Summer                 17.536249
## f.prev_contacted=No-contacted    5.579747
## f.contact=f.telephone            5.186613
## f.day=f.day.tue                  2.781287
## f.housing=f.no                   2.231595
## f.housing=f.yes                 -2.231595
## f.day=f.day.fri                 -2.654008
## f.contact=f.cellular            -5.186613
## f.prev_contacted=Contacted      -5.579747
## f.season=Aut-Win                -7.972213
## f.season=Spring                -13.436657
##
## $`7`
##                                 Cla/Mod     Mod/Cla    Global
## f.contact=f.telephone          38.074156  65.5238095 36.292428
## f.season=Spring                32.508491  63.8095238 41.393854
## f.prev_contacted=No-contacted 21.998743 100.0000000 95.862623
## f.marital=f.married            23.851999  68.7619048 60.795340
## f.age=f.age-(40,50]            25.441413  30.1904762 25.025105
## f.day=f.day.tue                25.149701  24.0000000 20.124523
## f.jobsituation=Worker          22.826476  60.7619048 56.135770
## f.day=f.day.mon                18.639053  18.0000000 20.365535
## f.jobsituation=Other           18.746373  30.7619048 34.605342
## f.day=f.day.thu                17.560976  17.1428571 20.586463
## f.marital=f.single             15.565032  20.8571429 28.258686
## f.season=Summer                16.526362  35.5238095 45.330388
## f.age=f.age-[17,30]            11.199095   9.4285714 17.754569
## f.prev_contacted=Contacted      0.000000   0.0000000  4.137377
```

```
## f.season=Aut-Win               1.059002   0.6666667 13.275758
## f.contact=f.cellular          11.412358  34.4761905 63.707572
##                                     p.value     v.test
## f.contact=f.telephone         2.097715e-105  21.804613
## f.season=Spring                3.474101e-61  16.503295
## f.prev_contacted=No-contacted  2.007732e-22   9.741398
## f.marital=f.married            1.825860e-09   6.012587
## f.age=f.age-(40,50]            1.824763e-05   4.285320
## f.day=f.day.tue                5.175943e-04   3.471482
## f.jobsituation=Worker          6.513133e-04   3.409294
## f.day=f.day.mon                3.080611e-02  -2.159568
## f.jobsituation=Other           3.042168e-03  -2.963445
## f.day=f.day.thu                1.631759e-03  -3.150169
## f.marital=f.single             8.962670e-10  -6.126866
## f.season=Summer                4.723635e-13  -7.233022
## f.age=f.age-[17,30]            4.141770e-17  -8.408814
## f.prev_contacted=Contacted     2.007732e-22  -9.741398
## f.season=Aut-Win               8.694864e-62 -16.586714
## f.contact=f.cellular          2.097715e-105 -21.804613
##
## $`8`
##                                 Cla/Mod   Mod/Cla    Global       p.value
## f.season=Summer                56.00354  85.52097 45.330388 2.869286e-319
## f.contact=f.telephone          40.89651  50.00000 36.292428  2.765253e-38
## f.prev_contacted=No-contacted 30.96585 100.00000 95.862623  4.873451e-33
## f.education=Mandatory          31.54562  57.30717 53.926491  1.860217e-03
## f.housing=f.no                 31.44399  47.29364 44.647520  1.479675e-02
## f.jobsituation=Worker          30.87657  58.38972 56.135770  3.721353e-02
## f.jobsituation=Self-employed   33.83948  10.55480  9.258887  4.238536e-02
## f.housing=f.yes                28.26560  52.70636 55.352480  1.479675e-02
## f.day=f.day.tue                26.44711  17.92963 20.124523  1.154144e-02
## f.education=Non-Mandatory      27.27709  38.49797 41.895963  1.561059e-03
## f.jobsituation=Other           26.63958  31.05548 34.605342  5.914279e-04
## f.prev_contacted=Contacted      0.00000   0.00000  4.137377  4.873451e-33
## f.contact=f.cellular           23.29760  50.00000 63.707572  2.765253e-38
## f.season=Aut-Win                0.00000   0.00000 13.275758 7.705202e-111
## f.season=Spring                10.38331  14.47903 41.393854 1.235639e-151
##                                    v.test
## f.season=Summer                 38.199510
## f.contact=f.telephone           12.937488
## f.prev_contacted=No-contacted   11.973816
## f.education=Mandatory            3.111687
## f.housing=f.no                   2.437316
## f.jobsituation=Worker            2.083414
## f.jobsituation=Self-employed     2.029717
## f.housing=f.yes                 -2.437316
## f.day=f.day.tue                 -2.525863
## f.education=Non-Mandatory       -3.163087
## f.jobsituation=Other            -3.435515
## f.prev_contacted=Contacted     -11.973816
## f.contact=f.cellular           -12.937488
## f.season=Aut-Win               -22.370049
## f.season=Spring                -26.229169
##
```

