

Course Practical Assignment - 1st Delivery (17 de març del 2019)

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Bank client data

Description of input variables:

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

Loading packages:

Loading data:

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

df<-read.table( paste0(dirwd, "/bank-additional/bank-additional-full.csv"), header=TRUE, sep=";")

# General description of the bank data
```

```
head(df)
```

```
##   age      job marital  education default housing loan  contact month
## 1  56 housemaid married  basic.4y      no      no  no telephone  may
## 2  57  services married high.school unknown      no  no telephone  may
## 3  37  services married high.school      no  yes  no telephone  may
## 4  40   admin. married  basic.6y      no      no  no telephone  may
## 5  56  services married high.school      no      no  yes telephone  may
## 6  45  services married  basic.9y unknown      no  no telephone  may
##   day_of_week duration campaign pdays previous  poutcome emp.var.rate
## 1         mon      261         1    999         0 nonexistent         1.1
## 2         mon      149         1    999         0 nonexistent         1.1
## 3         mon      226         1    999         0 nonexistent         1.1
## 4         mon      151         1    999         0 nonexistent         1.1
## 5         mon      307         1    999         0 nonexistent         1.1
## 6         mon      198         1    999         0 nonexistent         1.1
##   cons.price.idx cons.conf.idx euribor3m nr.employed  y
## 1         93.994        -36.4     4.857      5191 no
## 2         93.994        -36.4     4.857      5191 no
## 3         93.994        -36.4     4.857      5191 no
## 4         93.994        -36.4     4.857      5191 no
## 5         93.994        -36.4     4.857      5191 no
## 6         93.994        -36.4     4.857      5191 no
```

```
nrow(df)
```

```
## [1] 41188
```

```
ncol(df)
```

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

```
dim(df)
```

```
## [1] 41188    21
```

```
# Selection of our 5000 samples with a specific seed value
```

```
set.seed(17041998)
```

```
llista<-sample(size=5000, x=1:nrow(df), replace=FALSE)
```

```
llista<-sort(llista)
```

```
# Overwrite the dataframe with our chosen sample and save the RData
```

```
df<-df[llista,]
```

```
save.image( paste0(dirwd, "/bank-additional/Bank5000_raw.RData") )
```

Our chosen sample:

```
#load( paste0(dirwd, "/bank-additional/Bank5000_raw.RData") )
```

```
summary(df)
```

```
##      age      job      marital
## Min.   :18.00  admin.   :1234  divorced: 556
## 1st Qu.:32.00  blue-collar:1154  married :3053
## Median :38.00  technician : 794  single  :1381
## Mean   :40.07  services   : 500  unknown : 10
## 3rd Qu.:47.00  management : 413
```

```

## Max.      :87.00   retired      : 205
##              (Other)      : 700
##              education      default      housing      loan
## university.degree :1472   no      :3966   no      :2219   no      :4091
## high.school       :1171   unknown:1034   unknown: 137   unknown: 137
## basic.9y          : 716   yes      : 0   yes      :2644   yes      : 772
## professional.course: 602
## basic.4y          : 513
## basic.6y          : 291
## (Other)           : 235
##              contact      month      day_of_week      duration
## cellular :3130   may      :1743   fri: 924   Min.      : 1.0
## telephone:1870   jul      : 831   mon:1018   1st Qu.: 101.0
##              aug      : 699   thu:1039   Median   : 178.0
##              jun      : 653   tue:1045   Mean      : 254.8
##              nov      : 509   wed: 974   3rd Qu.: 317.0
##              apr      : 310           Max.      :3785.0
##              (Other): 255
##              campaign      pdays      previous      poutcome
## Min.      : 1.000   Min.      : 0.0   Min.      :0.0000   failure      : 478
## 1st Qu.: 1.000   1st Qu.:999.0   1st Qu.:0.0000   nonexistent:4363
## Median : 2.000   Median :999.0   Median :0.0000   success      : 159
## Mean      : 2.583   Mean      :963.2   Mean      :0.1606
## 3rd Qu.: 3.000   3rd Qu.:999.0   3rd Qu.:0.0000
## Max.      :33.000   Max.      :999.0   Max.      :4.0000
##
## emp.var.rate      cons.price.idx      cons.conf.idx      euribor3m
## Min.      : -3.40000   Min.      :92.20   Min.      : -50.80   Min.      :0.635
## 1st Qu.: -1.80000   1st Qu.:93.08   1st Qu.: -42.70   1st Qu.:1.334
## Median : 1.10000   Median :93.77   Median : -41.80   Median :4.857
## Mean      : 0.06326   Mean      :93.57   Mean      : -40.43   Mean      :3.613
## 3rd Qu.: 1.40000   3rd Qu.:93.99   3rd Qu.: -36.40   3rd Qu.:4.961
## Max.      : 1.40000   Max.      :94.77   Max.      : -26.90   Max.      :5.000
##
## nr.employed      y
## Min.      :4964   no :4435
## 1st Qu.:5099   yes: 565
## Median :5191
## Mean      :5166
## 3rd Qu.:5228
## Max.      :5228
##

```

Inicialització del control d'errors, missings i outliers:

```

columnes <- names(df) #list of column names

# creem 3 dataframes inicialitzats a 0 d'una fila amb les columnes de la nostra mostra;
# en ells hi posarem el nombre d'errors, missings i outliers per a cada variable
errors <- data.frame(matrix(0, ncol = length(columnes), nrow = 1))
colnames(errors)<-columnes

missings <- data.frame(matrix(0, ncol = length(columnes), nrow = 1))

```

```
colnames(missings)<-columnes

outliers <- data.frame(matrix(0, ncol = length(columnes), nrow = 1))
colnames(outliers)<-columnes

# columnes que portaran el control per individu:
df$num_missings <- 0
df$num_outliers <- 0
df$num_errors <- 0
```

UNIVARIATE DESCRIPTIVE ANALYSIS (to be included for each variable):

Aquí estudiem cada variable buscant missing values, outliers i possibles errors. En el cas que en trobem, els transformem en NAs i procedim a una imputació manual o els eliminem, o una imputació automàtica (en un chunk posterior d'Imputation).

QUALITATIVE VARIABLES:

També factoritzem aquí les categories (levels) de les variables qualitatives (discretes).

Job

Jobs "unknown" són considerats com a categoria.

```
# Jobs "unknown" will be considered a category, not a missing value.
table(df$job, useNA="always")

##
##      admin.   blue-collar  entrepreneur   housemaid   management
##      1234      1154         155         135         413
##      retired self-employed   services      student   technician
##      205        149         500        100         794
##      unemployed   unknown      <NA>
##      122          39          0

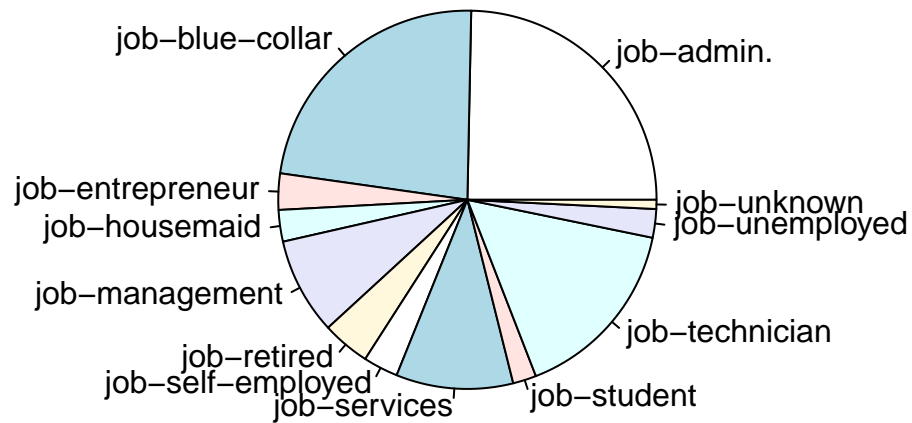
# Missings:
miss<-which(is.na(df$job));
missings$job<-length(miss); length(miss)

## [1] 0

df[miss, "num_missings"]<- df[miss, "num_missings"]+1

# Factoritzem les categories (levels) de la columna i afegim l'etiqueta "job-":
df$job<-factor(df$job)
levels(df$job)<-paste0("job-",levels(df$job))

pie(summary(df$job))
```



Marital

Els “unknowns” seran imputats més endavant automàticament.

```
# Marital "unknown" will be a missing value (set to NA):
sel<-which(df$marital=="unknown");length(sel)
```

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

```
df$marital[sel]<-NA
```

```
# Missings:
```

```
miss<-which(is.na(df$marital));
missings$marital<-length(miss); length(miss)
```

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

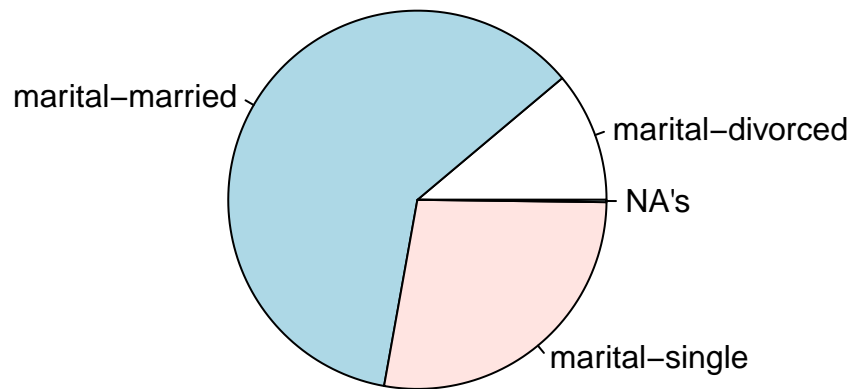
```
df[miss, "num_missings"]<- df[miss, "num_missings"]+1
```

```
# Factoritzem les categories (levels) de la columna i afegim l'etiqueta "marital-":
```

```
df$marital<-factor(df$marital)
levels(df$marital)<-paste0("marital-",levels(df$marital))
summary(df$marital)
```

```
## marital-divorced marital-married marital-single      NA's
##           556           3053           1381           10
```

```
pie(summary(df$marital))
```



Education

Education “unknown” és considerada com a categoria. La categoria “illiterate” és inclosa manualment a “basic.4y”.

Education “unknown” will be considered a category, not a missing value.

```
table(df$education, useNA="always")
```

```
##
##      basic.4y      basic.6y      basic.9y
##      513        291        716
##      high.school      illiterate professional.course
##      1171             3        602
##      university.degree      unknown      <NA>
##      1472             232        0
```

Illiterates are consired as basic.4y.educated:

```
sel<-which(df$education=="illiterate");length(sel)
```

```
## [1] 3
```

```
df[sel, "education"]<-"basic.4y"
```

Missings:

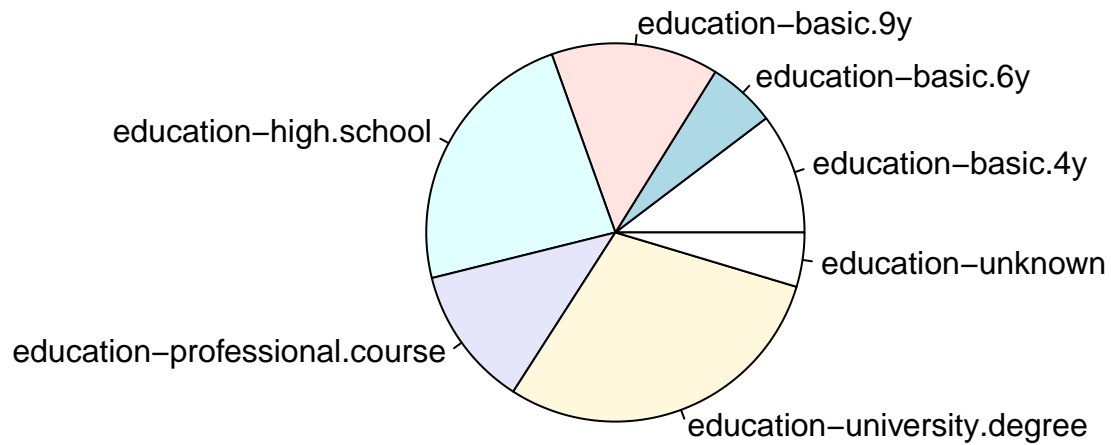
```
miss<-which(is.na(df$education));
missings$education<-length(miss); length(miss)
```

```
## [1] 0
```

```
df[miss, "num_missings"]<- df[miss, "num_missings"]+1

# Factoritzem les categories (levels) de la columna i afegim l'etiqueta "education-":
df$education<-factor(df$education)
levels(df$education)<-paste0("education-",levels(df$education))

pie(summary(df$education))
```



Default (has credit in default?)

Default (owes credit) “unknown” will be considered a category, not a missing value.

```
table(df$default, useNA="always")

##
##      no unknown      yes      <NA>
##    3966    1034         0         0

# Missings:
miss<-which(is.na(df$default));
missings$default<-length(miss); length(miss)
```

```
## [1] 0
```

```
df[miss, "num_missings"]<- df[miss, "num_missings"]+1

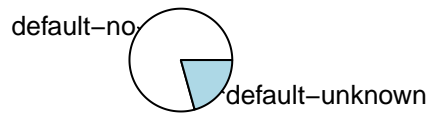
# Factoritzem les categories (levels) de la columna i afegim l'etiqueta "default-":
df$default<-factor(df$default)
```

```

levels(df$default)<-paste0("default-",levels(df$default))

par(mfrow=c(2,2))
pie(summary(df$default))

```



Housing

Housing “unknown” will be considered a category, not a missing value.

```
table(df$housing, useNA="always")
```

```
##
##      no unknown      yes      <NA>
##    2219      137    2644         0
```

```
# Missings:
```

```
miss<-which(is.na(df$housing));
missings$housing<-length(miss); length(miss)
```

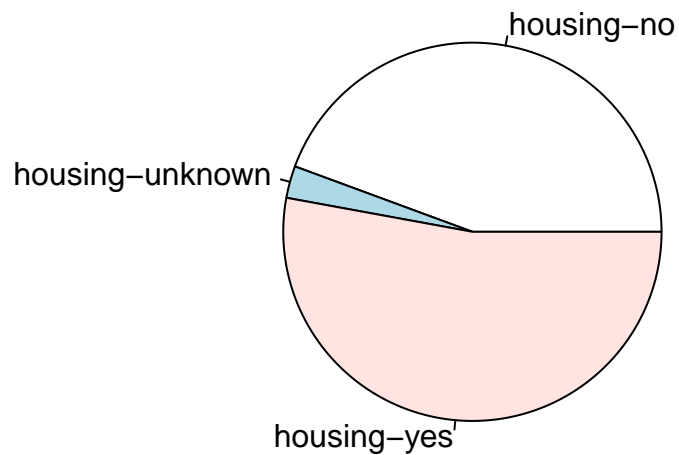
```
## [1] 0
```

```
df[miss, "num_missings"]<- df[miss, "num_missings"]+1
```

```
# Factoritzem les categories (levels) de la columna i afegim l'etiqueta "housing-":
```

```
df$housing<-factor(df$housing)
levels(df$housing)<-paste0("housing-",levels(df$housing))
```

```
pie(summary(df$housing))
```

Loan (has personal loan?)

Loan “unknown” will be a missing value (set to NA) i serà imputat més endavant automàticament.

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

```
## [1] 137
```

```
df$loan[sel]<-NA
```

```
# Missings:
```

```
miss<-which(is.na(df$loan));
```

```
missings$loan<-length(miss); length(miss)
```

```
## [1] 137
```

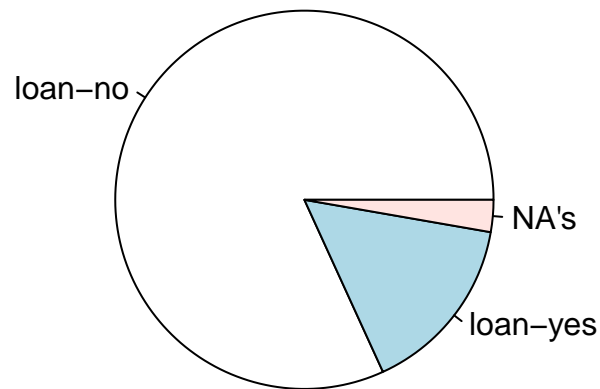
```
df[miss, "num_missings"]<- df[miss, "num_missings"]+1
```

```
# Factoritzem les categories (levels) de la columna i afegim l'etiqueta "loan-":
```

```
df$loan<-factor(df$loan)
```

```
levels(df$loan)<-paste0("loan-",levels(df$loan))
```

```
pie(summary(df$loan))
```



Contact

```
summary(df$contact)
```

```
## cellular telephone
##      3130      1870
```

```
# Missings:
```

```
miss<-which(is.na(df$contact));
missings$contact<-length(miss); length(miss)
```

```
## [1] 0
```

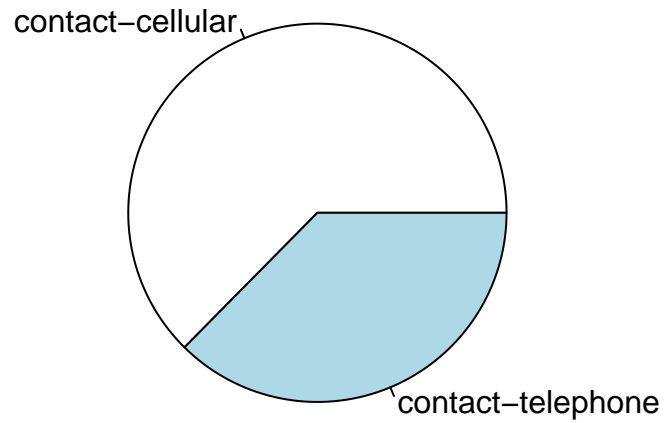
```
df[miss, "num_missings"]<- df[miss, "num_missings"]+1
```

```
# Factoritzem les categories (levels) de la columna i afegim l'etiqueta "contact-":
```