```
##
## Link between the cluster variable and the quantitative variables
## ================================================================
##                      Eta2 P-value
## campaign       0.4922609       0
## pdays          0.6167808       0
## previous       0.3030681       0
## emp.var.rate   0.9672291       0
## cons.price.idx 0.6084482       0
## cons.conf.idx  0.6521304       0
## euribor3m      0.9945648       0
## nr.employed    0.8854108       0
##
## Description of each cluster by quantitative variables
## =====================================================
## $`1`
##                    v.test Mean in category Overall mean sd in category
## pdays           52.866518       11.1176471    5.3888741      1.9965368
## previous        13.984999        1.1030733    0.1469431      0.4115099
## cons.price.idx -3.398825        93.2513235   93.5831516      0.7591678
## emp.var.rate   -7.860980       -1.9823529    0.1023700      0.5506523
## euribor3m      -8.954788        0.9998529    3.6389677      0.2525389
## nr.employed    -9.859286     5047.9411765 5168.1679454     50.1994910
##                Overall sd      p.value
## pdays           0.6339641 0.000000e+00
## previous        0.3999801 1.924809e-44
## cons.price.idx  0.5711736 6.767606e-04
## emp.var.rate    1.5515130 3.811407e-15
## euribor3m       1.7241963 3.403881e-19
## nr.employed    71.3410455 6.249222e-23
##
## $`2`
##                     v.test Mean in category Overall mean sd in category
## cons.conf.idx   30.151936      -33.4791789  -40.5975497      5.2193589
## previous        27.786925        0.7278942    0.1469431      0.7377902
## campaign        -8.145421        1.5777126    2.2706305      0.9304094
## pdays          -17.571354        4.8065957    5.3888741      1.2570502
## cons.price.idx -25.142023       92.8325161   93.5831516      0.6401125
## euribor3m      -31.067188        0.8390235    3.6389677      0.2573116
## emp.var.rate   -34.052249       -2.6592375    0.1023700      0.7328957
## nr.employed    -35.463784     5035.9211144 5168.1679454     36.8844199
##                Overall sd       p.value
## cons.conf.idx   4.5165276 1.011749e-199
## previous        0.3999801 6.241502e-170
## campaign        1.6274493  3.779638e-16
## pdays           0.6339641  4.083064e-69
## cons.price.idx  0.5711736 1.727655e-139
## euribor3m       1.7241963 6.685843e-212
## emp.var.rate    1.5515130 3.759369e-254
## nr.employed    71.3410455 1.778609e-275
##
## $`3`
##                    v.test Mean in category Overall mean sd in category
## previous        14.19336        0.2872673    0.1469431      0.4909763
```

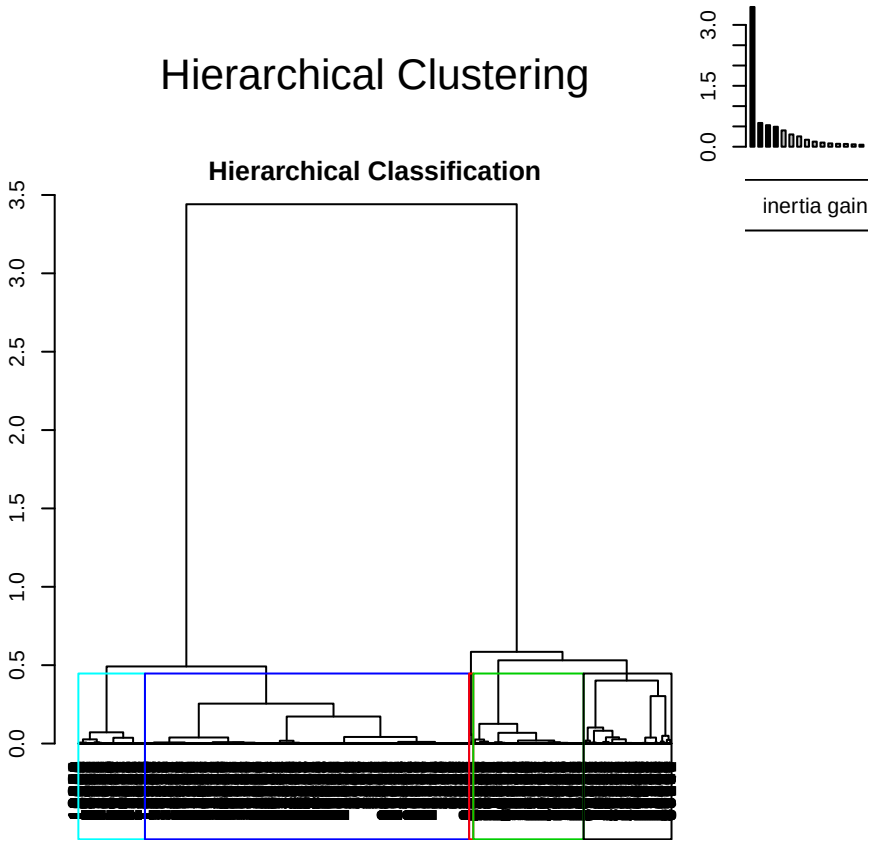
```
## pdays            2.40260       5.4265232    5.3888741      0.2314812
## cons.price.idx -35.49852      93.0819789   93.5831516      0.4123410
## cons.conf.idx  -43.29709     -45.4311688  -40.5975497      2.9919241
## nr.employed    -47.60642    5084.2192370 5168.1679454     37.2331422
## emp.var.rate   -50.59823      -1.8380682    0.1023700      0.3208205
## euribor3m      -55.54677       1.2716607    3.6389677      0.1791309
##                Overall sd       p.value
## previous        0.3999801  1.007190e-45
## pdays           0.6339641  1.627900e-02
## cons.price.idx  0.5711736 5.180812e-276
## cons.conf.idx   4.5165276  0.000000e+00
## nr.employed    71.3410455  0.000000e+00
## emp.var.rate    1.5515130  0.000000e+00
## euribor3m       1.7241963  0.000000e+00
##
## $`4`
##                   v.test Mean in category Overall mean sd in category
## nr.employed     5.332697    5195.69402174 5168.1679454     1.43364734
## euribor3m       3.624386       4.09111413    3.6389677     0.06933538
## campaign        2.917167       2.61413043    2.2706305     0.94869264
## previous       -2.823985       0.06521739    0.1469431     0.24690906
## cons.conf.idx  -4.356517     -42.02119565  -40.5975497     0.28672947
## cons.price.idx -9.329774      93.19758696   93.5831516     0.03264305
##                Overall sd      p.value
## nr.employed    71.3410455 9.676480e-08
## euribor3m       1.7241963 2.896483e-04
## campaign        1.6274493 3.532267e-03
## previous        0.3999801 4.743056e-03
## cons.conf.idx   4.5165276 1.321487e-05
## cons.price.idx  0.5711736 1.060965e-20
##
## $`5`
##                    v.test Mean in category Overall mean sd in category
## previous         6.585110        0.3053435    0.1469431     0.46055277
## nr.employed      6.440489     5195.8000000 5168.1679454     0.00000000
## euribor3m        4.708953        4.1272443    3.6389677     0.09619296
## emp.var.rate    -2.168881       -0.1000000    0.1023700     0.00000000
## cons.conf.idx   -5.163307      -42.0000000  -40.5975497     0.00000000
## cons.price.idx -11.154438       93.2000000   93.5831516     0.00000000
## campaign       -11.500555        1.1450382    2.2706305     0.43898108
##                Overall sd      p.value
## previous        0.3999801 4.545480e-11
## nr.employed    71.3410455 1.190890e-10
## euribor3m       1.7241963 2.489922e-06
## emp.var.rate    1.5515130 3.009170e-02
## cons.conf.idx   4.5165276 2.426246e-07
## cons.price.idx  0.5711736 6.812203e-29
## campaign        1.6274493 1.310700e-30
##
## $`6`
##                   v.test Mean in category Overall mean sd in category
## campaign       46.564277         5.914573    2.2706305      1.5491086
## emp.var.rate   16.463871         1.330653    0.1023700      0.2381146
## nr.employed    15.980573      5222.988442 5168.1679454     12.6493020
```

```
## euribor3m      15.464656         4.921116    3.6389677      0.1350120
## cons.price.idx 14.693416        93.986706   93.5831516      0.3529350
## previous       -7.640111         0.000000    0.1469431      0.0000000
##                Overall sd      p.value
## campaign        1.6274493 0.000000e+00
## emp.var.rate    1.5515130 6.669491e-61
## nr.employed    71.3410455 1.745356e-57
## euribor3m       1.7241963 6.009340e-54
## cons.price.idx  0.5711736 7.104069e-49
## previous        0.3999801 2.170339e-14
##
## $`7`
##                   v.test Mean in category Overall mean sd in category
## cons.conf.idx   34.54314       -36.320095  -40.5975497     0.36366650
## euribor3m       26.59982         4.896399    3.6389677     0.05189715
## emp.var.rate    25.77010         1.198571    0.1023700     0.17847998
## nr.employed     18.42753      5204.211333 5168.1679454    17.73605193
## cons.price.idx  13.67580        93.797312   93.5831516     0.26273487
## previous       -13.39960         0.000000    0.1469431     0.00000000
## campaign       -18.01188         1.466946    2.2706305     0.51895636
##                Overall sd       p.value
## cons.conf.idx   4.5165276 1.806939e-261
## euribor3m       1.7241963 6.820926e-156
## emp.var.rate    1.5515130 1.919347e-146
## nr.employed    71.3410455  7.900327e-76
## cons.price.idx  0.5711736  1.416375e-42
## previous        0.3999801  6.078735e-41
## campaign        1.6274493  1.571975e-72
##
## $`8`
##                    v.test Mean in category Overall mean sd in category
## emp.var.rate    37.057622         1.356563    0.1023700     0.10556677
## cons.price.idx  36.412511        94.036832   93.5831516     0.31318902
## nr.employed     35.059537      5222.728281 5168.1679454    13.05509087
## euribor3m       34.526536         4.937555    3.6389677     0.04338448
## cons.conf.idx   -2.171606       -40.811502  -40.5975497     2.67049033
## previous       -16.841449         0.000000    0.1469431     0.00000000
##                Overall sd       p.value
## emp.var.rate    1.5515130 1.353721e-300
## cons.price.idx  0.5711736 2.698575e-290
## nr.employed    71.3410455 2.790375e-269
## euribor3m       1.7241963 3.207593e-261
## cons.conf.idx   4.5165276  2.988543e-02
## previous        0.3999801  1.212306e-63
```

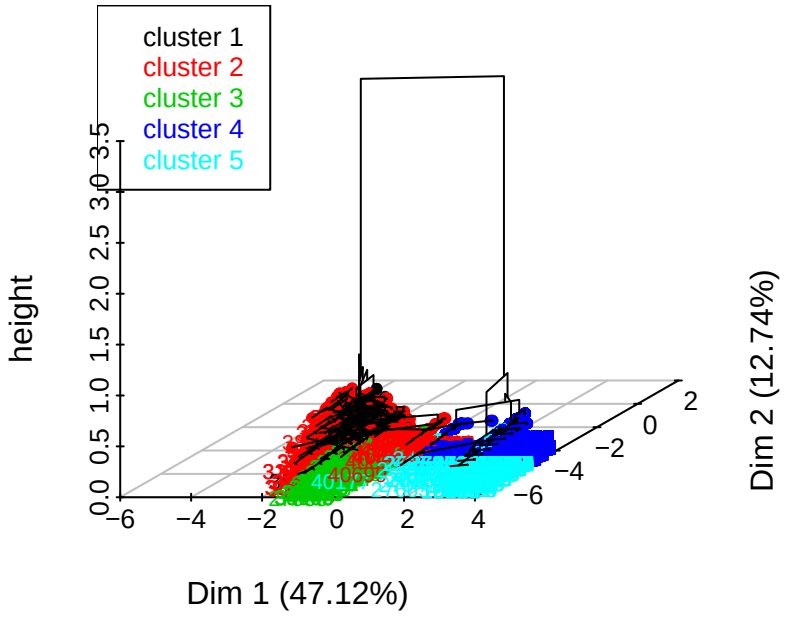
```
###### TODO JOSEP
```

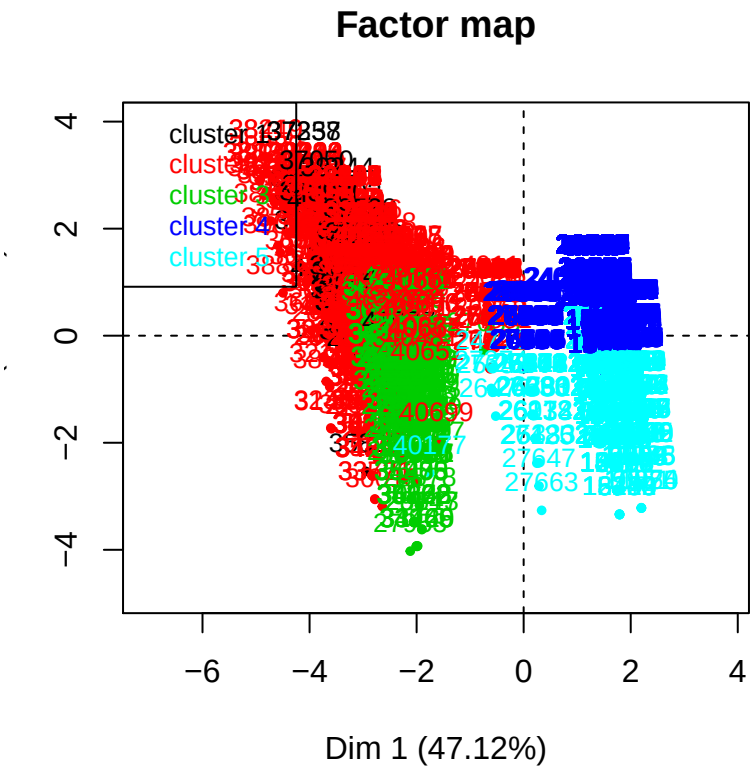
12.3 Hierarchical Clustering