```
df$contact<-factor(df$contact)
```

```
levels(df$contact)<-paste0("contact-",levels(df$contact))
```

```
pie(summary(df$contact))
```



Month

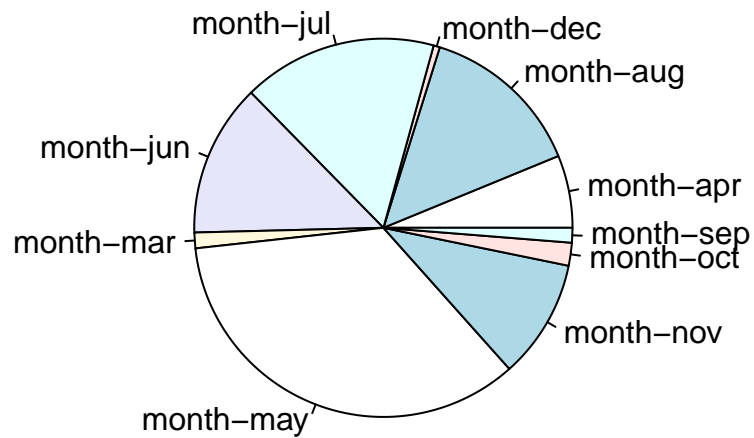
```
miss<-which(is.na(df$month));
missings$month<-length(miss); length(miss)

## [1] 0

df[miss, "num_missings"]<- df[miss, "num_missings"]+1

# Factoritzem les categories (levels) de la columna i afegim l'etiqueta "month-":
df$month<-factor(df$month)
levels(df$month)<-paste0("month-",levels(df$month))

par(mfrow=c(1,1))
pie(summary(df$month))
```



Month -> definim novas factor categories per Season.

New factors grouping original levels will be considered very positively.

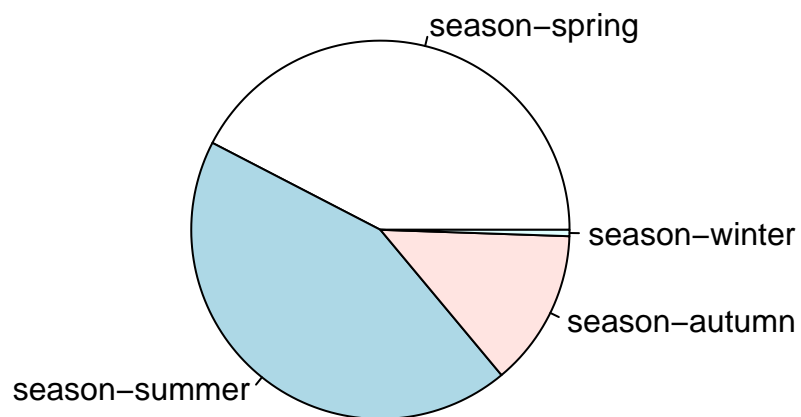
```
# Define new factor categories: 1- Spring 2-Summer 3-Autumn, 4-Winter
df$f.season <- 4
# 1 level - spring
sel<-which(df$month %in% c("month-mar","month-apr","month-may"))
df$f.season[sel] <-1

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

# 3 level - autumn
sel<-which(df$month %in% c("month-sep","month-oct","month-nov"))
df$f.season[sel] <-3

df$f.season<-factor(df$f.season, levels=1:4, labels=c("season-spring","season-summer","season-autumn",
summary(df$f.season);pie(summary(df$f.season))

## season-spring season-summer season-autumn season-winter
##          2120          2183          670          27
```



Day_of_week

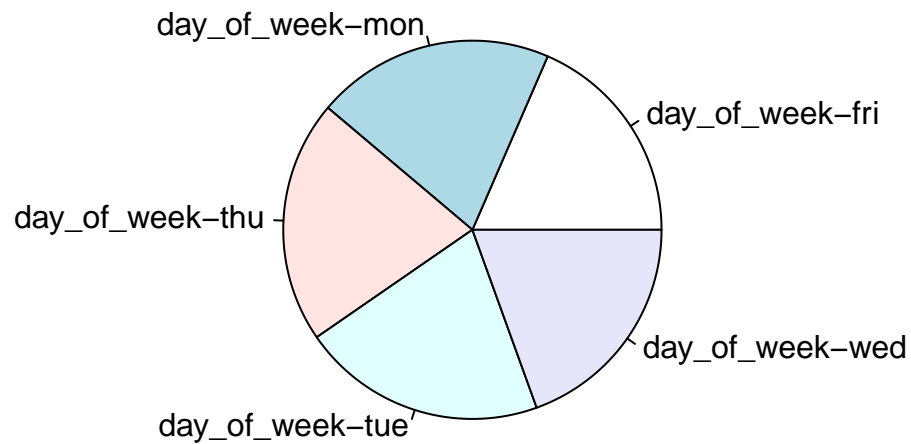
```
miss<-which(is.na(df$day_of_week));
missings$day_of_week<-length(miss); length(miss)

## [1] 0

df[miss, "num_missings"]<- df[miss, "num_missings"]+1

# Factoritzem les categories (levels) de la columna i afegim l'etiqueta "day_of_week-":
df$day_of_week<-factor(df$day_of_week)
levels(df$day_of_week)<-paste0("day_of_week-",levels(df$day_of_week))

pie(summary(df$day_of_week))
```



Poutcome (outcome of previous marketing campaign)

Poutcome "nonexistent" will be considered a category, not a missing value.
`table(df$poutcome, useNA="always")`

```
##
##      failure nonexistent      success      <NA>
##         478         4363         159         0
```

All missing data indicated as NA:
`miss<-which(is.na(df$poutcome));`
`missings$poutcome<-length(miss); length(miss)`

```
## [1] 0
```

```
df[miss, "num_missings"]<- df[miss, "num_missings"]+1
```

Factoritzem les categories (levels) de la columna i afegim l'etiqueta "poutcome-":
`df$poutcome<-factor(df$poutcome)`
`levels(df$poutcome)<-paste0("poutcome-",levels(df$poutcome))`

```
par(mfrow=c(2,1))
pie(summary(df$poutcome))
```

poutcome=nonexistent
 
 poutcome=success

 poutcome=failure

y (has the client subscribed a term deposit?)

```
miss<-which(is.na(df$y));
missings$y<-length(miss); length(miss)
```

```
## [1] 0
```

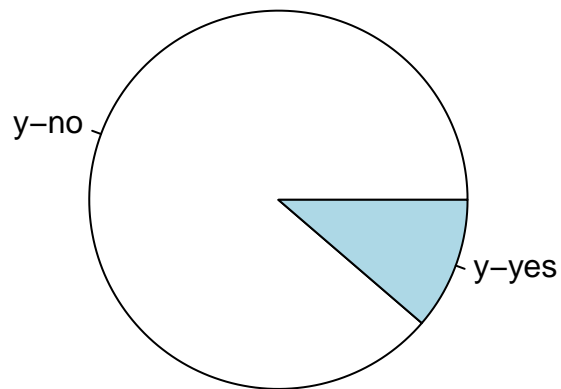
```
df[miss, "num_missings"]<- df[miss, "num_missings"]+1
```

Factoritzem les categories (levels) de la columna i afegim l'etiqueta "y-":

```
df$y<-factor(df$y)
```

```
levels(df$y)<-paste0("y-",levels(df$y))
```

```
pie(summary(df$y))
```



QUANTITATIVES VARIABLES:

Defining some useful function for outliers detection:

```
calcQ <- function(x){

  # summary(df$duration)
  # Min. 1st Qu. Median Mean 3rd Qu. Max.
  # 0.0 102.0 180.0 258.3 319.0 4918.0

  s.x <- summary(x)

  iqr <- s.x[5]-s.x[2] # IQR = Q3([5]) - Q1([2])

  list(souti=s.x[2]-3*iqr, mouti=s.x[2]-1.5*iqr, min=s.x[1], q1=s.x[2],
       q2=s.x[3], q3=s.x[5], max=s.x[6], mouts=s.x[5]+1.5*iqr, souts=s.x[5]+3*iqr)
}
```

Age

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

```
##      Min. 1st Qu. Median      Mean 3rd Qu.      Max.
## 18.00   32.00   38.00   40.07   47.00   87.00
```



```

# No tenim cap missing NA!
miss<-which(is.na(df$age))
missings$age<-length(miss); length(miss)

## [1] 0

df[miss, "num_missings"]<- df[miss, "num_missings"]+1

par(mfrow=c(1,2))
hist(df$age, breaks=10, main="age - histogram")
Boxplot(df$age)

## [1] 4570 4634 3623 3628 3631 4755 4612 4734 4740 4512

# Errors are under aged people:
err<-which(df$age < 18)
errors$age<-length(err); length(err)

## [1] 0

if(length(err)>0) df<-df[-err,]

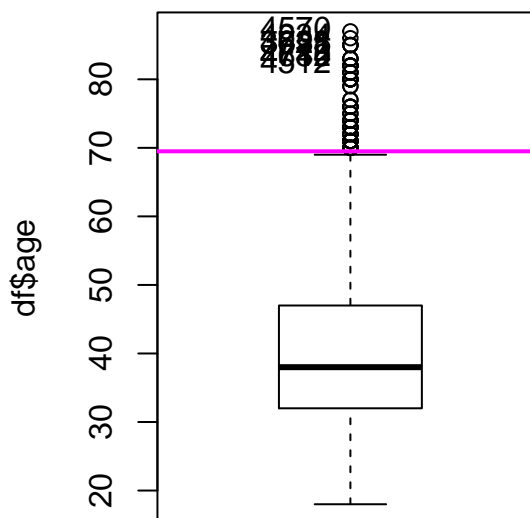
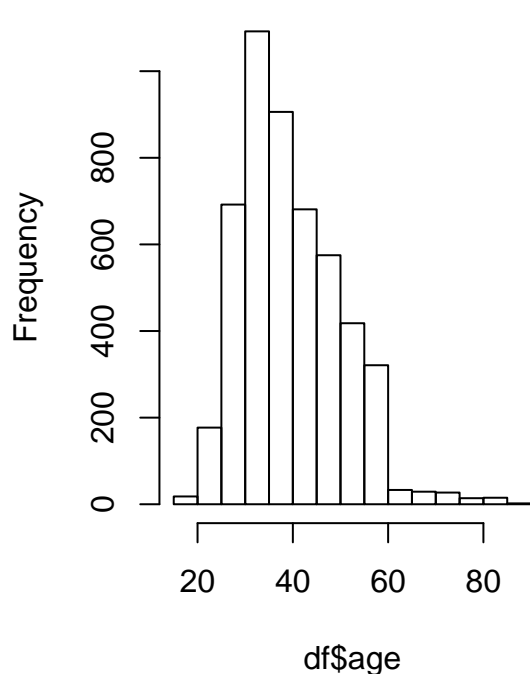
# Outliers:
out.var <- calcQ(df$age)
abline(h=out.var[["mouts"]], col="magenta", lwd=2); out.var[["mouts"]]

## 3rd Qu.
## 69.5

# But our outliers will be the ones above 100 years (there is none):
abline(h=100, col="red", lwd=2)

```

age – histogram



```
out<-which(df$age > 100)
outliers$age<-length(out); length(out)
```

```
## [1] 0
```

```
if(length(out)>0) df<-df[-out,]
```

Duration

Els outliers en la variable duració han estat eliminats. Corresponen a duracions per sota els 5 segons (trucada massa curta a un client que potser no podia parlar en aquell moment o penja per error) i per sobre dels 1600 segons (26 minuts).

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

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      1.0   101.0   178.0   254.8   317.0  3785.0
```

```
# No tenim cap missing NA!
```

```
miss<-which(is.na(df$duration));
missings$duration<-length(miss); length(miss)
```

```
## [1] 0
```

```
df[miss, "num_missings"]<- df[miss, "num_missings"]+1
```

```
par(mfrow=c(1,2))
hist(df$duration, breaks=20, main="duration - histogram")
Boxplot(df$duration)
```

```
## [1] 4929 3368 2817 4759 1285 2907 2033 3815 4998 3280

# Outliers:
out.var <- calcQ(df$duration)
abline(h=out.var[["mouts"]], col="magenta", lwd=2); out.var[["mouts"]]

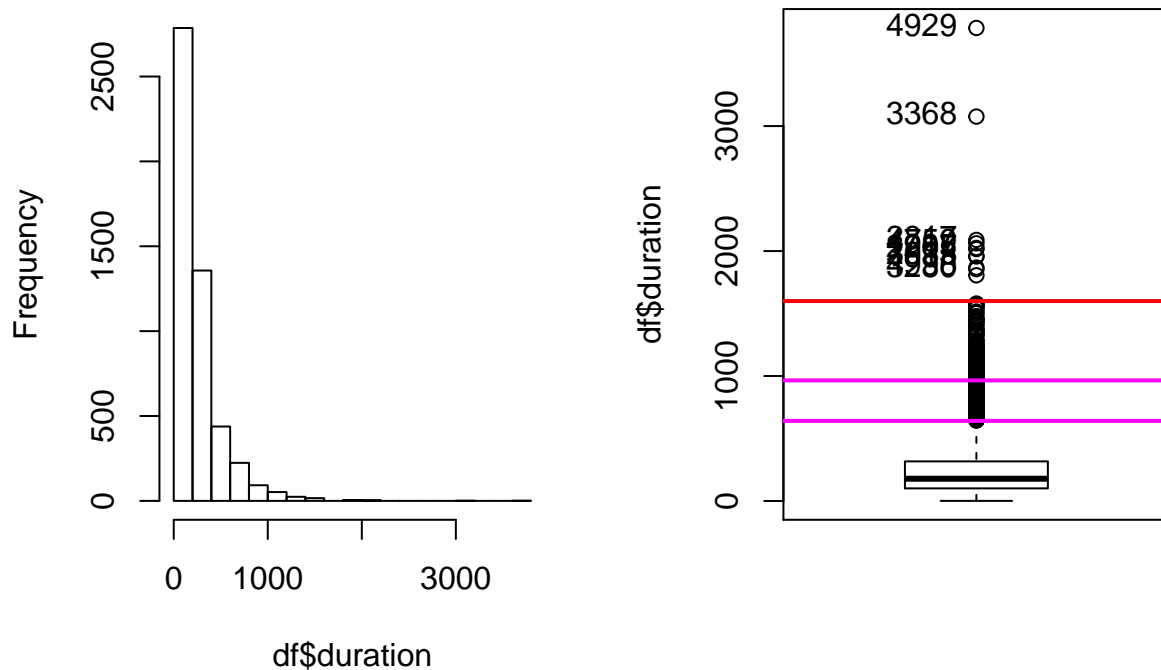
## 3rd Qu.
##      641

abline(h=out.var[["souts"]], col="magenta", lwd=2); out.var[["souts"]]

## 3rd Qu.
##      965

# But our outliers will be the ones above 1600 and below 5 seconds:
abline(h=1600, col="red", lwd=2)
```

duration – histogram



```
out<-which( (df$duration < 5) | (df$duration > 1600) )
outliers$duration=length(out); length(out)

## [1] 14

df[out, "num_outliers"]<- df[out, "num_outliers"]+1
df[out, "duration"]<-NA

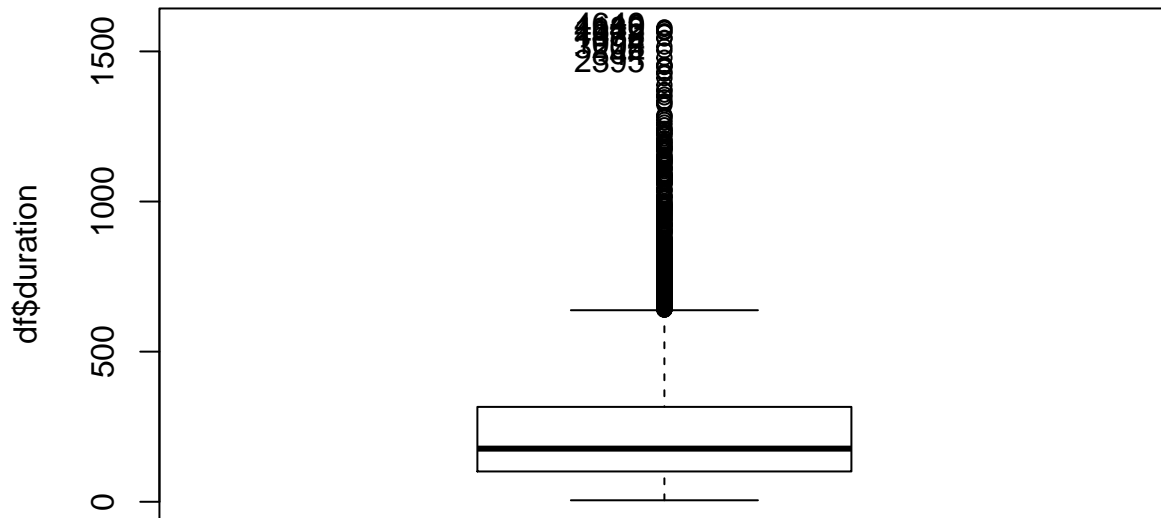
# Eliminem els outliers:
if(length(out)>0) df<-df[-out,]

# Final summary of duration variable:
```

```
par(mfrow=c(1,1))
summary(df$duration)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      5.0   101.0   177.0   250.6   316.0   1580.0
```

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



```
## [1] 4649 10 1182 4843 1972 4438 1094 3208 844 2395
```

Duration -> creem una columna de duració en minuts:

```
df$minutes<-df$duration/60
summary(df$minutes)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## 0.08333 1.68333 2.95000 4.17703 5.26667 26.33333
```

Campaign

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

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      1.000 1.000 2.000 2.584 3.000 33.000
```

```
# No tenim cap missing NA!
```

```
miss<-which(is.na(df$campaign));
missings$campaign<-length(miss); length(miss)
```