```
#Després de comprovar el nombre optim de cluster a definir interaccionant amb el plot, hem vist que és
clust <- HCPC(res.pca, nb.clust = 5, order = TRUE)
```


Hierarchical Clustering
Hierarchical Classification
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
0.0
1.5
3.0
inertia gain

Hierarchical clustering on the factor map





###Description of clusters

```
clust$desc.var
```

```
##
## Link between the cluster variable and the quantitative variables
## ================================================================
##                     Eta2 P-value
## campaign       0.5135931       0
## pdays          0.5736642       0
## previous       0.6463952       0
## emp.var.rate   0.8735959       0
## cons.price.idx 0.4666171       0
## cons.conf.idx  0.2876758       0
## euribor3m      0.9277479       0
## nr.employed    0.8034334       0
##
## Description of each cluster by quantitative variables
## ======================================================
## $`1`
##                   v.test Mean in category Overall mean sd in category
## pdays          52.936829        11.212121    5.3888741      1.9502537
## previous       13.384792         1.075894    0.1469431      0.3864648
## cons.price.idx -3.637888        93.222606   93.5831516      0.7521708
## emp.var.rate   -7.843050        -2.009091    0.1023700      0.5367487
## euribor3m      -8.808883         1.003545    3.6389677      0.2554308
## nr.employed    -9.505769      5050.496970 5168.1679454     48.7263943
```

```
##                Overall sd      p.value
## pdays           0.6339641 0.000000e+00
## previous        0.3999801 7.420521e-41
## cons.price.idx  0.5711736 2.748824e-04
## emp.var.rate    1.5515130 4.397334e-15
## euribor3m       1.7241963 1.263986e-18
## nr.employed    71.3410455 1.985758e-21
##
## $`2`
##                    v.test Mean in category Overall mean sd in category
## previous         54.601436        0.8460976    0.1469431      0.5770173
## cons.conf.idx     7.400120      -39.5275735  -40.5975497      6.7866064
## campaign         -6.558706        1.9289216    2.2706305      1.3448693
## pdays            -9.172576        5.2027139    5.3888741      0.9283452
## cons.price.idx -29.371876       93.0460821   93.5831516      0.5792142
## euribor3m      -41.268815        1.3610429    3.6389677      0.9937786
## emp.var.rate   -41.621890       -1.9649510    0.1023700      0.9301312
## nr.employed    -43.247602     5069.3963235 5168.1679454     62.5784272
##                Overall sd       p.value
## previous        0.3999801  0.000000e+00
## cons.conf.idx   4.5165276  1.360616e-13
## campaign        1.6274493  5.427680e-11
## pdays           0.6339641  4.618470e-20
## cons.price.idx  0.5711736 1.256157e-189
## euribor3m       1.7241963  0.000000e+00
## emp.var.rate    1.5515130  0.000000e+00
## nr.employed    71.3410455  0.000000e+00
##
## $`3`
##                    v.test Mean in category Overall mean sd in category
## previous       -11.65178     8.398215e-04    0.1469431     0.01060273
## cons.price.idx -31.01940     9.302772e+01   93.5831516     0.33423662
## nr.employed    -34.67972     5.090607e+03 5168.1679454    27.85533532
## cons.conf.idx  -37.82280    -4.595290e+01  -40.5975497     2.13113449
## emp.var.rate   -40.45508    -1.865325e+00    0.1023700     0.31941892
## euribor3m      -43.15513     1.306323e+00    3.6389677     0.16092179
##                Overall sd       p.value
## previous        0.3999801  2.247220e-31
## cons.price.idx  0.5711736 2.951813e-211
## nr.employed    71.3410455 1.592855e-263
## cons.conf.idx   4.5165276  0.000000e+00
## emp.var.rate    1.5515130  0.000000e+00
## euribor3m       1.7241963  0.000000e+00
##
## $`4`
##                    v.test Mean in category Overall mean sd in category
## euribor3m        52.64690         4.823374    3.6389677      0.2696129
## emp.var.rate     50.51197         1.124935    0.1023700      0.4802150
## nr.employed      48.29887      5213.127050 5168.1679454     17.6645147
## cons.price.idx   37.02986        93.859121   93.5831516      0.3835478
## cons.conf.idx    18.99887       -39.477922  -40.5975497      2.9964714
## campaign        -26.18570         1.714582    2.2706305      0.7436116
## previous        -28.15591         0.000000    0.1469431      0.0000000
##                Overall sd       p.value
```

```
## euribor3m       1.7241963  0.000000e+00
## emp.var.rate    1.5515130  0.000000e+00
## nr.employed    71.3410455  0.000000e+00
## cons.price.idx  0.5711736 3.789174e-300
## cons.conf.idx   4.5165276  1.742638e-80
## campaign        1.6274493 3.867302e-151
## previous        0.3999801 2.028395e-174
##
## $`5`
##                   v.test Mean in category Overall mean sd in category
## campaign       49.984100     5.415254e+00    2.2706305     1.49533892
## emp.var.rate   18.750173     1.226949e+00    0.1023700     0.39454223
## euribor3m      18.432707     4.867553e+00    3.6389677     0.27199300
## nr.employed    17.733867     5.217075e+03 5168.1679454    18.89857603
## cons.price.idx 13.490940     9.388103e+01   93.5831516     0.37532374
## cons.conf.idx   6.104696    -3.953169e+01  -40.5975497     3.03354056
## previous       -8.955367     8.474576e-03    0.1469431     0.09166656
##                Overall sd      p.value
## campaign        1.6274493 0.000000e+00
## emp.var.rate    1.5515130 1.929612e-78
## euribor3m       1.7241963 7.179853e-76
## nr.employed    71.3410455 2.296785e-70
## cons.price.idx  0.5711736 1.768316e-41
## cons.conf.idx   4.5165276 1.029966e-09
## previous        0.3999801 3.386078e-19
```

```
clust$desc.axes
```

```
##
## Link between the cluster variable and the quantitative variables
## ================================================================
##            Eta2 P-value
## Dim.1 0.9191789       0
## Dim.2 0.4450225       0
## Dim.3 0.5497222       0
## Dim.4 0.4098434       0
## Dim.5 0.2984519       0
##
## Description of each cluster by quantitative variables
## =====================================================
## $`1`
##           v.test Mean in category  Overall mean sd in category Overall sd
## Dim.3  51.398588         8.951013 -7.344825e-13      2.8976185  1.0036410
## Dim.4  11.930668         2.015231  9.709110e-13      1.3810674  0.9734587
## Dim.2   6.944085         1.216613  4.468775e-13      1.2383845  1.0097057
## Dim.1 -10.049127        -3.385357 -3.915432e-12      0.4548905  1.9414825
##            p.value
## Dim.3 0.000000e+00
## Dim.4 8.191371e-33
## Dim.2 3.809211e-12
## Dim.1 9.268528e-24
##
## $`2`
##          v.test Mean in category  Overall mean sd in category Overall sd
## Dim.5  30.34007        0.8354515 -2.563362e-12      1.5992376  0.8601496
```

```
## Dim.2  16.83824        0.5442796  4.468775e-13      1.1477283  1.0097057
## Dim.4  16.50144        0.5142450  9.709110e-13      1.1257317  0.9734587
## Dim.3 -11.07431       -0.3558163 -7.344825e-13      1.4938443  1.0036410
## Dim.1 -45.99890       -2.8589830 -3.915432e-12      0.9059308  1.9414825
##             p.value
## Dim.5 3.397393e-202
## Dim.2  1.279947e-63
## Dim.4  3.582524e-61
## Dim.3  1.671594e-28
## Dim.1  0.000000e+00
##
## $`3`
##          v.test Mean in category  Overall mean sd in category Overall sd
## Dim.4 -23.38948       -0.7137853  9.709110e-13      0.7313931  0.9734587
## Dim.2 -27.41583       -0.8678120  4.468775e-13      0.7683096  1.0097057
## Dim.5 -29.19190       -0.7871652 -2.563362e-12      0.2547806  0.8601496
## Dim.1 -37.36288       -2.2740669 -3.915432e-12      0.1550095  1.9414825
##             p.value
## Dim.4 5.467981e-121
## Dim.2 1.776165e-165
## Dim.5 2.456920e-187
## Dim.1 1.566731e-305
##
## $`4`
##           v.test Mean in category  Overall mean sd in category Overall sd
## Dim.1  50.714279        1.2847096 -3.915432e-12      0.5067072  1.9414825
## Dim.2  28.208382        0.3716330  4.468775e-13      0.5530912  1.0097057
## Dim.5  -2.183965       -0.0245110 -2.563362e-12      0.3374144  0.8601496
## Dim.4 -18.983718       -0.2411238  9.709110e-13      0.5634599  0.9734587
##             p.value
## Dim.1  0.000000e+00
## Dim.2 4.615007e-175
## Dim.5  2.896480e-02
## Dim.4  2.325448e-80
##
## $`5`
##           v.test Mean in category  Overall mean sd in category Overall sd
## Dim.4  34.539170       1.29974688  9.709110e-13      0.8023248  0.9734587
## Dim.1  20.413868       1.53210358 -3.915432e-12      0.4658507  1.9414825
## Dim.5   2.633085       0.08755244 -2.563362e-12      0.3695755  0.8601496
## Dim.3  -3.061863      -0.11879371 -7.344825e-13      0.2086902  1.0036410
## Dim.2 -32.677417      -1.27547477  4.468775e-13      0.7901854  1.0097057
##             p.value
## Dim.4 2.072702e-261
## Dim.1  1.259146e-92
## Dim.5  8.461313e-03
## Dim.3  2.199642e-03
## Dim.2 3.269755e-234
```