```
## [1] 0
df[miss, "num_missings"]<- df[miss, "num_missings"]+1

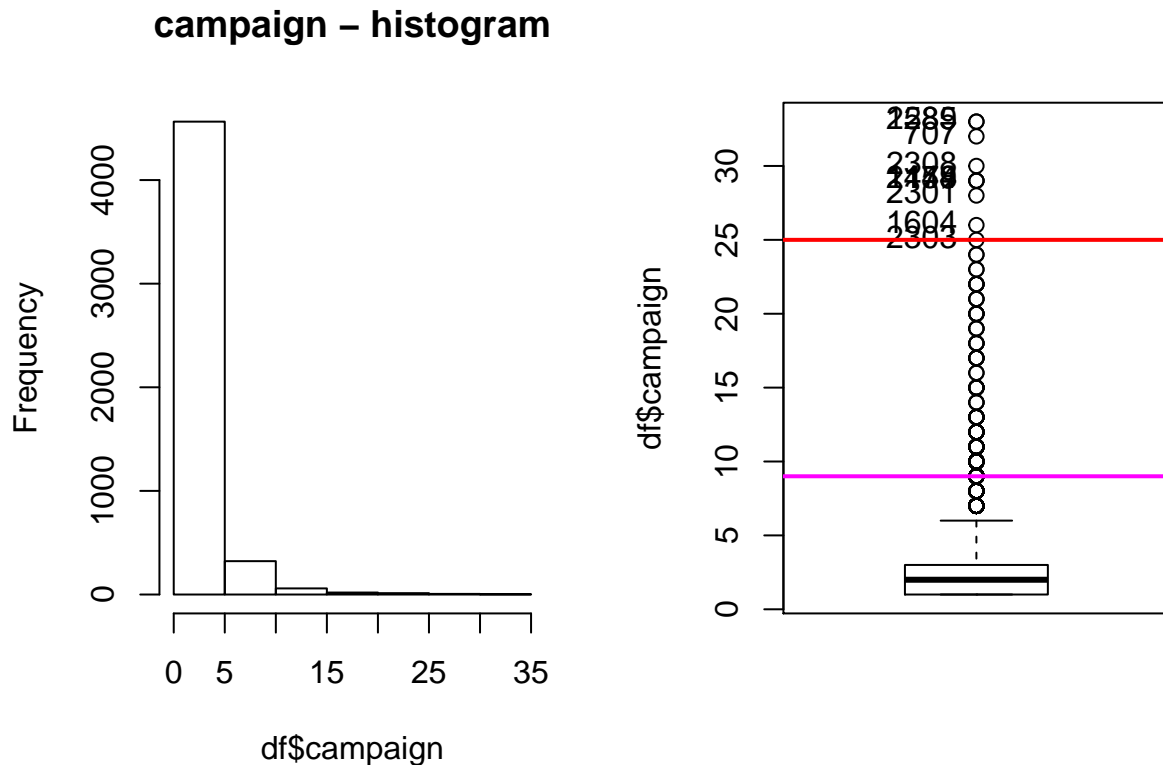
par(mfrow=c(1,2))
hist(df$campaign, breaks=10, main="campaign - histogram")
Boxplot(df$campaign)

## [1] 1589 2285 707 2308 1158 1474 2149 2301 1604 2303

# Outliers:
out.var <- calcQ(df$campaign)
abline(h=out.var[["souts"]], col="magenta", lwd=2); out.var[["souts"]]

## 3rd Qu.
## 9

# But our outliers will be the ones contacted more than 25 times:
abline(h=25, col="red", lwd=2)
```



```
out<-which(df$campaign > 25)
df[out, "num_outliers"]<- df[out, "num_outliers"]+1
outliers$campaign=length(out); length(out)

## [1] 9

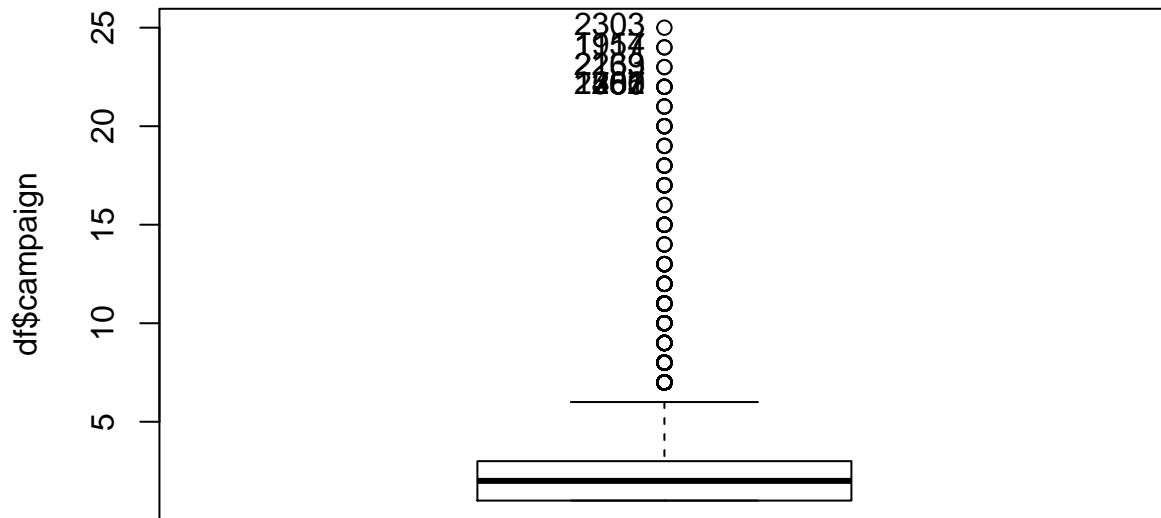
df[out, "campaign"]<-NA

# Final summary of campaign variable:
```

```
par(mfrow=c(1,1))
summary(df$campaign)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.     NA's
##      1.000   1.000   2.000   2.535   3.000   25.000         9
```

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



```
## [1] 2303 1157 1914 2139 2263 401 502 755 1280 2267
```

Pdays

```
# No tenim cap missing NA!
miss<-which(is.na(df$pdays));
missings$pdays<-length(miss); length(miss)
```

```
## [1] 0
```

```
df[miss, "num_missings"]<- df[miss, "num_missings"]+1
```

```
# Values that are 999 mean never contacted before:
never<-which(df$pdays==999); length(never)/5000*100
```

```
## [1] 96.18
```

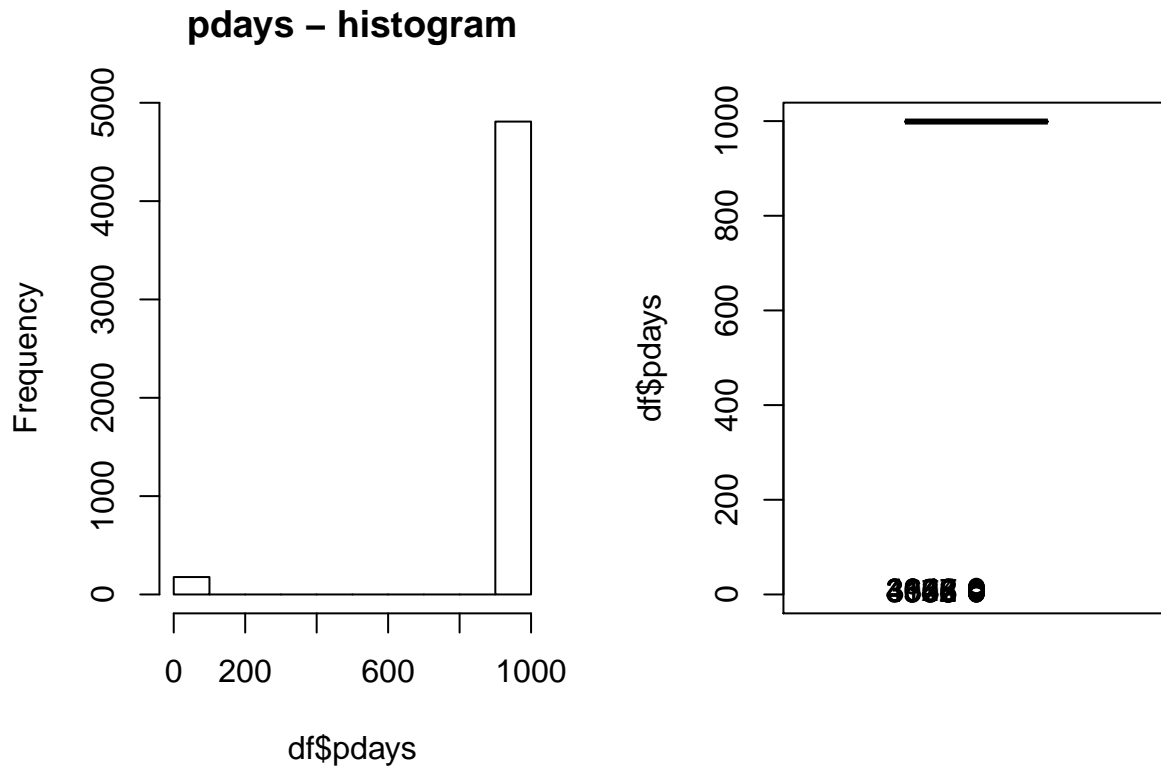
```
# No outliers!
```

```
# Final summary of pdays variable:
```

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

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      0.0   999.0   999.0   963.7   999.0   999.0
```

```
par(mfrow=c(1,2))
hist(df$pdays, breaks=10, main="pdays - histogram")
Boxplot(df$pdays)
```



```
## [1] 3148 4902 3576 4135 4366 3627 3642 3644 3646 4352
```

Previous

```
# No tenim cap missing NA!
miss<-which(is.na(df$previous));
missings$previous<-length(miss); length(miss)
```

```
## [1] 0
```

```
df[miss, "num_missings"]<- df[miss, "num_missings"]+1
```

```
par(mfrow=c(1,2))
hist(df$previous, main="previous - histogram")
```

```
# Final summary of previous variable:
summary(df$previous)
```

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

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

The left plot is a histogram showing the frequency distribution of the variable `df$previous`. The x-axis is labeled `df$previous` and ranges from 0 to 4. The y-axis is labeled `Frequency` and ranges from 0 to 4000. The distribution is highly right-skewed, with the highest frequency (over 4000) occurring at the value 0. The frequency drops sharply for subsequent values: approximately 500 for 1, 100 for 2, 50 for 3, and 20 for 4.

The right plot is a scatter plot showing the relationship between `df$previous` (x-axis) and `df$previous` (y-axis). The x-axis ranges from 0 to 4, and the y-axis ranges from 0 to 4. The plot displays a series of points where the value on the y-axis is equal to the value on the x-axis. The points are labeled with their respective values: 0, 1, 2, 3, and 4. A horizontal line is drawn at y=0, indicating the frequency of the value 0.

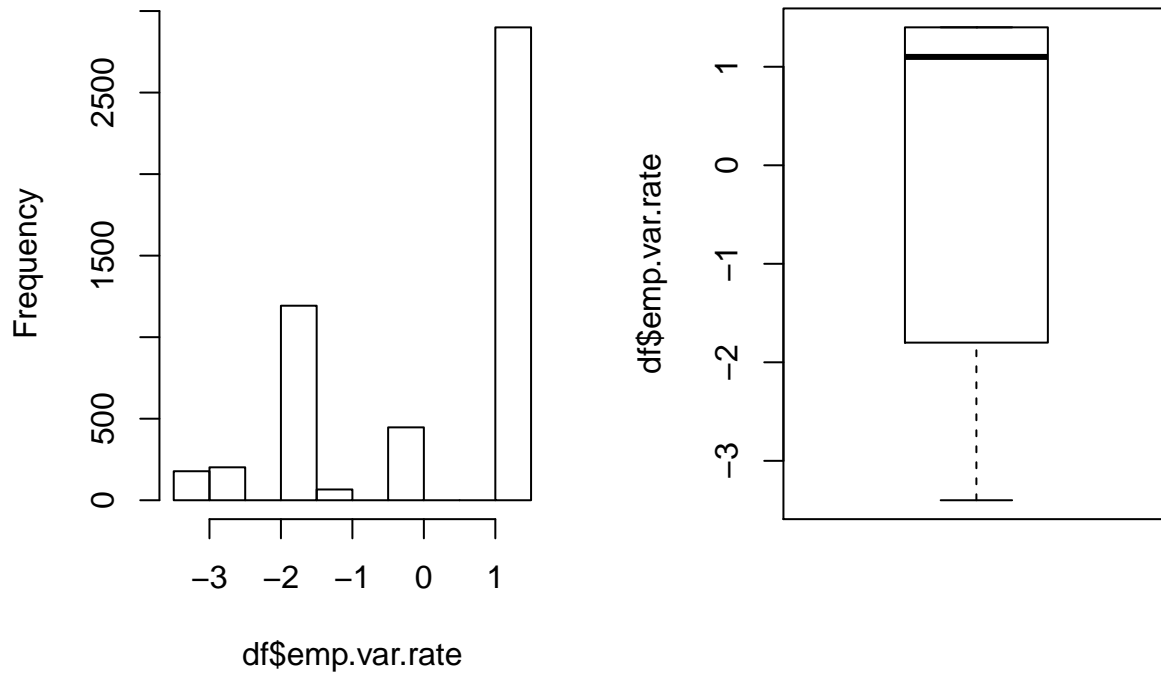
emp.var.rate

```
# Neither missing, outliers nor error values.
par(mfrow=c(1,2))

hist(df$emp.var.rate, main="emp.var.rate - histogram")
summary(df$emp.var.rate)
```

```
Boxplot(df$emp.var.rate)
```


emp.var.rate – histogram



cons.price.idx

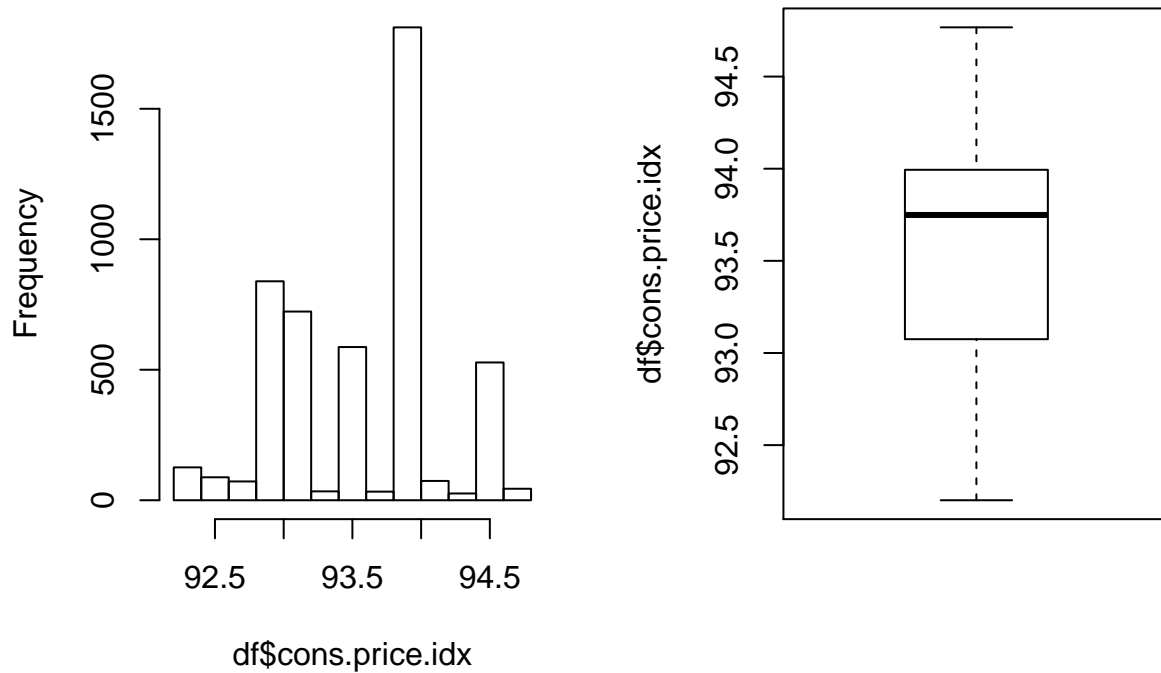
```
# Neither missing, outliers nor error values.
par(mfrow=c(1,2))

hist(df$cons.price.idx, main="cons.price.idx - histogram")
summary(df$cons.price.idx)
```

##	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
##	92.20	93.08	93.75	93.57	93.99	94.77

```
Boxplot(df$cons.price.idx)
```

cons.price.idx – histogram



cons.conf.idx

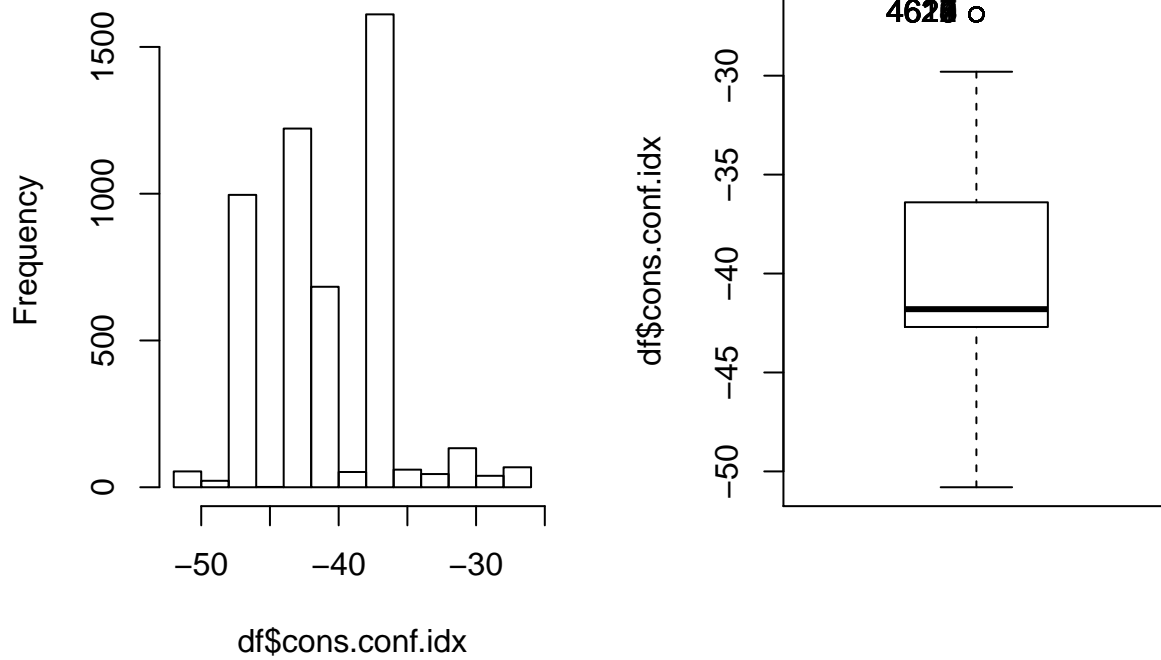
```
# Neither missing, outliers nor error values.
par(mfrow=c(1,2))

hist(df$cons.conf.idx, main="cons.conf.idx - histogram")
summary(df$cons.conf.idx)

##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -50.80 -42.70  -41.80  -40.43  -36.40  -26.90

Boxplot(df$cons.conf.idx)
```

cons.conf.idx – histogram



```
## [1] 4617 4618 4619 4620 4621 4622 4623 4624 4625 4626
```