```
clust$desc.ind
```

```
## $para
## Cluster: 1
##    39728    31073    34770    35219    31241
## 1.305872 1.448076 1.798985 1.799196 1.870738
```

```
## ------------------------------------------------------------
## Cluster: 2
##     36450     36741     36890     36686     36836
## 0.6644885 0.7354002 0.7747697 0.8770443 0.8895529
## ------------------------------------------------------------
## Cluster: 3
##     33221     35442     30983     31837     31859
## 0.1280541 0.1383877 0.1450067 0.1464073 0.1464073
## ------------------------------------------------------------
## Cluster: 4
##      1562      1496      1529      1754      1970
## 0.6944152 0.6944408 0.6944408 0.6944408 0.6944408
## ------------------------------------------------------------
## Cluster: 5
##      3890      5049      7050      2762      3306
## 0.7413756 0.7413900 0.7413907 0.7414199 0.7416763
##
## $dist
## Cluster: 1
##    37851    37238    37357    41089    40049
## 15.61562 15.60960 15.60957 13.18075 12.80459
## ------------------------------------------------------------
## Cluster: 2
##    30418    38200    37688    39757    38875
## 8.869425 8.589632 8.126727 7.608229 7.495552
## ------------------------------------------------------------
## Cluster: 3
##    27953    34965    33740    33466    31129
## 4.631202 4.577766 4.569714 4.568274 4.556035
## ------------------------------------------------------------
## Cluster: 4
##    10886     9586    11274    11299     9144
## 2.884114 2.883392 2.882757 2.882757 2.882483
## ------------------------------------------------------------
## Cluster: 5
##    27663    11050     9951    10825    10574
## 4.716676 4.577871 4.577766 4.576886 4.575903
```

```
######### TODO ÀLEX
```

```
summary(df$duration)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##     4.0   103.0   181.0   256.6   326.0  1499.0
```

```
qulist<-quantile(df$duration,seq(0,1,0.125),na.rm=TRUE)
df$f.duration<-factor(cut(df$duration,breaks=c(4,64,103,140,181,235,326,496,1499),include.lowest=T))

summary(df$f.duration)
```

```
##        [4,64]      (64,103]     (103,140]     (140,181]     (181,235]
##           576           672           627           629           609
##     (235,326]     (326,496] (496,1.5e+03]
##           622           621           623
```

```
levels(df$f.duration)<-paste0("f.duration-",levels(df$f.duration))
```

12.4 CA analysis

Per a realitzar l'anàlisis de correspondència simples utilitzarem dos factors sorgits de la neteja de les dades. En aquest cas farem l'estudi amb el factor f.jobsituation i el factor f.age. ### f.duration - f.job

```
t <- table(df$f.job, df$f.duration); t;
```

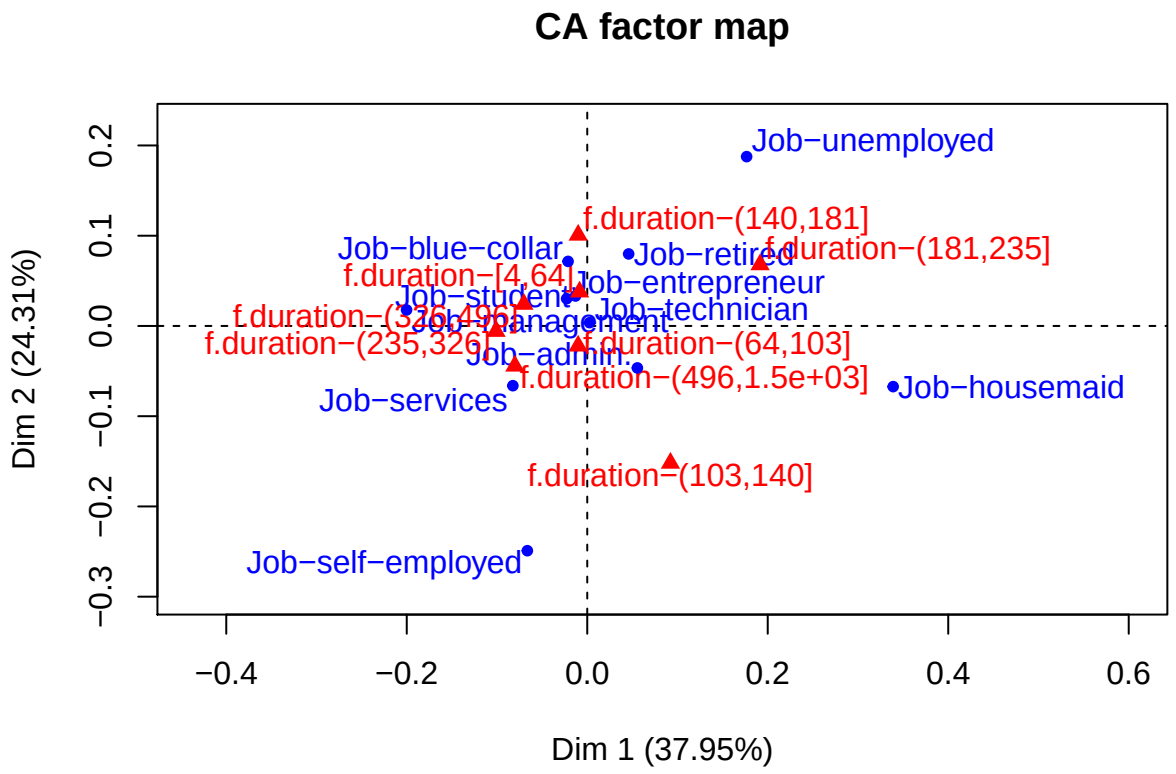
```
##
##                     f.duration-[4,64] f.duration-(64,103]
##   Job-admin.                      153                 170
##   Job-blue-collar                 138                 149
##   Job-entrepreneur                 21                  26
##   Job-housemaid                    13                  22
##   Job-management                   43                  53
##   Job-retired                      16                  25
##   Job-self-employed                13                  20
##   Job-services                     51                  68
##   Job-student                       8                  11
##   Job-technician                  104                 114
##   Job-unemployed                   16                  14
##
##                     f.duration-(103,140] f.duration-(140,181]
##   Job-admin.                         195                 154
##   Job-blue-collar                    128                 174
##   Job-entrepreneur                    18                  23
##   Job-housemaid                       24                  14
##   Job-management                      34                  46
##   Job-retired                         21                  32
##   Job-self-employed                   28                  18
##   Job-services                        58                  47
##   Job-student                         10                   8
##   Job-technician                     101                  96
##   Job-unemployed                      10                  17
##
##                     f.duration-(181,235] f.duration-(235,326]
##   Job-admin.                         168                 163
##   Job-blue-collar                    144                 155
##   Job-entrepreneur                    23                  23
##   Job-housemaid                       26                  11
##   Job-management                      22                  53
##   Job-retired                         26                  17
##   Job-self-employed                   11                  17
##   Job-services                        48                  63
##   Job-student                         16                  16
##   Job-technician                     103                  96
##   Job-unemployed                      22                   8
##
##                     f.duration-(326,496] f.duration-(496,1.5e+03]
##   Job-admin.                         154                      146
##   Job-blue-collar                    146                      141
##   Job-entrepreneur                    17                       28
##   Job-housemaid                       12                        9
```

```
##   Job-management                    50                    42
##   Job-retired                       22                    27
##   Job-self-employed                 14                    30
##   Job-services                      65                    69
##   Job-student                       18                    12
##   Job-technician                   111                   104
##   Job-unemployed                    12                    15
```

```
chisq.test(t)
```

```
##
##  Pearson's Chi-squared test
##
## data:  t
## X-squared = 108.72, df = 70, p-value = 0.002084
```

```
t <- CA(t)
```



Com que el p-value és més petit que 0,05 rebutgem la hipòtesis de independència entre els dos factors. Trobem una certa relació entre les trucades amb més durada i els treballadors en el sector dels serveis. Per altre banda, retirats i estudiants son els que més relació tenen amb les trucades curtes. ####Eigenvalues and dominant axes analysis

```
t(t$eig)
```

```
##                                        dim 1        dim 2        dim 3
## eigenvalue                       0.008287759  0.005308914  0.003718622
## percentage of variance          37.954044478 24.312333499 17.029540434
## cumulative percentage of variance 37.954044478 62.266377977 79.295918411
```

```
##                                        dim 4        dim 5        dim 6
## eigenvalue                          0.002121133  0.001192038  0.000707237
## percentage of variance              9.713794962  5.458972020  3.238813160
## cumulative percentage of variance 89.009713373 94.468685393 97.707498554
##                                        dim 7
## eigenvalue                         5.005975e-04
## percentage of variance             2.292501e+00
## cumulative percentage of variance 1.000000e+02
```

En aquest punt escollim utilitzar les 4 primeres dimensions, aquestes superen en escreix el limit del 80% de representació.