euribor3m

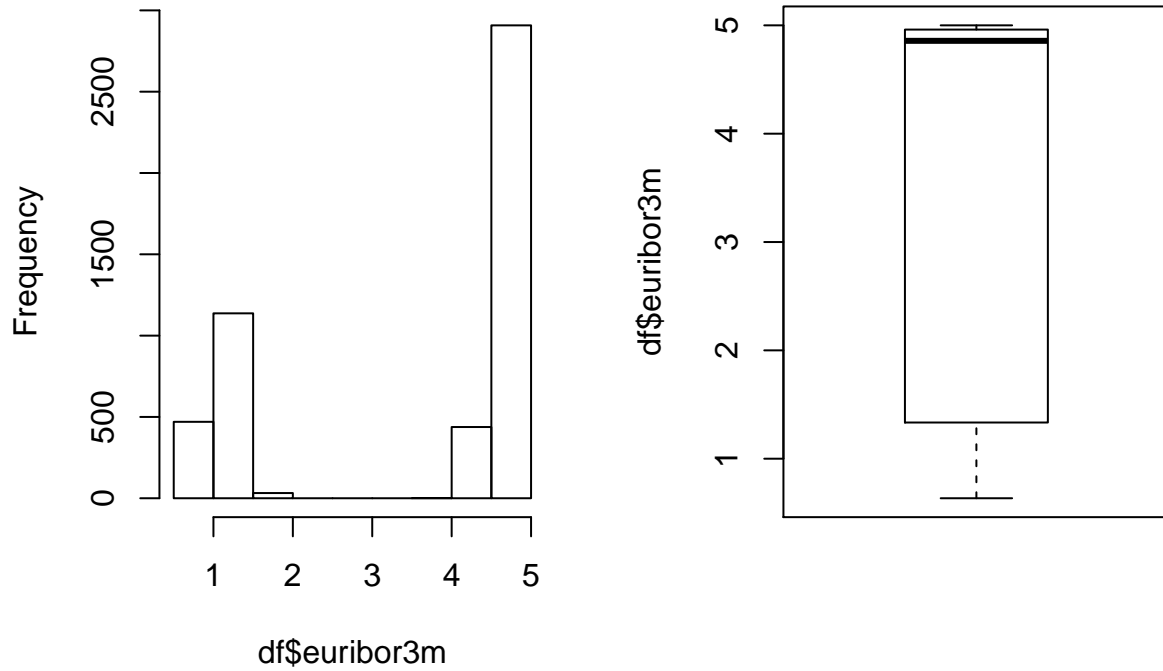
```
# Neither missing, outliers nor error values.
par(mfrow=c(1,2))

hist(df$euribor3m, main="euribor3m - histogram")
summary(df$euribor3m)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.635   1.334   4.857   3.614   4.961   5.000
```

```
Boxplot(df$euribor3m)
```

euribor3m – histogram



nr.employed

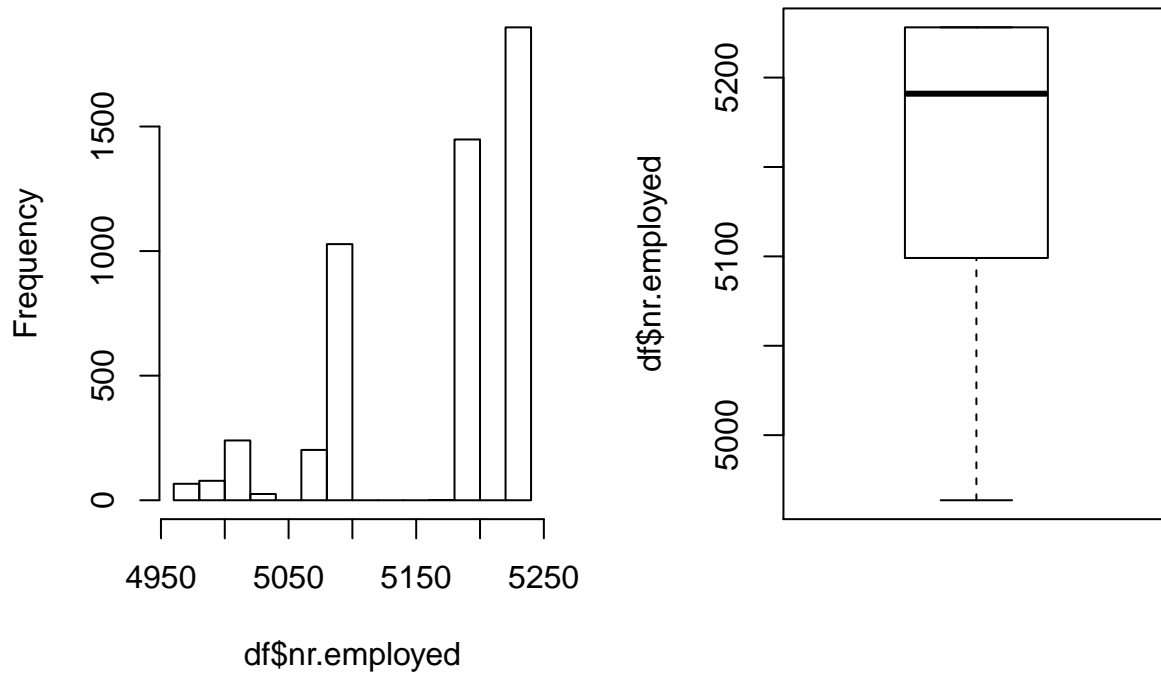
```
# Neither missing, outliers nor error values.
par(mfrow=c(1,2))

hist(df$nr.employed, main="nr.employed - histogram")
summary(df$nr.employed)
```

##	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
##	4964	5099	5191	5166	5228	5228

```
Boxplot(df$nr.employed)
```

nr.employed – histogram



DISCRETITZACIÓ DE VARIABLES NUMÈRIQUES:

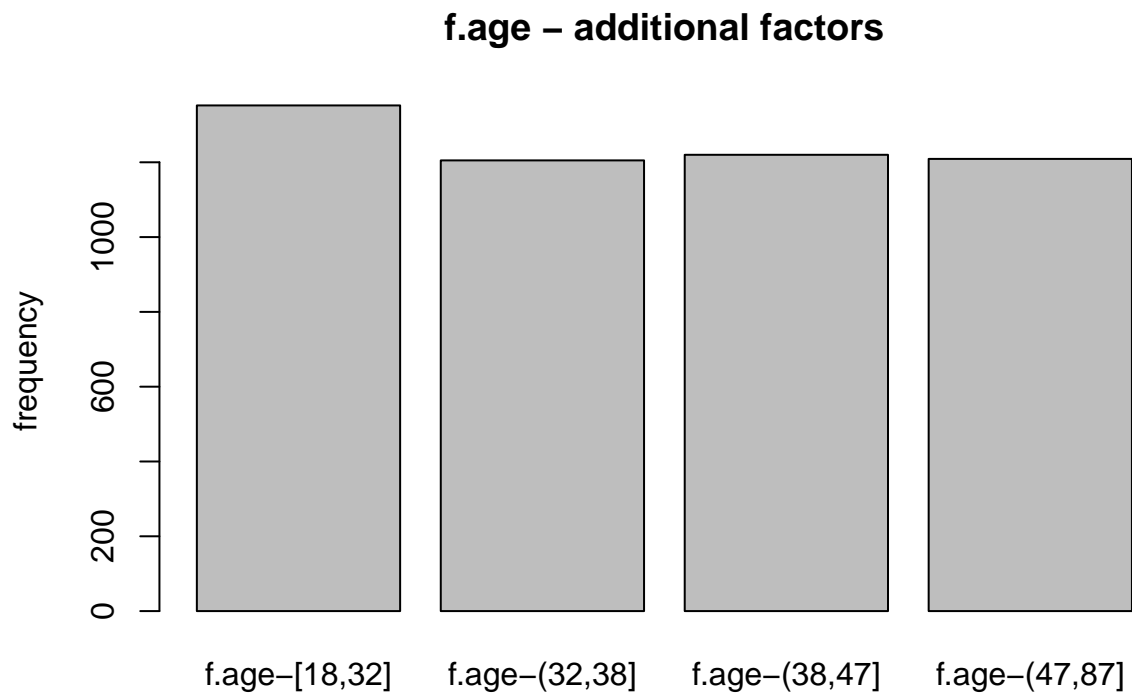
Original numeric variables corresponding to real quantitative concepts are kept as numeric but additional factors should also be created as a discretization of each numeric variable.

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

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

df$f.age<-factor( cut(df$age, breaks=qulist, include.lowest=T) )
levels(df$f.age)<-paste0("f.age-", levels(df$f.age) )

# Es mostra una distribució d'edats equitativa amb aquesta factorització:
barplot(table(df$f.age), main="f.age - additional factors", ylab="frequency")
```



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

```
## f.age-[18,32] f.age-(32,38] f.age-(38,47] f.age-(47,87]
##           1352           1205           1220           1209
```

```
# DURATION
```

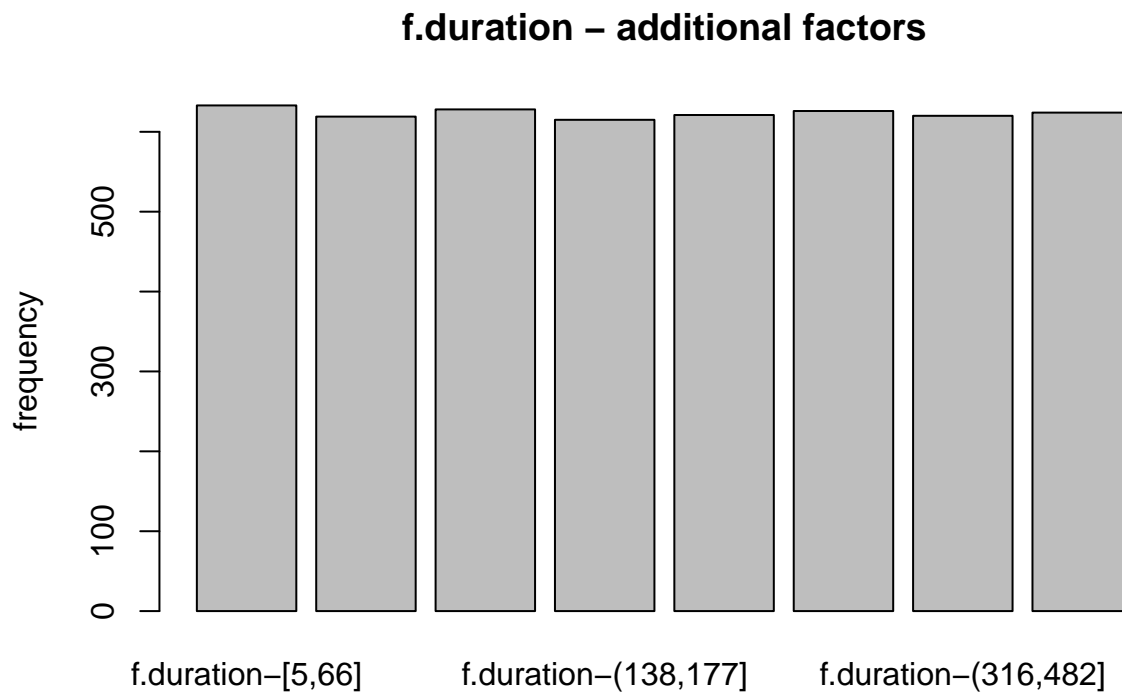
```
qulist<-quantile(df$duration, seq(0,1,0.125), na.rm=TRUE)
```

```
df$f.duration<-factor( cut(df$duration, breaks=qulist, include.lowest=T) )
```

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

```
# Es mostra una distribució de duracions de la trucada equitativa amb aquesta factorització:
```

```
barplot(table(df$f.duration), main="f.duration - additional factors", ylab="frequency")
```



```
summary(df$f.duration)
```

```
##          f.duration-[5,66]          f.duration-(66,101]
##                633                619
##          f.duration-(101,138]        f.duration-(138,177]
##                628                615
##          f.duration-(177,235]        f.duration-(235,316]
##                621                626
##          f.duration-(316,482] f.duration-(482,1.58e+03]
##                620                624
```

```
# CAMPAIGN
```

```
qulist<-quantile(df$campaign, seq(0,1,0.5), na.rm=TRUE)
```

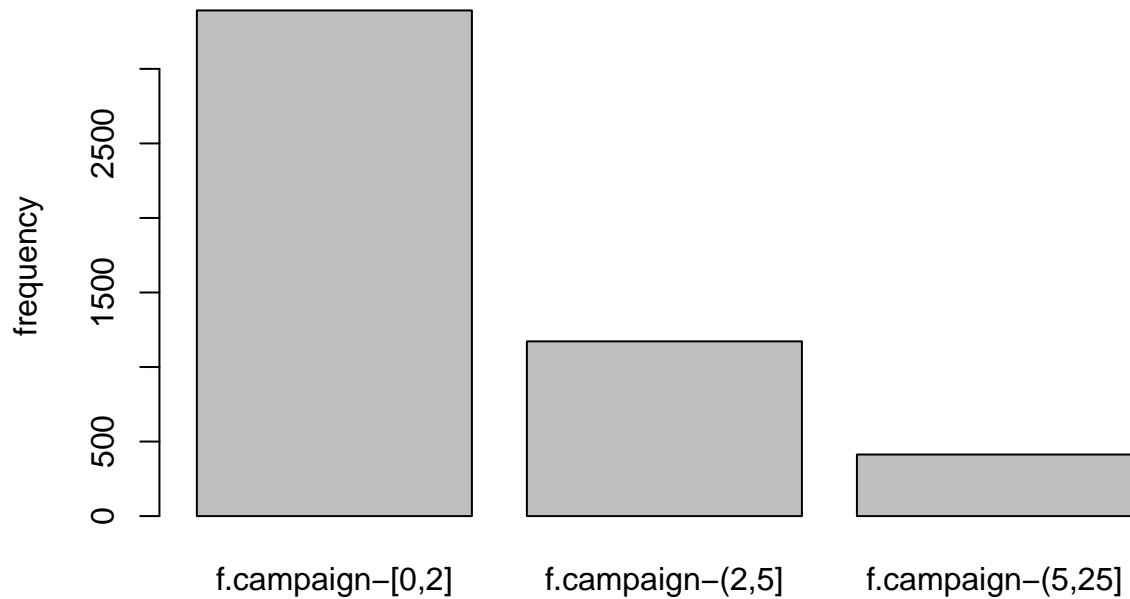
```
df$f.campaign<-factor( cut(df$campaign, breaks=c(0,2,5,25), include.lowest=T) )
```

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

```
# Resultat de la factorització de cops que s'ha contactat al client en la campanya actual:
```

```
barplot(table(df$f.campaign), main="f.campaign - additional factors", ylab="frequency")
```

f.campaign – additional factors



```
summary(df$f.campaign)
```

```
## f.campaign-[0,2] f.campaign-(2,5] f.campaign-(5,25] NA's
##           3392           1172           413           9
```

```
# PDAYS
```

```
df$f.pdays<-factor( cut(df$pdays, breaks=c(0, 7, 998, 999), include.lowest=T) )
```

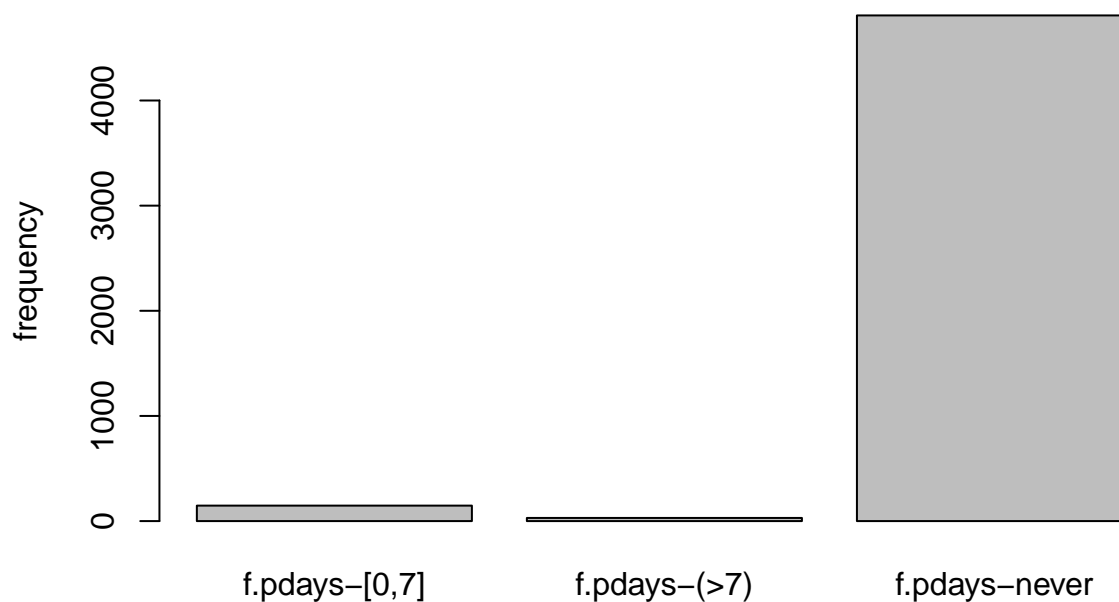
```
levels(df$f.pdays)<-paste0("f.pdays-", levels(df$f.pdays) )
```

```
levels(df$f.pdays)<-c("f.pdays-[0,7]", "f.pdays-(>7)", "f.pdays-never")
```

```
# Resultat de la factorització? dels dies que fa que s'ha contactat al client en una altra campanya:
```

```
barplot(table(df$f.pdays), main="f.pdays - additional factors", ylab="frequency")
```


f.pdays – additional factors



```
summary(df$f.pdays)
```

```
## f.pdays-[0,7] f.pdays-(>7) f.pdays-never
##           147           30          4809
```

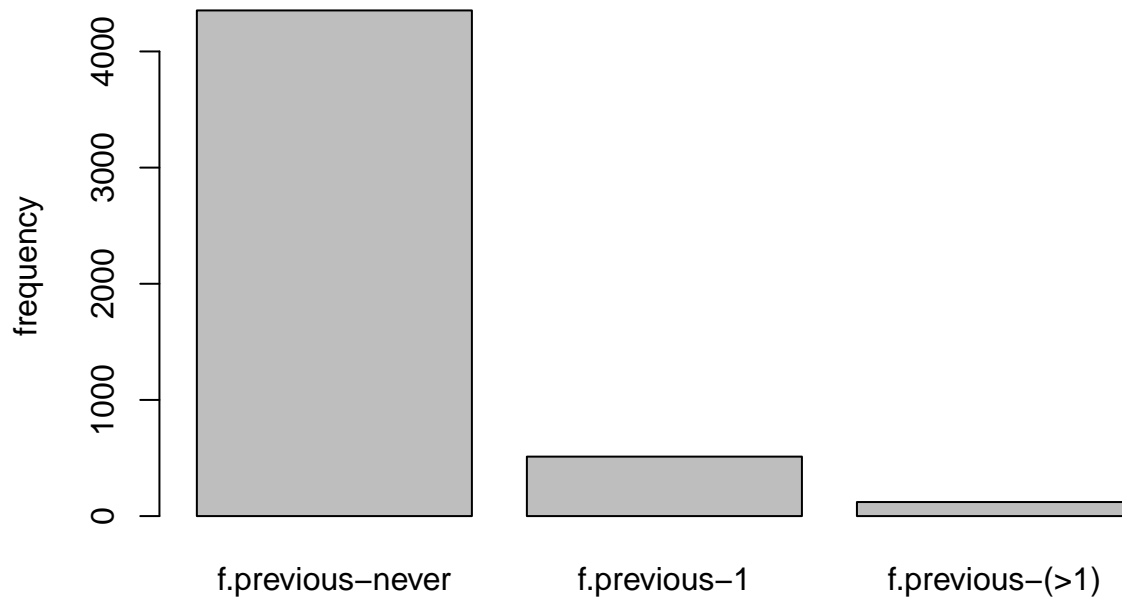
```
# PREVIOUS
```

```
df$f.previous<-factor( cut(df$previous, breaks=c(-Inf, 0, 1, +Inf), include.lowest=T) )
levels(df$f.previous)<-paste0("f.previous-", levels(df$f.previous) )
```

```
levels(df$f.previous)<-c("f.previous-never", "f.previous-1", "f.previous-(>1)")
```

```
# Resultat de la factorització de number of contacts performed before this campaign and for this client
barplot(table(df$f.previous), main="f.previous - additional factors", ylab="frequency")
```

f.previous – additional factors



```
summary(df$f.previous)
```

```
## f.previous-never    f.previous-1  f.previous-(>1)
##              4353              512              121
```

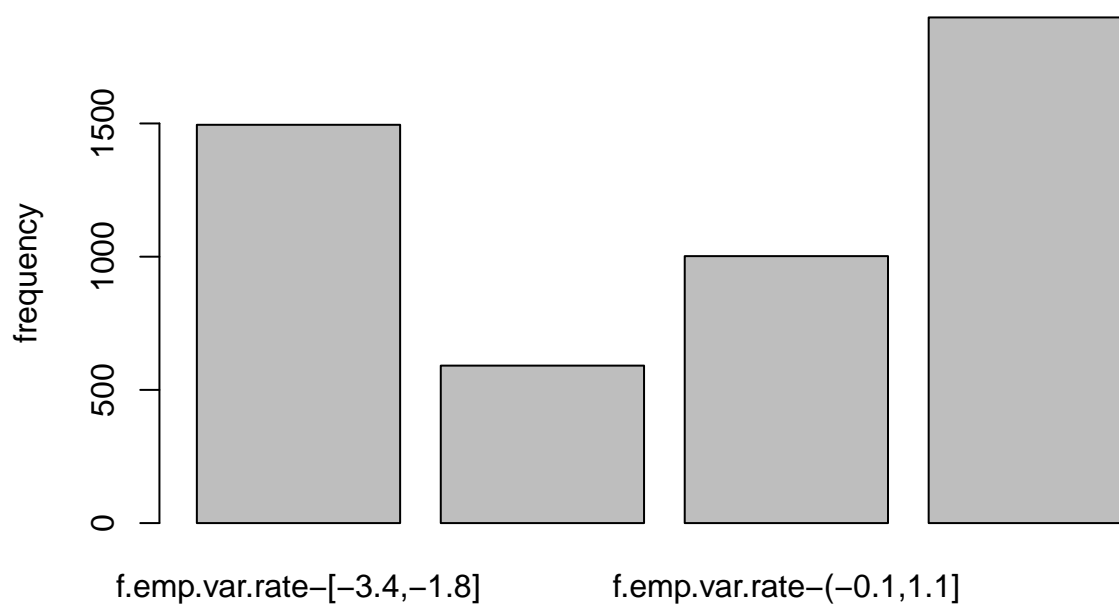
```
# EMP.VAR.RATE
```

```
qulist<-quantile(df$emp.var.rate, seq(0,1,0.125), na.rm=TRUE)
```

```
df$f.emp.var.rate <-factor( cut(df$emp.var.rate , breaks=unique(qulist), include.lowest=T) )
levels(df$f.emp.var.rate)<-paste0("f.emp.var.rate-", levels(df$f.emp.var.rate) )
```

```
barplot(table(df$f.emp.var.rate), main="f.emp.var.rate - additional factors", ylab="frequency")
```

f.emp.var.rate – additional factors



```
summary(df$f.emp.var.rate)
```

```
## f.emp.var.rate-[-3.4,-1.8] f.emp.var.rate-(-1.8,-0.1]
##                1495                591
## f.emp.var.rate-(-0.1,1.1] f.emp.var.rate-(1.1,1.4]
##                1002                1898
```

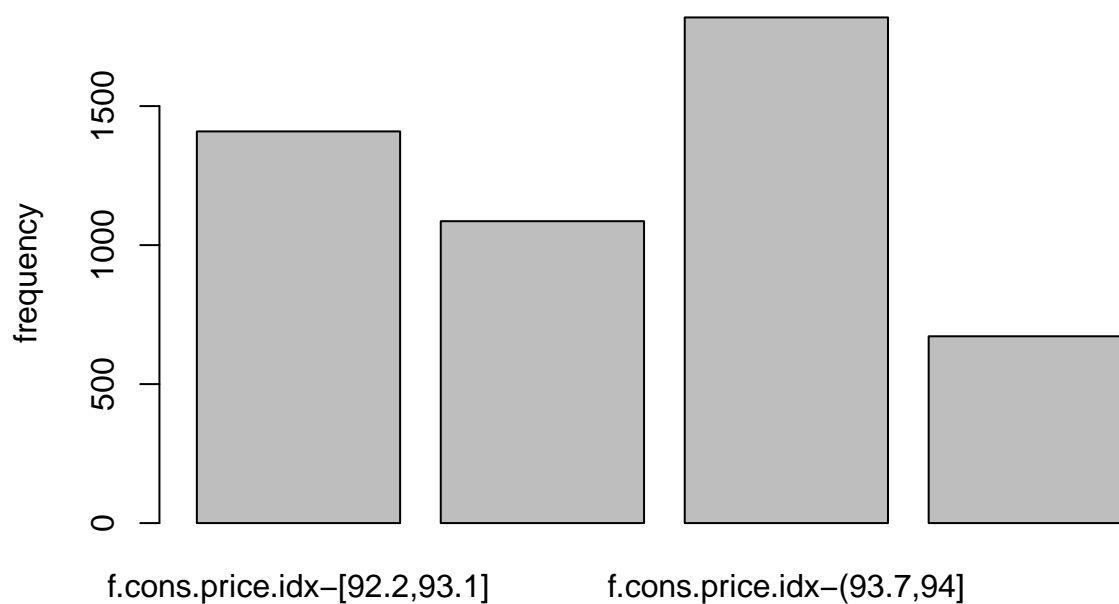
```
# CONS.PRICE.IDX
```

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

```
df$f.cons.price.idx <-factor( cut(df$cons.price.idx , breaks=unique(qulist), include.lowest=T) )
levels(df$f.cons.price.idx)<-paste0("f.cons.price.idx-", levels(df$f.cons.price.idx) )
```

```
barplot(table(df$f.cons.price.idx), main="f.cons.price.idx - additional factors", ylab="frequency")
```

f.cons.price.idx – additional factors



```
summary(df$f.cons.price.idx)
```

```
## f.cons.price.idx-[92.2,93.1] f.cons.price.idx-(93.1,93.7]
##                1409                1086
## f.cons.price.idx-(93.7,94]   f.cons.price.idx-[94,94.8]
##                1819                672
```

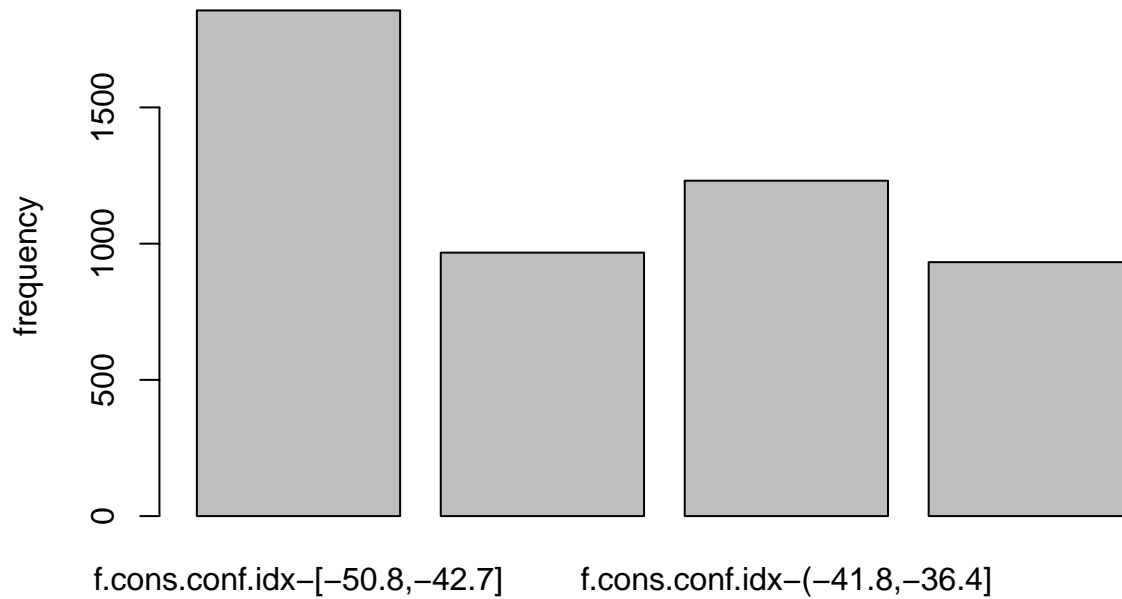
```
# CONS.CONF.IDX
```

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

```
df$f.cons.conf.idx <-factor( cut(df$cons.conf.idx , breaks=unique(qulist), include.lowest=T) )
levels(df$f.cons.conf.idx)<-paste0("f.cons.conf.idx-", levels(df$f.cons.conf.idx) )
```

```
barplot(table(df$f.cons.conf.idx), main="f.cons.conf.idx - additional factors", ylab="frequency")
```

f.cons.conf.idx – additional factors



```
summary(df$f.cons.conf.idx)
```

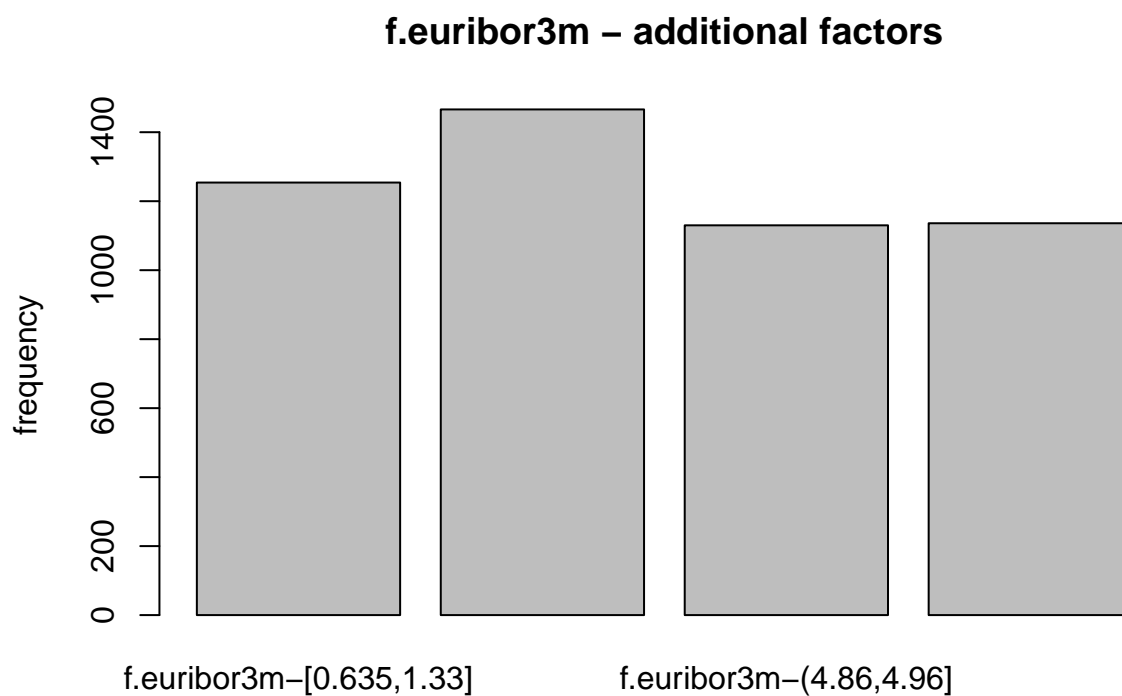
```
## f.cons.conf.idx-[-50.8,-42.7] f.cons.conf.idx-(-42.7,-41.8]
##                               1856                               967
## f.cons.conf.idx-(-41.8,-36.4] f.cons.conf.idx-(-36.4,-26.9]
##                               1231                               932
```

```
# EURIBOR3M
```

```
qulist<-quantile(df$euribor3m, seq(0,1,0.25), na.rm=TRUE)
```

```
df$f.euribor3m <-factor( cut(df$euribor3m , breaks=unique(qulist), include.lowest=T) )
levels(df$f.euribor3m)<-paste0("f.euribor3m-", levels(df$f.euribor3m) )
```

```
barplot(table(df$f.euribor3m), main="f.euribor3m - additional factors", ylab="frequency")
```



```
summary(df$f.euribor3m)
```

```
## f.euribor3m-[0.635,1.33]  f.euribor3m-(1.33,4.86]  f.euribor3m-(4.86,4.96]
##                      1254                      1466                      1130
##    f.euribor3m-(4.96,5]
##                      1136
```

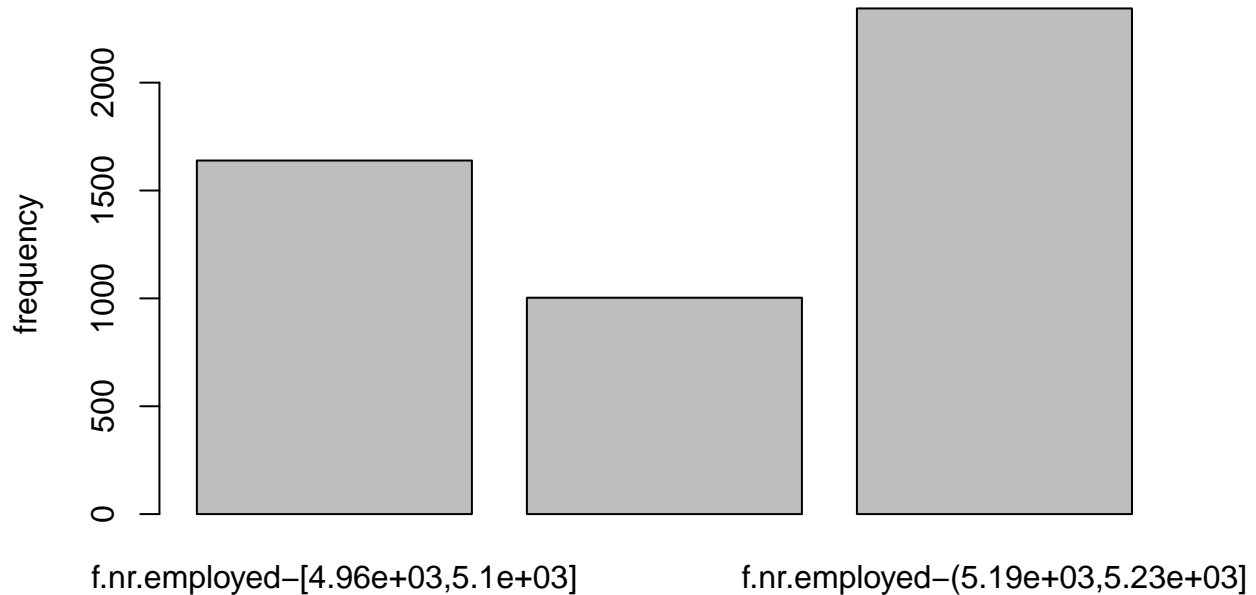
```
# NR.EMPLOYED
```

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

```
df$f.nr.employed <-factor( cut(df$nr.employed , breaks=unique(qulist), include.lowest=T) )
levels(df$f.nr.employed)<-paste0("f.nr.employed-", levels(df$f.nr.employed) )
```

```
barplot(table(df$f.nr.employed), main="f.nr.employed - additional factors", ylab="frequency")
```

f.nr.employed – additional factors



```
summary(df$f.nr.employed)
```

```
## f.nr.employed-[4.96e+03,5.1e+03] f.nr.employed-(5.1e+03,5.19e+03]
##                                     1639                             1003
## f.nr.employed-(5.19e+03,5.23e+03]
##                                     2344
```

Llistat de variables contínues i discretes:

```
vars<-names(df); vars
```

```
## [1] "age"           "job"           "marital"
## [4] "education"     "default"       "housing"
## [7] "loan"          "contact"       "month"
## [10] "day_of_week"   "duration"      "campaign"
## [13] "pdays"        "previous"      "poutcome"
## [16] "emp.var.rate"  "cons.price.idx" "cons.conf.idx"
## [19] "euribor3m"     "nr.employed"   "y"
## [22] "num_missings"  "num_outliers"  "num_errors"
## [25] "f.season"      "minutes"       "f.age"
## [28] "f.duration"    "f.campaign"    "f.pdays"
## [31] "f.previous"    "f.emp.var.rate" "f.cons.price.idx"
## [34] "f.cons.conf.idx" "f.euribor3m"   "f.nr.employed"
```

```
# Variables contínues
```

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

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