```
t$col$cos2[,1:4]
```

```
##                                  Dim 1       Dim 2        Dim 3      Dim 4
## f.duration-[4,64]         0.007255284 0.143539053 8.759853e-02 0.10367470
## f.duration-(64,103]       0.017662737 0.084975935 8.333259e-03 0.01217276
## f.duration-(103,140]      0.251000251 0.681835067 3.673305e-05 0.04971561
## f.duration-(140,181]      0.004478179 0.451220658 2.990549e-01 0.19867418
## f.duration-(181,235]      0.822078155 0.103433663 5.339270e-03 0.06100023
## f.duration-(235,326]      0.567974086 0.001926722 2.330852e-01 0.01501167
## f.duration-(326,496]      0.318967399 0.037656024 3.891893e-01 0.11573080
## f.duration-(496,1.5e+03] 0.254086183 0.077750091 4.603492e-01 0.19768454
```

Destaquem que la dimensió 3 i 4 realitzen una representació molt lleu de les nostres dades. En canvi la dimensió 1 té en compte les trucades de durada mitjana i en canvi en la tercera dimensió i juguen un paper bastant important les trucades de major durada de la mostra.

12.4.1 f.duration - f.age

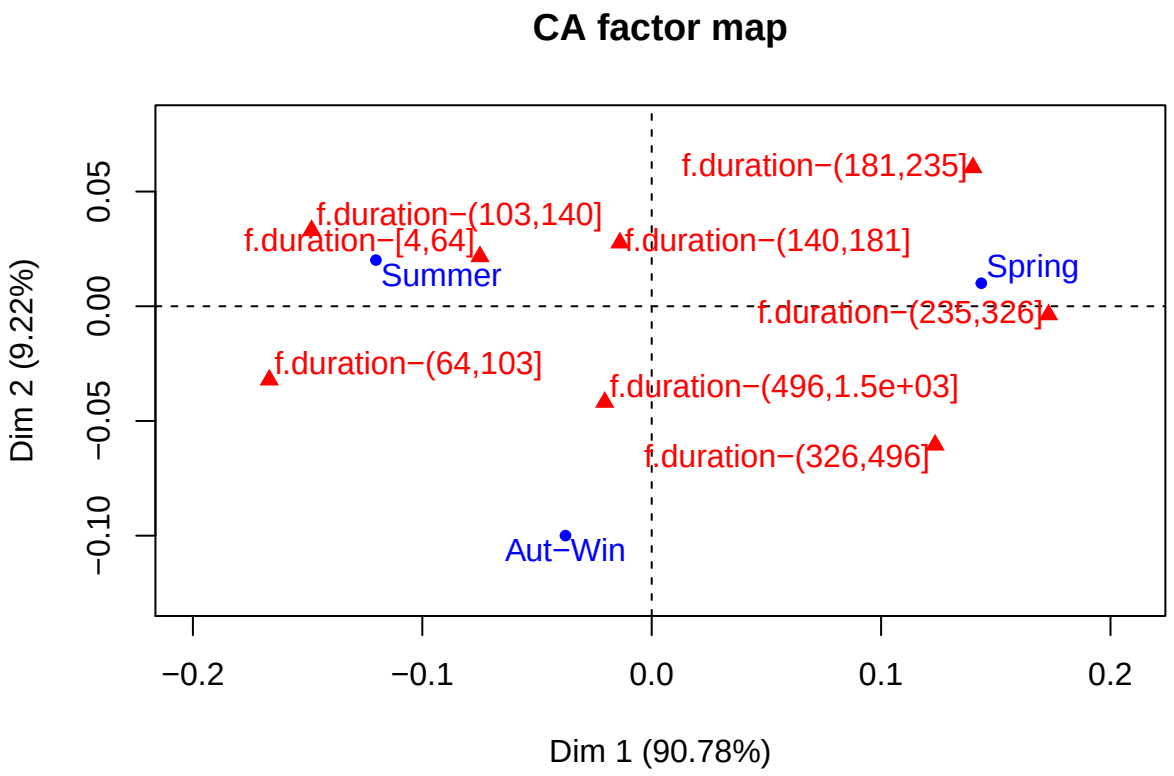
```
t <- table(df$f.season, df$f.duration); t;
```

```
##
##           f.duration-[4,64] f.duration-(64,103] f.duration-(103,140]
##   Spring                219                 222                  217
##   Summer                283                 349                  330
##   Aut-Win                74                 101                   80
##
##           f.duration-(140,181] f.duration-(181,235] f.duration-(235,326]
##   Spring                   258                  297                  309
##   Summer                   293                  247                  234
##   Aut-Win                   78                   65                   79
##
##           f.duration-(326,496] f.duration-(496,1.5e+03]
##   Spring                   290                     249
##   Summer                   239                     282
##   Aut-Win                   92                      92
```

```
chisq.test(t)
```

```
##
##  Pearson's Chi-squared test
##
## data:  t
## X-squared = 83.826, df = 14, p-value = 5.487e-12
```

```
t <- CA(t)
```



Com que el p-value és més petit que 0,05 rebutgem la hipòtesis de independència entre els dos factors. En conjunt podem veure que al voltant de la primavera es situen les trucades amb una durada superior. En canvi, a l'estiu passa totalment el contrari. ####Eigenvalues and dominant axes analysis

```
t(t$eig)
```

```
##                                       dim 1        dim 2
## eigenvalue                      0.01528409 1.551901e-03
## percentage of variance         90.78224362 9.217756e+00
## cumulative percentage of variance 90.78224362 1.000000e+02
```

En aquest punt escollim utilitzar les dues uniques dimensión per a poder fer-ne una posterior valoració.

```
t$col$cos2[,1:2]
```

```
##                              Dim 1        Dim 2
## f.duration-[4,64]        0.9225859 0.0774141059
## f.duration-(64,103]      0.9642447 0.0357552505
## f.duration-(103,140]     0.9525546 0.0474454013
## f.duration-(140,181]     0.2014826 0.7985173967
## f.duration-(181,235]     0.8427807 0.1572192538
## f.duration-(235,326]     0.9995529 0.0004471099
## f.duration-(326,496]     0.8066524 0.1933475905
## f.duration-(496,1.5e+03] 0.1932805 0.8067194776
```

Tot i que la primera dimensió representa en gran escreix la major part de les dades, podem comentar que en la dimensió numero dos es veuen molt millor representades les trucades amb una major durada i també les de

durades intermitges.