```
# Variables discretas
```

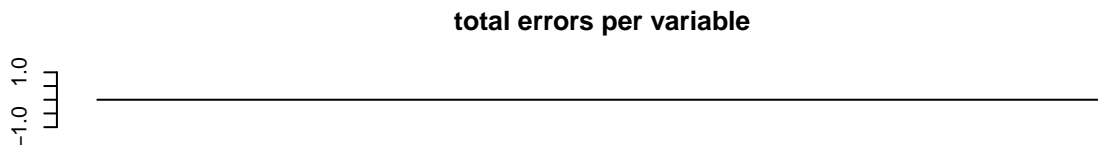
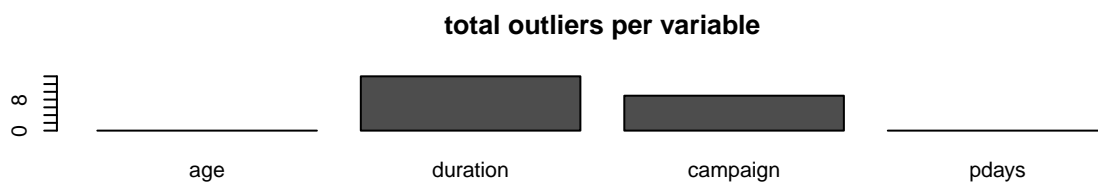
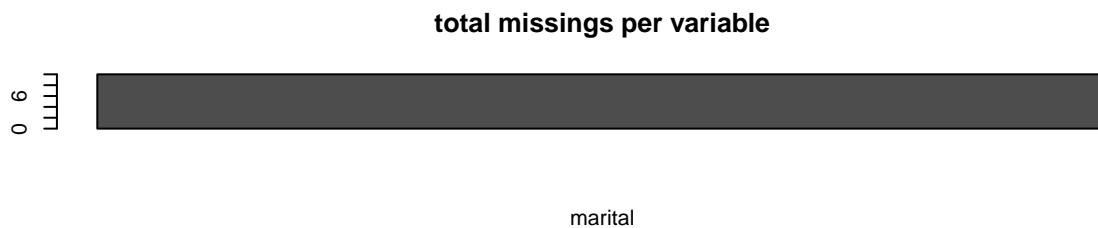
```
vars_dis<-names(df)[c(2:10, 15, 21, 25, 27:36)]; vars_dis
```

```
## [1] "job"          "marital"       "education"
## [4] "default"      "housing"       "loan"
## [7] "contact"      "month"         "day_of_week"
## [10] "poutcome"     "y"             "f.season"
## [13] "f.age"         "f.duration"    "f.campaign"
## [16] "f.pdays"     "f.previous"    "f.emp.var.rate"
## [19] "f.cons.price.idx" "f.cons.conf.idx" "f.euribor3m"
## [22] "f.nr.employed"
```

DATA QUALITY REPORT:

Per variable:

```
par(mfrow=c(3,1))
barplot( t(c(missings[, 3])), main="total missings per variable", xlab="marital")
barplot( t(c(outliers[, c(1, 11, 12, 13)])), main="total outliers per variable")
barplot( t(c(errors[, 13])), main="total errors per variable")
```



Per individu:

Cap individu en té més d'un. Es mostra en format taula el número d'individus que tenen 0 i/o 1(o més) missings, errors i outliers. Per últim, es mostren els individus que han tingut algun outlier i que aquest ha estat imputat.

```
par(mfrow=c(1,1))
table(df$num_missings)
```

```
##
##      0      1
## 4839  147
```

```
table(df$num_errors)
```

```
##
##      0
## 4986
```

```
table(df$num_outliers)
```

```
##
##      0      1
## 4977      9
```

```
df[which(df$num_outliers>0), ] #individus amb algun outlier
```

```
##      age      job      marital      education
## 5565   39  job-admin. marital-married education-university.degree
## 9014   30 job-blue-collar marital-married      education-basic.9y
## 11631  31  job-admin. marital-single education-university.degree
## 12643  54  job-services marital-married      education-high.school
## 12751  30  job-services marital-married      education-high.school
## 17524  46 job-blue-collar marital-married      education-high.school
## 18568  53  job-admin. marital-married education-university.degree
## 18686  25  job-admin. marital-single      education-basic.9y
## 18759  25  job-admin. marital-single      education-basic.9y
##      default housing loan      contact      month
## 5565 default-no housing=yes loan=no contact-telephone month-may
## 9014 default-no housing=no loan=no contact-telephone month-jun
## 11631 default-no housing=no loan=no contact-telephone month-jun
## 12643 default-unknown housing=yes loan=no contact-cellular month-jul
## 12751 default-no housing=yes loan=no contact-cellular month-jul
## 17524 default-unknown housing=no loan=no contact-cellular month-jul
## 18568 default-no housing=yes loan=no contact-cellular month-jul
## 18686 default-no housing=yes loan=no contact-cellular month-jul
## 18759 default-no housing=yes loan=yes contact-cellular month-jul
##      day_of_week duration campaign pdays previous
## 5565 day_of_week-mon      14      NA  999      0
## 9014 day_of_week-thu      53      NA  999      0
## 11631 day_of_week-fri      34      NA  999      0
## 12643 day_of_week-mon      36      NA  999      0
## 12751 day_of_week-tue      24      NA  999      0
## 17524 day_of_week-mon      33      NA  999      0
## 18568 day_of_week-thu      51      NA  999      0
## 18686 day_of_week-thu      14      NA  999      0
## 18759 day_of_week-thu      14      NA  999      0
```

##		poutcome	emp.var.rate	cons.price.idx	cons.conf.idx		
##	5565	poutcome-nonexistent	1.1	93.994	-36.4		
##	9014	poutcome-nonexistent	1.4	94.465	-41.8		
##	11631	poutcome-nonexistent	1.4	94.465	-41.8		
##	12643	poutcome-nonexistent	1.4	93.918	-42.7		
##	12751	poutcome-nonexistent	1.4	93.918	-42.7		
##	17524	poutcome-nonexistent	1.4	93.918	-42.7		
##	18568	poutcome-nonexistent	1.4	93.918	-42.7		
##	18686	poutcome-nonexistent	1.4	93.918	-42.7		
##	18759	poutcome-nonexistent	1.4	93.918	-42.7		
##		euribor3m	nr.employed	y	num_missings	num_outliers	num_errors
##	5565	4.857	5191.0	y-no	0	1	0
##	9014	4.866	5228.1	y-no	0	1	0
##	11631	4.959	5228.1	y-no	0	1	0
##	12643	4.960	5228.1	y-no	0	1	0
##	12751	4.962	5228.1	y-no	0	1	0
##	17524	4.962	5228.1	y-no	0	1	0
##	18568	4.968	5228.1	y-no	0	1	0
##	18686	4.968	5228.1	y-no	0	1	0
##	18759	4.968	5228.1	y-no	0	1	0
##		f.season	minutes	f.age	f.duration	f.campaign	
##	5565	season-spring	0.2333333	f.age-(38,47]	f.duration-[5,66]	<NA>	
##	9014	season-summer	0.8833333	f.age-[18,32]	f.duration-[5,66]	<NA>	
##	11631	season-summer	0.5666667	f.age-[18,32]	f.duration-[5,66]	<NA>	
##	12643	season-summer	0.6000000	f.age-(47,87]	f.duration-[5,66]	<NA>	
##	12751	season-summer	0.4000000	f.age-[18,32]	f.duration-[5,66]	<NA>	
##	17524	season-summer	0.5500000	f.age-(38,47]	f.duration-[5,66]	<NA>	
##	18568	season-summer	0.8500000	f.age-(47,87]	f.duration-[5,66]	<NA>	
##	18686	season-summer	0.2333333	f.age-[18,32]	f.duration-[5,66]	<NA>	
##	18759	season-summer	0.2333333	f.age-[18,32]	f.duration-[5,66]	<NA>	
##		f.pdays	f.previous	f.emp.var.rate			
##	5565	f.pdays-never	f.previous-never	f.emp.var.rate-(-0.1,1.1]			
##	9014	f.pdays-never	f.previous-never	f.emp.var.rate-(1.1,1.4]			
##	11631	f.pdays-never	f.previous-never	f.emp.var.rate-(1.1,1.4]			
##	12643	f.pdays-never	f.previous-never	f.emp.var.rate-(1.1,1.4]			
##	12751	f.pdays-never	f.previous-never	f.emp.var.rate-(1.1,1.4]			
##	17524	f.pdays-never	f.previous-never	f.emp.var.rate-(1.1,1.4]			
##	18568	f.pdays-never	f.previous-never	f.emp.var.rate-(1.1,1.4]			
##	18686	f.pdays-never	f.previous-never	f.emp.var.rate-(1.1,1.4]			
##	18759	f.pdays-never	f.previous-never	f.emp.var.rate-(1.1,1.4]			
##		f.cons.price.idx	f.cons.conf.idx				
##	5565	f.cons.price.idx-(93.7,94]	f.cons.conf.idx-(-41.8,-36.4]				
##	9014	f.cons.price.idx-(94,94.8]	f.cons.conf.idx-(-42.7,-41.8]				
##	11631	f.cons.price.idx-(94,94.8]	f.cons.conf.idx-(-42.7,-41.8]				
##	12643	f.cons.price.idx-(93.7,94]	f.cons.conf.idx-[-50.8,-42.7]				
##	12751	f.cons.price.idx-(93.7,94]	f.cons.conf.idx-[-50.8,-42.7]				
##	17524	f.cons.price.idx-(93.7,94]	f.cons.conf.idx-[-50.8,-42.7]				
##	18568	f.cons.price.idx-(93.7,94]	f.cons.conf.idx-[-50.8,-42.7]				
##	18686	f.cons.price.idx-(93.7,94]	f.cons.conf.idx-[-50.8,-42.7]				
##	18759	f.cons.price.idx-(93.7,94]	f.cons.conf.idx-[-50.8,-42.7]				
##		f.euribor3m	f.nr.employed				
##	5565	f.euribor3m-(1.33,4.86]	f.nr.employed-(5.1e+03,5.19e+03]				
##	9014	f.euribor3m-(4.86,4.96]	f.nr.employed-(5.19e+03,5.23e+03]				
##	11631	f.euribor3m-(4.86,4.96]	f.nr.employed-(5.19e+03,5.23e+03]				

```
## 12643 f.euribor3m-(4.86,4.96] f.nr.employed-(5.19e+03,5.23e+03]
## 12751 f.euribor3m-(4.96,5] f.nr.employed-(5.19e+03,5.23e+03]
## 17524 f.euribor3m-(4.96,5] f.nr.employed-(5.19e+03,5.23e+03]
## 18568 f.euribor3m-(4.96,5] f.nr.employed-(5.19e+03,5.23e+03]
## 18686 f.euribor3m-(4.96,5] f.nr.employed-(5.19e+03,5.23e+03]
## 18759 f.euribor3m-(4.96,5] f.nr.employed-(5.19e+03,5.23e+03]
```

Outliers Multivariants:

No hem aconseguit trobar una configuració del `aq.plot` que ens doni una bona gràfica per a veure les distàncies de Mahalanobis i detectar outliers multivariants.

```
# Consider subset of numeric variables:
```

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

```
##      age      duration      campaign      pdays
## Min.   :18.00   Min.    :  5.0   Min.    : 1.000   Min.    :  0.0
## 1st Qu.:32.00   1st Qu.: 101.0   1st Qu.: 1.000   1st Qu.:999.0
## Median :38.00   Median : 177.0   Median : 2.000   Median :999.0
## Mean   :40.07   Mean    : 250.6   Mean    : 2.535   Mean    :963.7
## 3rd Qu.:47.00   3rd Qu.: 316.0   3rd Qu.: 3.000   3rd Qu.:999.0
## Max.    :87.00   Max.    :1580.0   Max.    :25.000   Max.    :999.0
##                                     NA's    :9
##      previous      emp.var.rate      cons.price.idx      cons.conf.idx
## Min.    :0.0000   Min.    :-3.40000   Min.    :92.20   Min.    : -50.80
## 1st Qu.:0.0000   1st Qu.: -1.80000   1st Qu.:93.08   1st Qu.: -42.70
## Median :0.0000   Median :  1.10000   Median :93.75   Median : -41.80
## Mean    :0.1598   Mean     : 0.06446   Mean     :93.57   Mean     : -40.43
## 3rd Qu.:0.0000   3rd Qu.:  1.40000   3rd Qu.:93.99   3rd Qu.: -36.40
## Max.    :4.0000   Max.     :  1.40000   Max.     :94.77   Max.     : -26.90
##
##      euribor3m      nr.employed
## Min.    :0.635   Min.    :4964
## 1st Qu.:1.334   1st Qu.:5099
## Median :4.857   Median :5191
## Mean    :3.614   Mean     :5166
## 3rd Qu.:4.961   3rd Qu.:5228
## Max.    :5.000   Max.     :5228
##
```

```
vars_con_sub<-vars_con[c(1,2,3,6:10)]
```

```
x<-df[,vars_con_sub]
```

```
#aq.plot(x, delta=qchisq(0.995, df=ncol(x)) )
```

IMPUTATION:

Factors:

De totes les variables discretes que hem analitzat, hem vist que el “marital” status es podria imputar fàcilment amb `imputeMCA()`, ja que els unknown (passats prèviament a NA) corresponen només una petita part de la mostra. El mateix fem amb la variable “loan”. Com hem vist prèviament, els unknowns han estat considerats categoria pròpia en altres variables.

```
res.impf<-imputeMCA(df[,vars_dis], ncp=10)
```

```
# Original:
```

```
summary(df$marital)
```

```
## marital-divorced marital-married marital-single NA's
##                554             3046             1376             10
```

```
summary(df$loan)
```

```
## loan-no loan-yes NA's
##    4080     769    137
```

```
# Amb dades imputades:
```

```
summary(res.impf$completeObs$marital)
```

```
## marital-divorced marital-married marital-single
##                554             3055             1377
```

```
summary(res.impf$completeObs$loan)
```

```
## loan-no loan-yes
##    4217     769
```

```
# Acceptem la imputació:
```

```
df$loan<-res.impf$completeObs[, "marital"]
```

```
df$loan<-res.impf$completeObs[, "loan"]
```

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

```
##                job                marital
## job-admin.      :1231 marital-divorced: 554
## job-blue-collar:1151 marital-married  :3046
## job-technician : 793 marital-single   :1376
## job-services   : 498 NA's              : 10
## job-management : 411
## job-retired    : 204
## (Other)        : 698
##
##                education                default
## education-basic.4y      : 516 default-no      :3954
## education-basic.6y      : 289 default-unknown:1032
## education-basic.9y      : 715
## education-high.school   :1168
## education-professional.course: 599
## education-university.degree :1468
## education-unknown       : 231
##
##                housing                loan                contact
## housing-no      :2212 loan-no :4217 contact-cellular :3122
## housing-unknown: 137 loan-yes: 769 contact-telephone:1864
## housing-yes     :2637
##
##
##
##
##                month                day_of_week                poutcome
## month-may:1741 day_of_week-fri: 922 poutcome-failure : 477
## month-jul: 829 day_of_week-mon:1016 poutcome-nonexistent:4353
## month-aug: 697 day_of_week-thu:1034 poutcome-success : 156
## month-jun: 652 day_of_week-tue:1043
## month-nov: 507 day_of_week-wed: 971
```

```

## month-apr: 310
## (Other) : 250
##      y              f.season              f.age
## y-no :4429  season-spring:2117  f.age-[18,32]:1352
## y-yes: 557  season-summer:2178  f.age-(32,38]:1205
##              season-autumn: 665  f.age-(38,47]:1220
##              season-winter:  26  f.age-(47,87]:1209
##
##
##
##      f.duration              f.campaign
## f.duration-[5,66]      : 633  f.campaign-[0,2] :3392
## f.duration-(101,138]   : 628  f.campaign-(2,5] :1172
## f.duration-(235,316]   : 626  f.campaign-(5,25]: 413
## f.duration-(482,1.58e+03]: 624  NA's          :    9
## f.duration-(177,235]   : 621
## f.duration-(316,482]   : 620
## (Other)                :1234
##      f.pdays              f.previous
## f.pdays-[0,7]: 147  f.previous-never:4353
## f.pdays-(>7) :  30  f.previous-1      : 512
## f.pdays-never:4809  f.previous-(>1) : 121
##
##
##
##
##      f.emp.var.rate              f.cons.price.idx
## f.emp.var.rate-[-3.4,-1.8]:1495  f.cons.price.idx-[92.2,93.1]:1409
## f.emp.var.rate-(-1.8,-0.1]: 591  f.cons.price.idx-(93.1,93.7]:1086
## f.emp.var.rate-(-0.1,1.1] :1002  f.cons.price.idx-(93.7,94]  :1819
## f.emp.var.rate-(1.1,1.4]  :1898  f.cons.price.idx-(94,94.8]  : 672
##
##
##
##      f.cons.conf.idx              f.euribor3m
## f.cons.conf.idx-[-50.8,-42.7]:1856  f.euribor3m-[0.635,1.33]:1254
## f.cons.conf.idx-(-42.7,-41.8]: 967  f.euribor3m-(1.33,4.86] :1466
## f.cons.conf.idx-(-41.8,-36.4]:1231  f.euribor3m-(4.86,4.96] :1130
## f.cons.conf.idx-(-36.4,-26.9]: 932  f.euribor3m-(4.96,5]    :1136
##
##
##
##      f.nr.employed
## f.nr.employed-[4.96e+03,5.1e+03] :1639
## f.nr.employed-(5.1e+03,5.19e+03] :1003
## f.nr.employed-(5.19e+03,5.23e+03]:2344
##
##
##
##

```

Numeric Variables:

La variable numèrica campaign té certs individus que han estat considerats outliers prèviament. Aquí els imputem mitjançant la imputació automàtica imputePCA().

```
res.imp<-imputePCA(df[,vars_con], ncp=8)
```

```
# Original:
```

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

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.     NA's
##      1.000   1.000   2.000   2.535   3.000   25.000         9
```

```
# Amb dades imputades:
```

```
# Acceptem la imputació:
```

```
df$campaign<-res.imp$completeObs[,"campaign"]
```

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

```
##      age      duration      campaign      pdays
##  Min.   :18.00   Min.    :  5.0   Min.    : 1.000   Min.    :  0.0
## 1st Qu.:32.00   1st Qu.: 101.0   1st Qu.: 1.000   1st Qu.:999.0
## Median :38.00   Median : 177.0   Median : 2.000   Median :999.0
## Mean   :40.07   Mean    : 250.6   Mean    : 2.535   Mean    :963.7
## 3rd Qu.:47.00   3rd Qu.: 316.0   3rd Qu.: 3.000   3rd Qu.:999.0
## Max.   :87.00   Max.    :1580.0   Max.    :25.000   Max.    :999.0
## previous emp.var.rate cons.price.idx cons.conf.idx
##  Min.    :0.0000   Min.    :-3.40000   Min.    :92.20   Min.    : -50.80
## 1st Qu.:0.0000   1st Qu.: -1.80000   1st Qu.:93.08   1st Qu.: -42.70
## Median :0.0000   Median :  1.10000   Median :93.75   Median : -41.80
## Mean    :0.1598   Mean     : 0.06446   Mean     :93.57   Mean     : -40.43
## 3rd Qu.:0.0000   3rd Qu.:  1.40000   3rd Qu.:93.99   3rd Qu.: -36.40
## Max.    :4.0000   Max.     :  1.40000   Max.     :94.77   Max.     : -26.90
## euribor3m nr.employed
##  Min.     :0.635   Min.     :4964
## 1st Qu.:1.334   1st Qu.:5099
## Median :4.857   Median :5191
## Mean    :3.614   Mean     :5166
## 3rd Qu.:4.961   3rd Qu.:5228
## Max.    :5.000   Max.     :5228
```

PROFILING:

CONTINUOUS DESCRIPTION - Numeric Target (Duration):

```
pos_duration<-which(names(df)=="duration"); pos_duration
```

```
## [1] 11
```

```
condes(df, num.var=pos_duration, proba = 0.05)
```

```
## $quanti
```

```
##      correlation      p.value
## <NA>             NA          NA
## minutes          1.00000000 0.000000e+00
## pdays          -0.03478274 1.404179e-02
```

```

## euribor3m      -0.03512962 1.311237e-02
## num_outliers  -0.04065979 4.085021e-03
## nr.employed   -0.04831097 6.438109e-04
## campaign      -0.07479201 1.241577e-07
##
## $quali
##              R2      p.value
## f.duration    0.855794028 0.000000e+00
## y             0.164777620 3.759496e-197
## f.campaign    0.006187857 8.807648e-07
## f.cons.conf.idx 0.004067507 1.465565e-04
## f.nr.employed 0.002912867 6.975062e-04
## f.cons.price.idx 0.003246051 1.031905e-03
## month         0.005064462 2.674014e-03
## f.euribor3m   0.002462249 6.473152e-03
## f.season      0.002391458 7.627865e-03
## poutcome     0.001851161 9.887924e-03
## day_of_week   0.002352912 1.942616e-02
## f.pdays      0.001214169 4.846375e-02
## f.emp.var.rate 0.001574759 4.916221e-02
##
## $category
##              Estimate      p.value
## f.duration-(482,1.58e+03] 493.613665 0.000000e+00
## y=yes                    148.441504 3.759496e-197
## f.duration-(316,482]    134.394010 8.476109e-56
## f.campaign-(5,25]       14.794426 2.638343e-06
## season-spring           17.952283 5.877554e-04
## poutcome-success        38.359032 5.480212e-03
## f.campaign-[0,2]        71.765001 7.136472e-03
## f.nr.employed-[4.96e+03,5.1e+03] 9.017147 8.355482e-03
## f.duration-(235,316]    22.169724 9.317648e-03
## f.cons.conf.idx-[-50.8,-42.7] 14.076002 1.238528e-02
## NA                      132.886872 1.491425e-02
## month-may               9.867780 1.599295e-02
## f.cons.price.idx-(93.7,94] 11.621760 2.081111e-02
## f.pdays-[0,7]          16.460640 2.262020e-02
## f.cons.conf.idx-(-41.8,-36.4] 16.349262 2.392080e-02
## month-apr               27.731238 2.403940e-02
## education-high.school    9.358222 4.228302e-02
## day_of_week-wed         13.376659 4.495212e-02
## month-nov              -20.376410 4.421467e-02
## education-university.degree -14.109465 2.294239e-02
## f.emp.var.rate-(1.1,1.4] -10.129703 2.036833e-02
## day_of_week-mon        -15.133836 1.838350e-02
## season-summer           -3.899443 1.752241e-02
## f.pdays-never          -27.755294 1.396985e-02
## f.cons.conf.idx-(-36.4,-26.9] -14.862166 7.024095e-03
## f.cons.conf.idx-(-42.7,-41.8] -15.563098 4.192506e-03
## NA                     -154.540521 4.085021e-03
## f.euribor3m-(4.96,5]    -19.423787 1.079935e-03
## month-aug              -28.383026 6.707022e-04
## f.nr.employed-(5.19e+03,5.23e+03] -16.466612 1.395228e-04
## f.cons.price.idx-(93.1,93.7] -22.699701 8.027710e-05

```

```
## f.duration-(177,235]          -47.149040  5.572506e-08
## f.duration-(138,177]         -94.204089  1.668437e-27
## f.duration-(101,138]         -131.656740  5.328783e-54
## f.duration-(66,101]          -167.038569  1.102835e-85
## f.duration-[5,66]            -210.128961  1.924209e-141
## y-no                         -148.441504  3.759496e-197

#crea un llistat de les quantitatives-> associació global:
#   les variables que dona estan relacionades amb duration.
#   llista les variables que tinguin un p-value per sota del 5%

#crea un llistat de les qualitatives->

##crea un llistat de les categories->
#   #Estimate: unitats que està per sobre la duració global quan el registre pertany a la categoria e
# el p-valor ens diu si l'estimació que f.duration-(484,1.58e+03] sigui 494 per sobre la mitja és per u

tapply(df$duration, df$f.duration, mean) #mitjana de la duració per categoria de la duració

##          f.duration-[5,66]          f.duration-(66,101]
##                40.71090                83.80129
##    f.duration-(101,138]    f.duration-(138,177]
##                119.18312                156.63577
##    f.duration-(177,235]    f.duration-(235,316]
##                203.69082                273.00958
##    f.duration-(316,482] f.duration-(482,1.58e+03]
##                385.23387                744.45353

summary(df$duration) #duració global

##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      5.0   101.0   177.0   250.6   316.0   1580.0

tapply(df$duration, df$y, mean) #mitjana de la duració per categoria de la y

##      y-no      y-yes
## 217.4563 514.3393

oneway.test(df$duration~df$y)

##
## One-way analysis of means (not assuming equal variances)
##
## data:  df$duration and df$y
## F = 447.7, num df = 1.00, denom df = 605.83, p-value < 2.2e-16
```

CATEGORICAL DESCRIPTION - Factor (Y, Final Decision):

```
pos_y<-which(names(df)=="y"); pos_y

## [1] 21

catdes(df, num.var=pos_y, proba = 0.05)

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



```

##                p.value df
## f.duration      2.794524e-159  7
## f.pdays         9.362887e-100  2
## poutcome        3.053387e-95  2
## f.nr.employed   1.703080e-89  2
## f.euribor3m     5.470503e-79  3
## month          1.690776e-65  9
## f.emp.var.rate  7.969229e-62  3
## f.previous      5.590487e-45  2
## f.cons.price.idx 5.572278e-38  3
## f.cons.conf.idx  4.786677e-23  3
## contact        2.110136e-21  1
## job            8.420857e-16 11
## default        9.768051e-13  1
## f.season       1.176664e-10  3
## f.age          7.936723e-09  3
## education      6.361426e-06  6
## marital        1.452705e-04  3
## f.campaign     1.037416e-03  3
##
## Description of each cluster by the categories
## =====
## $`y-no`
##
##                Cla/Mod    Mod/Cla
## f.pdays=f.pdays-never    90.64255 98.4195078
## f.nr.employed=f.nr.employed-(5.19e+03,5.23e+03] 94.70990 50.1241815
## f.previous=f.previous-never    91.01769 89.4558591
## poutcome=poutcome-nonexistent 91.01769 89.4558591
## f.duration=f.duration-[5,66]   99.52607 14.2244299
## f.emp.var.rate=f.emp.var.rate-(1.1,1.4] 94.52055 40.5057575
## contact=contact-telephone      94.31330 39.6929329
## f.duration=f.duration-(66,101] 98.38449 13.7502822
## f.cons.price.idx=f.cons.price.idx-(93.7,94] 94.11765 38.6543238
## f.nr.employed=f.nr.employed-(5.1e+03,5.19e+03] 96.11167 21.7656356
## f.emp.var.rate=f.emp.var.rate-(-0.1,1.1] 96.10778 21.7430571
## f.cons.conf.idx=f.cons.conf.idx-(-42.7,-41.8] 96.07032 20.9753895
## default=default-unknown       95.05814 22.1494694
## month=month-may               93.33716 36.6899977
## f.euribor3m=f.euribor3m-(4.86,4.96] 94.51327 24.1137954
## f.euribor3m=f.euribor3m-(4.96,5]   94.36620 24.2041093
## f.duration=f.duration-(101,138] 96.01911 13.6148115
## job=job-blue-collar           93.74457 24.3621585
## f.euribor3m=f.euribor3m-(1.33,4.86] 92.70123 30.6841273
## f.duration=f.duration-(138,177] 94.79675 13.1632423
## f.cons.price.idx=f.cons.price.idx-(93.1,93.7] 92.90976 22.7816663
## f.age=f.age-(38,47]           92.54098 25.4910815
## f.campaign=f.campaign-(5,25]    94.18886  8.7830210
## education=education-basic.9y    92.72727 14.9695191
## marital=marital-married        89.92121 61.8424023
## month=month-jul               91.31484 17.0918943
## education=education-basic.6y    93.07958  6.0736058
## f.season=season-spring         90.08030 43.0571235
## f.age=f.age-(32,38]            90.62241 24.6556785
## f.season=season-summer        89.89899 44.2086250

```

## f.age=f.age-(47,87]	87.17949	23.7976970
## poutcome=poutcome-failure	85.53459	9.2120117
## education=education-unknown	82.68398	4.3124859
## f.cons.price.idx=f.cons.price.idx-(94,94.8]	85.41667	12.9600361
## f.campaign=f.campaign-[0,2]	87.94222	67.3515466
## f.season=season-winter	65.38462	0.3838338
## month=month-dec	65.38462	0.3838338
## education=education-university.degree	86.51226	28.6746444
## f.emp.var.rate=f.emp.var.rate-(-1.8,-0.1]	84.09475	11.2214947
## f.duration=f.duration-(316,482]	83.87097	11.7407993
## job=job-retired	78.92157	3.6351321
## marital=marital-single	85.68314	26.6200045
## f.age=f.age-[18,32]	85.35503	26.0555430
## f.pdays=f.pdays-(>7)	53.33333	0.3612554
## job=job-student	70.00000	1.5804922
## month=month-apr	78.70968	5.5091443
## f.season=season-autumn	82.25564	12.3504177
## month=month-sep	57.37705	0.7902461
## month=month-mar	57.57576	0.8579815
## f.cons.conf.idx=f.cons.conf.idx-(-36.4,-26.9]	81.22318	17.0918943
## default=default-no	87.20283	77.8505306
## f.previous=f.previous-1	77.53906	8.9636487
## month=month-oct	54.63918	1.1966584
## f.previous=f.previous-(>1)	57.85124	1.5804922
## contact=contact-cellular	85.55413	60.3070671
## f.cons.price.idx=f.cons.price.idx-[92.2,93.1]	80.48261	25.6039738
## f.emp.var.rate=f.emp.var.rate-[-3.4,-1.8]	78.59532	26.5296907
## f.pdays=f.pdays-[0,7]	36.73469	1.2192368
## poutcome=poutcome-success	37.82051	1.3321291
## f.euribor3m=f.euribor3m-[0.635,1.33]	74.16268	20.9979679
## f.nr.employed=f.nr.employed-[4.96e+03,5.1e+03]	75.96095	28.1101829
## f.duration=f.duration-(482,1.58e+03]	59.13462	8.3314518
##	Global	p.value
## f.pdays=f.pdays-never	96.4500602	2.410684e-59
## f.nr.employed=f.nr.employed-(5.19e+03,5.23e+03]	47.0116326	2.158488e-37
## f.previous=f.previous-never	87.3044525	1.438650e-30
## poutcome=poutcome-nonexistent	87.3044525	1.438650e-30
## f.duration=f.duration-[5,66]	12.6955475	1.487124e-30
## f.emp.var.rate=f.emp.var.rate-(1.1,1.4]	38.0665864	1.340920e-25
## contact=contact-telephone	37.3846771	3.447929e-23
## f.duration=f.duration-(66,101]	12.4147613	7.696941e-22
## f.cons.price.idx=f.cons.price.idx-(93.7,94]	36.4821500	7.057265e-21
## f.nr.employed=f.nr.employed-(5.1e+03,5.19e+03]	20.1163257	1.424235e-19
## f.emp.var.rate=f.emp.var.rate-(-0.1,1.1]	20.0962696	1.574618e-19
## f.cons.conf.idx=f.cons.conf.idx-(-42.7,-41.8]	19.3943041	1.401017e-18
## default=default-unknown	20.6979543	1.230324e-14
## month=month-may	34.9177698	1.726364e-14
## f.euribor3m=f.euribor3m-(4.86,4.96]	22.6634577	1.693548e-13
## f.euribor3m=f.euribor3m-(4.96,5]	22.7837946	6.639818e-13
## f.duration=f.duration-(101,138]	12.5952667	1.010774e-11
## job=job-blue-collar	23.0846370	1.884818e-10
## f.euribor3m=f.euribor3m-(1.33,4.86]	29.4023265	6.796806e-09
## f.duration=f.duration-(138,177]	12.3345367	5.342775e-08
## f.cons.price.idx=f.cons.price.idx-(93.1,93.7]	21.7809868	4.701642e-07

## f.age=f.age-(38,47]	24.4685118	9.135370e-07
## f.campaign=f.campaign-(5,25]	8.2831929	1.084374e-04
## education=education-basic.9y	14.3401524	1.876745e-04
## marital=marital-married	61.0910550	2.314946e-03
## month=month-jul	16.6265544	1.093857e-02
## education=education-basic.6y	5.7962294	1.335614e-02
## f.season=season-spring	42.4588849	1.562952e-02
## f.age=f.age-(32,38]	24.1676695	2.153346e-02
## f.season=season-summer	43.6823105	3.428174e-02
## f.age=f.age-(47,87]	24.2478941	3.872210e-02
## poutcome=poutcome-failure	9.5667870	1.986516e-02
## education=education-unknown	4.6329723	4.270710e-03
## f.cons.price.idx=f.cons.price.idx-(94,94.8]	13.4777377	3.445794e-03
## f.campaign=f.campaign-[0,2]	68.0304854	3.359672e-03
## f.season=season-winter	0.5214601	1.657365e-03
## month=month-dec	0.5214601	1.657365e-03
## education=education-university.degree	29.4424388	9.565525e-04
## f.emp.var.rate=f.emp.var.rate-(-1.8,-0.1]	11.8531889	1.984797e-04
## f.duration=f.duration-(316,482]	12.4348175	6.392065e-05
## job=job-retired	4.0914561	2.982842e-05
## marital=marital-single	27.5972724	2.055013e-05
## f.age=f.age-[18,32]	27.1159246	3.567657e-06
## f.pdays=f.pdays-(>7)	0.6016847	1.202754e-06
## job=job-student	2.0056157	2.508620e-07
## month=month-apr	6.2174087	1.047741e-07
## f.season=season-autumn	13.3373446	5.062563e-08
## month=month-sep	1.2234256	3.276634e-10
## month=month-mar	1.3237064	7.597160e-11
## f.cons.conf.idx=f.cons.conf.idx-(-36.4,-26.9]	18.6923385	1.352020e-14
## default=default-no	79.3020457	1.230324e-14
## f.previous=f.previous-1	10.2687525	7.464256e-15
## month=month-oct	1.9454473	8.959508e-18
## f.previous=f.previous-(>1)	2.4267950	1.002106e-18
## contact=contact-cellular	62.6153229	3.447929e-23
## f.cons.price.idx=f.cons.price.idx-[92.2,93.1]	28.2591256	3.335427e-29
## f.emp.var.rate=f.emp.var.rate-[-3.4,-1.8]	29.9839551	1.289177e-46
## f.pdays=f.pdays-[0,7]	2.9482551	6.682675e-54
## poutcome=poutcome-success	3.1287605	2.946325e-55
## f.euribor3m=f.euribor3m-[0.635,1.33]	25.1504212	3.042037e-70
## f.nr.employed=f.nr.employed-[4.96e+03,5.1e+03]	32.8720417	1.759629e-84
## f.duration=f.duration-(482,1.58e+03]	12.5150421	4.894928e-100
##	v.test	
## f.pdays=f.pdays-never	16.245323	
## f.nr.employed=f.nr.employed-(5.19e+03,5.23e+03]	12.778626	
## f.previous=f.previous-never	11.492513	
## poutcome=poutcome-nonexistent	11.492513	
## f.duration=f.duration-[5,66]	11.489650	
## f.emp.var.rate=f.emp.var.rate-(1.1,1.4]	10.458406	
## contact=contact-telephone	9.918824	
## f.duration=f.duration-(66,101]	9.603908	
## f.cons.price.idx=f.cons.price.idx-(93.7,94]	9.372891	
## f.nr.employed=f.nr.employed-(5.1e+03,5.19e+03]	9.050417	
## f.emp.var.rate=f.emp.var.rate-(-0.1,1.1]	9.039450	
## f.cons.conf.idx=f.cons.conf.idx-(-42.7,-41.8]	8.797336	

## default=default-unknown	7.712857
## month=month-may	7.669524
## f.euribor3m=f.euribor3m-(4.86,4.96]	7.370998
## f.euribor3m=f.euribor3m-(4.96,5]	7.186654
## f.duration=f.duration-(101,138]	6.804960
## job=job-blue-collar	6.370444
## f.euribor3m=f.euribor3m-(1.33,4.86]	5.795870
## f.duration=f.duration-(138,177]	5.439509
## f.cons.price.idx=f.cons.price.idx-(93.1,93.7]	5.038105
## f.age=f.age-(38,47]	4.909404
## f.campaign=f.campaign-(5,25]	3.870893
## education=education-basic.9y	3.735055
## marital=marital-married	3.046536
## month=month-jul	2.544655
## education=education-basic.6y	2.474129
## f.season=season-spring	2.417454
## f.age=f.age-(32,38]	2.298498
## f.season=season-summer	2.116742
## f.age=f.age-(47,87]	-2.067128
## poutcome=poutcome-failure	-2.328885
## education=education-unknown	-2.857442
## f.cons.price.idx=f.cons.price.idx-(94,94.8]	-2.924889
## f.campaign=f.campaign-[0,2]	-2.932757
## f.season=season-winter	-3.145618
## month=month-dec	-3.145618
## education=education-university.degree	-3.303003
## f.emp.var.rate=f.emp.var.rate-(-1.8,-0.1]	-3.720944
## f.duration=f.duration-(316,482]	-3.997849
## job=job-retired	-4.174772
## marital=marital-single	-4.258828
## f.age=f.age-[18,32]	-4.635100
## f.pdays=f.pdays-(>7)	-4.855183
## job=job-student	-5.157057
## month=month-apr	-5.318243
## f.season=season-autumn	-5.449099
## month=month-sep	-6.285090
## month=month-mar	-6.508368
## f.cons.conf.idx=f.cons.conf.idx-(-36.4,-26.9]	-7.700814
## default=default-no	-7.712857
## f.previous=f.previous-1	-7.776358
## month=month-oct	-8.586582
## f.previous=f.previous-(>1)	-8.834875
## contact=contact-cellular	-9.918824
## f.cons.price.idx=f.cons.price.idx-[92.2,93.1]	-11.217779
## f.emp.var.rate=f.emp.var.rate-[-3.4,-1.8]	-14.336770
## f.pdays=f.pdays-[0,7]	-15.457815
## poutcome=poutcome-success	-15.657639
## f.euribor3m=f.euribor3m-[0.635,1.33]	-17.718064
## f.nr.employed=f.nr.employed-[4.96e+03,5.1e+03]	-19.475855
## f.duration=f.duration-(482,1.58e+03]	-21.231431
##	
## \$`y=yes`	
##	
## f.duration=f.duration-(482,1.58e+03]	
	Cla/Mod Mod/Cla
	40.8653846 45.7809695

## f.nr.employed=f.nr.employed-[4.96e+03,5.1e+03]	24.0390482	70.7360862
## f.euribor3m=f.euribor3m-[0.635,1.33]	25.8373206	58.1687612
## poutcome=poutcome-success	62.1794872	17.4147217
## f.pdays=f.pdays-[0,7]	63.2653061	16.6965889
## f.emp.var.rate=f.emp.var.rate-[-3.4,-1.8]	21.4046823	57.4506284
## f.cons.price.idx=f.cons.price.idx-[92.2,93.1]	19.5173882	49.3716338
## contact=contact-cellular	14.4458680	80.9694794
## f.previous=f.previous-(>1)	42.1487603	9.1561939
## month=month-oct	45.3608247	7.8994614
## f.previous=f.previous-1	22.4609375	20.6463196
## default=default-no	12.7971674	90.8438061
## f.cons.conf.idx=f.cons.conf.idx-(-36.4,-26.9]	18.7768240	31.4183124
## month=month-mar	42.4242424	5.0269300
## month=month-sep	42.6229508	4.6678636
## f.season=season-autumn	17.7443609	21.1849192
## month=month-apr	21.2903226	11.8491921
## job=job-student	30.0000000	5.3859964
## f.pdays=f.pdays-(>7)	46.6666667	2.5134650
## f.age=f.age-[18,32]	14.6449704	35.5475763
## marital=marital-single	14.3168605	35.3680431
## job=job-retired	21.0784314	7.7199282
## f.duration=f.duration-(316,482]	16.1290323	17.9533214
## f.emp.var.rate=f.emp.var.rate-(-1.8,-0.1]	15.9052453	16.8761221
## education=education-university.degree	13.4877384	35.5475763
## f.season=season-winter	34.6153846	1.6157989
## month=month-dec	34.6153846	1.6157989
## f.campaign=f.campaign-[0,2]	12.0577830	73.4290844
## f.cons.price.idx=f.cons.price.idx-(94,94.8]	14.5833333	17.5942549
## education=education-unknown	17.3160173	7.1813285
## poutcome=poutcome-failure	14.4654088	12.3877917
## f.age=f.age-(47,87]	12.8205128	27.8276481
## f.season=season-summer	10.1010101	39.4973070
## f.age=f.age-(32,38]	9.3775934	20.2872531
## f.season=season-spring	9.9196977	37.7019749
## education=education-basic.6y	6.9204152	3.5906643
## month=month-jul	8.6851628	12.9263914
## marital=marital-married	10.0787919	55.1166966
## education=education-basic.9y	7.2727273	9.3357271
## f.campaign=f.campaign-(5,25]	5.8111380	4.3087971
## f.age=f.age-(38,47]	7.4590164	16.3375224
## f.cons.price.idx=f.cons.price.idx-(93.1,93.7]	7.0902394	13.8240575
## f.duration=f.duration-(138,177]	5.2032520	5.7450628
## f.euribor3m=f.euribor3m-(1.33,4.86]	7.2987722	19.2100539
## job=job-blue-collar	6.2554301	12.9263914
## f.duration=f.duration-(101,138]	3.9808917	4.4883303
## f.euribor3m=f.euribor3m-(4.96,5]	5.6338028	11.4901257
## f.euribor3m=f.euribor3m-(4.86,4.96]	5.4867257	11.1310592
## month=month-may	6.6628374	20.8258528
## default=default-unknown	4.9418605	9.1561939
## f.cons.conf.idx=f.cons.conf.idx-(-42.7,-41.8]	3.9296794	6.8222621
## f.emp.var.rate=f.emp.var.rate-(-0.1,1.1]	3.8922156	7.0017953
## f.nr.employed=f.nr.employed-(5.1e+03,5.19e+03]	3.8883350	7.0017953
## f.cons.price.idx=f.cons.price.idx-(93.7,94]	5.8823529	19.2100539
## f.duration=f.duration-(66,101]	1.6155089	1.7953321

## contact=contact-telephone	5.6866953	19.0305206
## f.emp.var.rate=f.emp.var.rate-(1.1,1.4]	5.4794521	18.6714542
## f.duration=f.duration-[5,66]	0.4739336	0.5385996
## f.previous=f.previous-never	8.9823110	70.1974865
## poutcome=poutcome-nonexistent	8.9823110	70.1974865
## f.nr.employed=f.nr.employed-(5.19e+03,5.23e+03]	5.2901024	22.2621185
## f.pdays=f.pdays-never	9.3574548	80.7899461
##	Global	p.value
## f.duration=f.duration-(482,1.58e+03]	12.5150421	4.894928e-100
## f.nr.employed=f.nr.employed-[4.96e+03,5.1e+03]	32.8720417	1.759629e-84
## f.euribor3m=f.euribor3m-[0.635,1.33]	25.1504212	3.042037e-70
## poutcome=poutcome-success	3.1287605	2.946325e-55
## f.pdays=f.pdays-[0,7]	2.9482551	6.682675e-54
## f.emp.var.rate=f.emp.var.rate-[-3.4,-1.8]	29.9839551	1.289177e-46
## f.cons.price.idx=f.cons.price.idx-[92.2,93.1]	28.2591256	3.335427e-29
## contact=contact-cellular	62.6153229	3.447929e-23
## f.previous=f.previous-(>1)	2.4267950	1.002106e-18
## month=month-oct	1.9454473	8.959508e-18
## f.previous=f.previous-1	10.2687525	7.464256e-15
## default=default-no	79.3020457	1.230324e-14
## f.cons.conf.idx=f.cons.conf.idx-(-36.4,-26.9]	18.6923385	1.352020e-14
## month=month-mar	1.3237064	7.597160e-11
## month=month-sep	1.2234256	3.276634e-10
## f.season=season-autumn	13.3373446	5.062563e-08
## month=month-apr	6.2174087	1.047741e-07
## job=job-student	2.0056157	2.508620e-07
## f.pdays=f.pdays-(>7)	0.6016847	1.202754e-06
## f.age=f.age-[18,32]	27.1159246	3.567657e-06
## marital=marital-single	27.5972724	2.055013e-05
## job=job-retired	4.0914561	2.982842e-05
## f.duration=f.duration-(316,482]	12.4348175	6.392065e-05
## f.emp.var.rate=f.emp.var.rate-(-1.8,-0.1]	11.8531889	1.984797e-04
## education=education-university.degree	29.4424388	9.565525e-04
## f.season=season-winter	0.5214601	1.657365e-03
## month=month-dec	0.5214601	1.657365e-03
## f.campaign=f.campaign-[0,2]	68.0304854	3.359672e-03
## f.cons.price.idx=f.cons.price.idx-(94,94.8]	13.4777377	3.445794e-03
## education=education-unknown	4.6329723	4.270710e-03
## poutcome=poutcome-failure	9.5667870	1.986516e-02
## f.age=f.age-(47,87]	24.2478941	3.872210e-02
## f.season=season-summer	43.6823105	3.428174e-02
## f.age=f.age-(32,38]	24.1676695	2.153346e-02
## f.season=season-spring	42.4588849	1.562952e-02
## education=education-basic.6y	5.7962294	1.335614e-02
## month=month-jul	16.6265544	1.093857e-02
## marital=marital-married	61.0910550	2.314946e-03
## education=education-basic.9y	14.3401524	1.876745e-04
## f.campaign=f.campaign-(5,25]	8.2831929	1.084374e-04
## f.age=f.age-(38,47]	24.4685118	9.135370e-07
## f.cons.price.idx=f.cons.price.idx-(93.1,93.7]	21.7809868	4.701642e-07
## f.duration=f.duration-(138,177]	12.3345367	5.342775e-08
## f.euribor3m=f.euribor3m-(1.33,4.86]	29.4023265	6.796806e-09
## job=job-blue-collar	23.0846370	1.884818e-10
## f.duration=f.duration-(101,138]	12.5952667	1.010774e-11

## f.euribor3m=f.euribor3m-(4.96,5]	22.7837946	6.639818e-13
## f.euribor3m=f.euribor3m-(4.86,4.96]	22.6634577	1.693548e-13
## month=month-may	34.9177698	1.726364e-14
## default=default-unknown	20.6979543	1.230324e-14
## f.cons.conf.idx=f.cons.conf.idx-(-42.7,-41.8]	19.3943041	1.401017e-18
## f.emp.var.rate=f.emp.var.rate-(-0.1,1.1]	20.0962696	1.574618e-19
## f.nr.employed=f.nr.employed-(5.1e+03,5.19e+03]	20.1163257	1.424235e-19
## f.cons.price.idx=f.cons.price.idx-(93.7,94]	36.4821500	7.057265e-21
## f.duration=f.duration-(66,101]	12.4147613	7.696941e-22
## contact=contact-telephone	37.3846771	3.447929e-23
## f.emp.var.rate=f.emp.var.rate-(1.1,1.4]	38.0665864	1.340920e-25
## f.duration=f.duration-[5,66]	12.6955475	1.487124e-30
## f.previous=f.previous-never	87.3044525	1.438650e-30
## poutcome=poutcome-nonexistent	87.3044525	1.438650e-30
## f.nr.employed=f.nr.employed-(5.19e+03,5.23e+03]	47.0116326	2.158488e-37
## f.pdays=f.pdays-never	96.4500602	2.410684e-59
##	v.test	
## f.duration=f.duration-(482,1.58e+03]	21.231431	
## f.nr.employed=f.nr.employed-[4.96e+03,5.1e+03]	19.475855	
## f.euribor3m=f.euribor3m-[0.635,1.33]	17.718064	
## poutcome=poutcome-success	15.657639	
## f.pdays=f.pdays-[0,7]	15.457815	
## f.emp.var.rate=f.emp.var.rate-[-3.4,-1.8]	14.336770	
## f.cons.price.idx=f.cons.price.idx-[92.2,93.1]	11.217779	
## contact=contact-cellular	9.918824	
## f.previous=f.previous-(>1)	8.834875	
## month=month-oct	8.586582	
## f.previous=f.previous-1	7.776358	
## default=default-no	7.712857	
## f.cons.conf.idx=f.cons.conf.idx-(-36.4,-26.9]	7.700814	
## month=month-mar	6.508368	
## month=month-sep	6.285090	
## f.season=season-autumn	5.449099	
## month=month-apr	5.318243	
## job=job-student	5.157057	
## f.pdays=f.pdays-(>7)	4.855183	
## f.age=f.age-[18,32]	4.635100	
## marital=marital-single	4.258828	
## job=job-retired	4.174772	
## f.duration=f.duration-(316,482]	3.997849	
## f.emp.var.rate=f.emp.var.rate-(-1.8,-0.1]	3.720944	
## education=education-university.degree	3.303003	
## f.season=season-winter	3.145618	
## month=month-dec	3.145618	
## f.campaign=f.campaign-[0,2]	2.932757	
## f.cons.price.idx=f.cons.price.idx-(94,94.8]	2.924889	
## education=education-unknown	2.857442	
## poutcome=poutcome-failure	2.328885	
## f.age=f.age-(47,87]	2.067128	
## f.season=season-summer	-2.116742	
## f.age=f.age-(32,38]	-2.298498	
## f.season=season-spring	-2.417454	
## education=education-basic.6y	-2.474129	
## month=month-jul	-2.544655	

```

## marital=marital-married -3.046536
## education=education-basic.9y -3.735055
## f.campaign=f.campaign-(5,25] -3.870893
## f.age=f.age-(38,47] -4.909404
## f.cons.price.idx=f.cons.price.idx-(93.1,93.7] -5.038105
## f.duration=f.duration-(138,177] -5.439509
## f.euribor3m=f.euribor3m-(1.33,4.86] -5.795870
## job=job-blue-collar -6.370444
## f.duration=f.duration-(101,138] -6.804960
## f.euribor3m=f.euribor3m-(4.96,5] -7.186654
## f.euribor3m=f.euribor3m-(4.86,4.96] -7.370998
## month=month-may -7.669524
## default=default-unknown -7.712857
## f.cons.conf.idx=f.cons.conf.idx-(-42.7,-41.8] -8.797336
## f.emp.var.rate=f.emp.var.rate-(-0.1,1.1] -9.039450
## f.nr.employed=f.nr.employed-(5.1e+03,5.19e+03] -9.050417
## f.cons.price.idx=f.cons.price.idx-(93.7,94] -9.372891
## f.duration=f.duration-(66,101] -9.603908
## contact=contact-telephone -9.918824
## f.emp.var.rate=f.emp.var.rate-(1.1,1.4] -10.458406
## f.duration=f.duration-[5,66] -11.489650
## f.previous=f.previous-never -11.492513
## poutcome=poutcome-nonexistent -11.492513
## f.nr.employed=f.nr.employed-(5.19e+03,5.23e+03] -12.778626
## f.pdays=f.pdays-never -16.245323
##
##
## Link between the cluster variable and the quantitative variables
## =====
##
##          Eta2      P-value
## duration      0.164777620 3.759496e-197
## minutes       0.164777620 3.759496e-197
## nr.employed   0.121012601 8.238443e-142
## pdays         0.090100788 2.433135e-104
## euribor3m     0.090010720 3.115343e-104
## emp.var.rate  0.085417483 8.992557e-99
## previous      0.042523921 5.101307e-49
## cons.price.idx 0.018386453 6.794885e-22
## cons.conf.idx 0.004669195 1.369222e-06
## campaign      0.004489049 2.189052e-06
## <NA>          NA          NA
##
## Description of each cluster by quantitative variables
## =====
## $`y-no`
##
##          v.test Mean in category Overall mean sd in category
## nr.employed 24.561104 5175.3298261 5166.47621340 64.3842715
## pdays       21.193217 983.3030029 963.73706378 123.8692868
## euribor3m   21.182621 3.7992890 3.61448034 1.6425449
## emp.var.rate 20.635071 0.2287424 0.06446049 1.4946001
## cons.price.idx 9.573739 93.6004884 93.57245006 0.5619158
## campaign     4.730529 2.5940750 2.53512998 2.5654605
## cons.conf.idx -4.824514 -40.5398961 -40.42591256 4.4454152
## previous    -14.559593 0.1255362 0.15984757 0.4004406

```



```
## duration      -28.660364      217.4563107  250.62194144    191.6321071
## minutes       -28.660364        3.6242718    4.17703236      3.1938685
##               Overall sd      p.value
## nr.employed   71.7679377 3.291367e-133
## pdays        183.8068310 1.102990e-99
## euribor3m     1.7370025 1.381286e-99
## emp.var.rate  1.5850448 1.329502e-94
## cons.price.idx 0.5830800 1.031083e-21
## campaign      2.4808187 2.239350e-06
## cons.conf.idx  4.7037753 1.403451e-06
## previous      0.4691873 5.075919e-48
## duration      230.3904064 1.190744e-180
## minutes       3.8398401 1.190744e-180
##
## `$y=yes`
##               v.test Mean in category Overall mean sd in category
## minutes       28.660364      8.572322    4.17703236    5.3967235
## duration      28.660364    514.339318  250.62194144  323.8034093
## previous      14.559593      0.432675    0.15984757    0.7821222
## cons.conf.idx  4.824514    -39.519569  -40.42591256  6.3242738
## campaign      -4.730529      2.066427    2.53512998    1.5845655
## cons.price.idx -9.573739     93.349503   93.57245006   0.6904449
## emp.var.rate  -20.635071    -1.241831    0.06446049    1.6751620
## euribor3m     -21.182621      2.144969    3.61448034    1.7676126
## pdays        -21.193217     808.157989  963.73706378  391.3731388
## nr.employed   -24.561104    5096.076481 5166.47621340  86.9764988
##               Overall sd      p.value
## minutes       3.8398401 1.190744e-180
## duration      230.3904064 1.190744e-180
## previous      0.4691873 5.075919e-48
## cons.conf.idx  4.7037753 1.403451e-06
## campaign      2.4808187 2.239350e-06
## cons.price.idx 0.5830800 1.031083e-21
## emp.var.rate  1.5850448 1.329502e-94
## euribor3m     1.7370025 1.381286e-99
## pdays        183.8068310 1.102990e-99
## nr.employed   71.7679377 3.291367e-133
```

```
# `$y=yes`
#               Cla/Mod   Mod/Cla Global      p.value      v.test
# f.duration=f.duration-(483,1.58e+03] 40.8064516 44.7787611 12.40 2.180784e-97 20.942837
# poutcome=poutcome=success          62.2641509 17.5221239  3.18 5.331532e-56 15.766007
# f.pdays=f.pdays-[0,6]             62.2222222 14.8672566  2.70 2.653287e-47 14.446089
# contact=contact-cellular            14.5686901 80.7079646 62.60 6.688527e-23  9.852462
```

```
# df: degrees of freedom, #categories - 1
```

```
# Dins el cluster que s'ha acceptat el producte financer, la "durada(483 a 1580]" és el 44,778% dels va
```

```
# Es donen per ordre d'importància (p-value), per cal interpretar les diferències a ull i veure quines
```